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Determinants of Per Capita State-Level Health Expenditures in the United States: A Spatial Panel Analysis

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Abstract. The United States ranks third in 2013 among the nations of the world in per capita health care expenditures. However, there is wide variation in health care spending across states. This paper explores factors that influence the per capita outlays in health care across the United States between 2000 and 2009. A Spatial Durbin Panel Model is used to account for the possibility that the health care expenditures of any particular state may influence health care expenditure patterns in neighboring states in the same way. Results indicate that, apart from the presence of positive spatial dependence in health care spending across the states, variables such as a state's gross domestic product (GDP), Medicaid expenditures, proportion of the population that is elderly, number of active physicians per 100,000 people, and poverty rate positively influence per capita state-level health expenditures. GDP (by state), proportion of population above age 65, and poverty rate negatively affect the neighboring states' per capita health expenditures. Furthermore, the number of hospital beds per 1,000 people and number of hospitals per 1,000 people positively influence bordering states' per capita health expenses.

1. Introduction

In 2010, the United States spent 18% of its GDP ($2.6 trillion) on health care (Bipartisan Policy Center, 2012). This was a significantly higher proportion than other major industrialized nations spent in 2010, including the United Kingdom (9.6% of its GDP), Germany (11.6%), and Japan (9.5%) (Bipartisan Policy Center, 2012). In 1960, the United States spent 5% of its GDP on health care, which grew to 16% in 2004 and then to 17% in 2009 (Health at a Glance, OECD Indicators, 2011). Thus, it can be seen that within the last 50 years, the total United States health care expenditures as a share of GDP has more than tripled. Also, health care expenditures have grown 2% faster than the U.S. GDP over the past 22 years (U.S. Healthcare Cost, Report on Healthcare Spending, 2013). Furthermore, the United States spends twice as much per capita on health care expenditures as any other advanced nation in the world (Rugy, 2013). Although this growth has declined in recent years (Roehrig et al., 2012), it has been predicted that health spending will reach 19.6% of the GDP by 2016 (Poisal et al., 2007) and 20% of the GDP by 2021 (Bipartisan Policy Center, 2012). Hall and Jones (2007) predicted that spending on health care is likely to increase to over 30% of GDP by the year 2050.

Despite ranking at the top of the list in spending, the United States health care system ranks thirty-seventh in the world (World Health Report, 2000). Among the OECD countries studied in the National Vital Statistics Report by MacDorman et al. (2014), the United States has the highest prevalence of infant mortality. It lacks in many measures of health care outcomes and quality (Bipartisan Policy Center, 2012). Therefore, it is evident that improvement in the quality of health care has not paralleled the growth exhibited in health care expenses. As stated in the report by the Bipartisan Policy Center (2012, p. 4), "This rapid growth in health expenditures is creating an unsustainable burden on America's economy, with far-reaching consequences." Due to the presence of such problems and mismatch with spending, it is necessary to "carefully examine the structural aspects of the health care system across the states that contribute to inefficiency and wasteful spending" (Bipartisan Policy Center, 2012, p. 4).

To understand the factors that result in health expenditure variations across the United States, it is important to frame health policies in ways that not only limit cost growth but also prevent decline in the quality of health care (Martin et al., 2002). It will help to control the factors that led to such growth in the cost structure of the health sector and reduce the waste of the economy's output by reallocating it to other sectors. To explain these variations in health care spending, it is necessary to conduct a spatial dependence model analysis. This is because changes in the health costs of one state not affect only the state itself but also neighboring states. As stated by Cebula and Toma (2008), if a state puts efforts toward providing beneficial health outcomes, it might lead to an increase in the cost of living and hence discourage relocating to that particular state. Cebula and Alexander (2006) further showed that a state's cost of living negatively influences its net immigration rate. Therefore, knowing the causes of variation in health spending is important because the variation in health care spending influences economic productivity, the policy initiatives taken by the government, and the migration patterns of people across the United States.

Variations can be seen in health spending across the 48 states of the continental United States and the District of Columbia for the year 2009, as reported in Table 1. The five states with the highest per capita health expenditures are New York, Delaware, Maine, Connecticut, and Massachusetts. The bottom five states were Utah, Arizona, Georgia, Idaho, and Nevada. It is necessary to obtain an explanation of the variation in spending across states. A study by Wang (2009) showed that variables such as gross state product, proportion of the population that is over the age of 65, degree of urbanization, and number of hospital beds play a vital role in determining the real per capita health expenditures for a state. In his study, Wang considered most of the social, economic, demographic, and institutional factors to determine per capita health expenditures and formulated policies to control the increasing growth in health expenses.

Table 1. Per capita health care expenditure statistics for the top five and the bottom five states of the U.S. for the year 2009.

States	Per capita Health care Expenditure ($) in 2009
Utah	5031
Arizona	5434
Georgia	5467
Idaho	5658
Nevada	5735
New York	8341
Delaware	8480
Maine	8521
Connecticut	8654
Massachusetts	9278

Source: Kaiser Family Foundation, State Health Facts (2013).

The current study is a *de facto* robustness check of Wang's analysis. In contrast to Wang's analysis, the present study uses a longer time period (2000 to 2009) and a different measure of analysis that controls for time and the effect of spatial dependence. The paper also eliminates relative price for health expenditures (as it was statistically insignificant) and population living in urban areas (as data are not available for all years) as potential explanatory variables. Finally, the paper includes three new explanatory variables: poverty rate, total number of hospitals, and unemployment rate. Wang used cross-sectional and pooled regression analyses for his study; however, pooling the observations resulted in biased model estimates and incorrect specification of the model. Wang did not consider the indirect impact of the health expenditure variation or the factors influencing the variation in neighboring states. Thus, a spatial panel approach provides a better estimation model, as it considers time and both direct and indirect effects of all of the variables on the health costs of the state and its neighbors.

Regarding the increase or decrease in the amount of health sector spending in the continental United States (including Washington D.C.) over a period of ten years (2000 to 2009), this paper addresses variables such as the GDP of a state, percentage of residents uninsured, hospitals and hospital beds relative to population, active physicians relative to population, percentage of the population in a health maintenance organization, poverty rate, percentages of the population below age 17 and above age 65, unemployment rate, and Medicaid expenditures. The paper also answers the following question: Is there any spatial dependence among the states and, if so, does it cause changes in a state's health costs? This paper expands on previous findings by analyzing the direct and indirect impacts of these variables on health spending across the United States. The remainder of this paper is organized as follows: Section 2 provides the literature review, Section 3 gives the description of the data and further review of relevant literature, Section 4 presents the model/framework, Section 5 provides estimation methods, Section 6 offers a detailed analysis of the results, and Section 7 presents conclusions.

2. Literature review

Several studies have focused on the factors that cause variations in health spending. Harmston (1981) concluded from his primary survey analysis that expenses pertaining to the age of the community members generate 43.5% of the income of the health services industry. Therefore, it can be inferred that the elderly boost health expenditures. Murthy and Ukpolo (1994) used time-series data for the period of 1960–87 and found that population, number of practicing physicians, and public financing of health care are important determinants of health care cost variation across the states.

Bopp and Cebula (2008) examined the factors that determined and differentiated states with higher than average hospital expenses from the states with lower than average hospital expenses for the years 1999 and 2003. They used panel regression analysis considering economic status, insurance coverage, health risk factors, and demographic factors as their explanatory variables. Their results showed that poverty rates did not significantly influence the increase in hospital costs, but insurance coverage, age of the population, and number of patient admissions did.

Cuckler et al. (2011) provided a detailed study on state-wise variation in health spending. According to this study, the ten states with the highest per capita health spending (13% to 36% higher than the national average) in the year 2009 had a higher density of elderly people and the highest per capita incomes. The ten states with the lowest per capita health spending (8% to 26% below the national average) had younger populations, lower per capita incomes, and higher rates of uninsured people.

Adhikari and Fannin (2013) used a modified community policy analysis model as an approach to study the local government expenditure value for Louisiana. The model used 2007 data. This study reported that health and welfare expenditures were greatly influenced by assessed property value, income, and the lagged value of health and welfare expenses.

Manski (1993) recommended three methods to explain the interaction among local governments/states that supports the concept of spatial dependence. The first method was expenditure spillover, which suggests that the gains from public health expenditures in one region enter into the welfare function of adjacent areas (Lundberg, 2014). For example, if there is an increase in the number of hospital beds in county A, and the beds in the neighboring state's county B are all occupied, patients from county B can be admitted in the new hospital beds in county A. Hence, the health spending in county A is not only benefiting citizens of county A, but also citizens of neighboring counties.

The second method suggested was the yardstick competition or exogenous effect (Manski, 1993; Lundberg, 2014). This method states that, because voters do not have proper information about the public services of their own state, they use information regarding public expenditures of neighboring states to judge the performance of their own government (Lundberg, 2014). The third method, known as the fiscal competition or the correlated effect, suggests that fiscal policies of one state or local government will affect the budget of its neighboring local or state governments in a similar manner (Lundberg, 2014).

Compared to the earlier experiments, a much smaller body of literature that is closely related to this paper has incorporated spatial dependence when analyzing relationships between health expenditures and their influencing factors. Costa-Font and Pons-Novell (2007) described potential expenditure spillovers across regions in Spain, as well as the influence of the political ideology of regional incumbents and institutional factors on public health expenditures. They found that income, number of doctors and hospital beds, and other institutional variables were the major factors influencing public health expenditures.

Bech and Lauridsen (2009) concluded that, as a public expenditure, health care spending will have a similar spatial pattern effect as that of local taxation. Per capita general practitioner expenditures of Danish municipalities were considered as the dependent variables for the period 1997–2004. Their results showed the "presence of substantial heterogeneity and dependence across time, as well as the presence of a significant spatial spillover effect" (p. 243). The spatial coefficient was strongly significant, suggesting that there was an indirect effect on expenditures of non-observable variables that are geographically concentrated. Therefore, according to their study, closely located municipalities had similar health policies and higher general practitioner utilization than distant ones.

Previous research on determinants of health expenditures in the United States has examined changes in only a few of the social or economic variables or only focused on comparative analysis, cross-sectional analysis, or panel analysis. Hence, previous literature has not only failed to address all of the aspects of health expenditure determinants, but also has provided biased or inefficient estimates. No research has analyzed the United States' state-level health expenditure data to see if there is any spatial dependence in a time period of ten years (2000 to 2009) using spatial panel data models. In addition to overcoming these limitations, this study calculates the direct and indirect impacts of the explanatory variables on the state's own health care expenditures and on the neighboring states' health care expenditures. Issues with previous research could pertain to omitted variables, which would generate improper inferences regarding health expenditure determinants.

3. Data

The data used in this paper come from three sources. The majority of the health care data originate from the State Health Facts website, which is produced annually by the Henry J. Kaiser Family Foundation. This nonprofit private operating foundation provides state- and national-level data on the major health care issues faced by people in the United States. The state-level variables obtained from this data source are per capita health expenditures[1], number of beds in community hospitals per thousand people, and total number of community hospitals.

As stated by The Kaiser Family Foundation's State Health Facts report and the American Hospital Association, community hospitals are the nonfederal, short-term general and specialty hospitals whose facilities and services are available to the public. Eighty-five percent of hospitals are considered community hospitals, and "Federal hospitals, long-term care hospitals, psychiatric hospitals, institutions for the mentally retarded, and alcoholism and other chemical dependency hospitals" are not included in this category. Although it is a source for very good data on health care, the State Health Facts report unfortunately does not contain data on other variables related to the demand for health care.

The second data source is the United States Census Bureau. Data obtained from this source include each state's GDP, percentage of population below age 17 and above age 65, and number of active physicians per 100,000 civilians. Data have also been obtained for poverty rates, percentage of uninsured people, Medicaid expenditures, percentage of the population enrolled in health maintenance organizations (HMOs), and unemployment rates. All variables from the Kaiser Family State Health Facts report and the census report are from the years 2000 to 2009[2] for the 48 continental states and Washington, D.C. Alaska and Hawaii are not included in the present analysis because states with no connecting states (neighbors) are inappropriate for the spatial dependence model.

The dependent variable of interest is real per capita health care expenditure data (logarithmic value). It is the measure of all private and public sources of spending on health services and health products by state of residence. The nominal per capita health care expenditure, GDP, and Medicaid expenditures for each year are converted into real dollars (year 2009 is considered the base year) using the consumer price index for medical care for each state. The state-specific consumer price index is calculated by computing an average for the price index data of the cities specified for each state from the United States Census Bureau data. When considering the states for which the price index is not specified, the United States CPI of that year is applied.

The independent variables of interest are the other variables mentioned above along with real GDP and real Medicaid expenditures. Most of the variables considered in the analysis have a significant impact on health expenditures, as shown in the previous references. With health care being a normal good, a rise in the GDP that leads to a rise in the living standard will lead to an overall increase in both

[1] It comprises spending on all private and public health care services and products.

[2] The years considered for the analysis are 2000 to 2009. This time period is considered because this is the most recent period for which data are available for all of the variables considered for the analysis. Increasing the number of years would lead to dropping explanatory variables, which may cause a decrease in the model's efficiency.

public and private health care spending (Firat & Kien, 2013; Hitris & Posnett, 1992; McCoskey and Thomas, 1998; Wang, 2009). The increase in supply-side variables, such as the total number of hospital beds or active physicians (Martin et al., 2002; Murthy and Ukpolo, 1994; Wang, 2009), increases the health costs for the state.

The rise in health spending due to an increase in the number of hospital beds can be caused by two other factors. First, if the physicians' and hospital workers' incomes depend upon the amount of services they provide, patients in regions and states with more physicians and hospital beds will witness more visits to physicians and more hospitalizations (Fisher et al., 2004). Second, if a region or state has more hospital beds, more Medicare and Medicaid reimbursements will be provided for hospital care, as these reimbursements are made based on the number of hospital beds. Thus, if the state provides more Medicaid reimbursements, there will be more real per capita health expenditures for the state (Martin et al., 2002).

An increase in the proportion of the population that is uninsured may lead to a decrease in a state's medical costs, as this population would not access health care due to high costs (Cuckler et al., 2011; Martin et al., 2002). Health costs rise with age, so an increase in a state's aged population increases health spending (Di Matteo and Di Matteo, 1998; Di Matteo, 2005; Mehrotra et al., 2001; Murthy and Ukpolo, 1994) while the healthier section, the population below age 17, decreases costs (Cuckler et al., 2011). It is anticipated that increased enrollment in HMOs will positively affect health expenditures (Wang, 2009). Increased poverty rates may decrease per capita expenditures, because people may decrease their health expenditures due to their inability to pay. Alternatively, increased poverty rates might lead to increased health costs, as more poor people may be admitted to costly emergency rooms and intensive care units, as they would be susceptible to severe health conditions.

Additionally, an increase in the total number of hospitals may result in a decline in the per capita spending. This is because the number of nonprofit and state hospitals has steadily declined over the years while the number of for-profit hospitals has increased (State Health Facts). Therefore, the rise in the total number of hospitals in recent years has only been due to the rise in the number of private hospitals, which offer services at a higher cost. As a result, the average population would not be able to afford those expenses, leading to reduced access to health services and thereby causing a decline in the per capita health spending.

The effect of the unemployment rate on health care expenditures is ambiguous. An unemployed person cannot afford high health costs, which in turn might lead to a reduction in per capita health expenditures (The White House, 2013). On the other hand, an increase in the number of unemployed people might lead to an increased use of emergency rooms and intensive care beds, thus increasing the total health expenditures of the state.

A complete list of the dependent and independent variables used for the analysis and their descriptive statistics are summarized in Table 2. Eleven independent variables are used in the logarithmic or percentage form for the analysis. The dependent variable is the logarithmic value of real per capita health expenditures. The statistical values indicate that some of the explanatory variables have a wide range of variation across states. The poverty rate ranges from 5.3% to 21.9%, whereas the unemployment rate reaches a maximum of 13.3% for Michigan. The uninsured rate also covers a large range, from 4.4% to 26.1%, with Florida, Georgia, Nevada, and Texas falling in the higher bracket.

Table 2. Descriptive statistics.

Variable	Mean	Std. Deviation	Minimum	Maximum
Log of real per capita health expenditures	8.788	0.149	8.363	9.244
Percentage in Health Maintenance Orgs	19.878	12.142	0.100	64.100
Log of real Medicaid expenditures	21.983	1.019	19.550	24.527
Active physicians per 100,000 residents	265.344	95.886	154.000	852.000
Hospital beds per 1,000 people	3.0416	1.008	1.700	6.200
Log of real Gross Domestic Product	25.884	1.027	23.924	28.314
Poverty rate	12.824	3.193	5.300	21.920
Percentage of population older than age 65	12.776	1.537	8.500	17.600
Percentage of population below age 17	24.591	2.099	18.93	43.757
Uninsured rate	13.553	3.901	4.400	26.100
Number of hospitals per 1,000 people	0.0231	0.014	0.0063	0.0670
Unemployment Rate	5.189	1.665	2.300	13.300

4. An eclectic model

To isolate the impact of each independent variable on the state health expenditure value, the basic regression model is specified as:

$$Log\ Health\ care\ expenditure_{it} = a + \beta_0\ HMO_{it} + \beta_1\ Log\ Medicaid_{it} + \beta_2\ Active\ Physicians_{it} + \beta_3\ Hospital\ Beds_{it} + \beta_4\ Log\ GDP_{it} + \beta_5\ Poverty\ rate_{it} + \beta_6\ Percentage\ of\ population\ above\ age\ 65_{it} + \beta_7\ Percentage\ of\ population\ below\ age\ 17_{it} + \beta_8\ Uninsured\ rate_{it} + \beta_9\ number\ of\ hospitals_{it} + \beta_{10}\ Unemployment\ rate_{it} + \mu_i + m_t + \varepsilon_{it} \quad (1)$$

The dependent and independent variables are defined in logarithmic or percentage format, with μ_i representing the effect of the individual states, m_t signifying the time period effect (2000 to 2009), and ε_{it} being the error term. Considering the basic model and using ordinary least square estimation techniques, the analysis for state-level data would lead to biased estimates. Rather, spatial econometric models should be used for state- or region-level data analysis, as these models include the "peculiarities caused by space in the statistical analysis of regional science models" (Anselin, 1988). LeSage and Pace (2009) also indicated that failing to consider spatial dependence while analyzing the effects of changes in local, regional, or state characteristics may lead to biased coefficients.

Thus, as specified by Elhorst (2012), Anselin (2008), and LeSage and Pace (2009), the three spatial panel data models that have been considered for the state-level data analysis are (i) the spatial auto regressive model (SAR), a model that has spatial dependence with a dependent variable; (ii) the spatial error model (SEM), a model that has spatial dependence with an error term; and (iii) the spatial Durbin model (SDM), a model that has spatial spillovers in the dependent variable through a spatially lagged dependent variable and spatially lagged independent variables.

Accordingly, three spatial panel data models (Elhorst, 2012) can be expressed as follows:

$$\text{SAR: } Y_{it} = \lambda \sum_{j=1}^{N} W_{ij} Y_{jt} + X_{it}\beta + \mu_i + \delta_t + \varepsilon_{it} \quad (2)$$

$$\text{SEM: } Y_{it} = X_{it}\beta + \mu_i + \delta_t + \phi_{it} \quad (3)$$

$$\text{where } \phi_{it} = \eta \sum_{j=1}^{N} W_{ij}\phi_{it} + \varepsilon_{it}$$

$$\text{SDM: } Y_{it} = \lambda \sum_{j=1}^{N} W_{ij} Y_{jt} + X_{it}\beta + \sum_{j=1}^{N} W_{ij} X_{jt}\,\theta + \mu_i + \delta_t + \varepsilon_{it} \quad (4)$$

where Y_{it} is the dependent variable (per capita health expenditures), λ is the spatial autocorrelation index of Y_{it}, W_{ij} is the $N \times N$ spatially weighted matrix[3], k is the number of nearest neighbors considered for each state, N is the number of states, X_{it} is a matrix of all the explanatory variables used for the analysis, βs represent the vector of coefficients of the non-spatially weighted explanatory variables, η is the coefficient of the spatial autocorrelation of the error term, θ is the coefficient vector for the spatial dependence of the independent variables, μ_i is the individual state effect, δ_t is the time period effect, and ε_i is the error variable[4] (Elhorst, 2012). $\sum_{j=1}^{N} W_{ij} Y_{jt}$ characterizes the interaction effect of Y_{it} with the neighboring states' dependent variable Y_{jt}, $\sum_{j=1}^{N} W_{ij} X_{jt}$ is the weighted average effect of the neighboring states on the explanatory variables, and $\sum_{j=1}^{N} W_{ij}\phi_{it}$ represents the weighted average effect of the adjacent states on the error term (Zhao et al., 2014).

5. Methods

The spatial econometric analysis used in the paper follows the specification tests mentioned in Elhorst (2012). The first step of analysis is to find out whether the non-spatial panel data models (Pooled Ordinary Least Square Model (OLS), Spatial Fixed Effects Model, Time Period Fixed Effects Model, and Spatial and Time Period Fixed Effects Model) are more appropriate for the study or whether the spatial panel data models (SAR or SEM) are more appropriate (Elhorst, 2012). For this purpose, Lagrange multiplier tests will be used. If the Lagrange multiplier test is rejected for the absence of spatial lag or spatial error in the model, it proves that a spatial panel model is the suitable method for the analysis.

The next step is to find out if there is joint significance of the individual spatial fixed effects and time period fixed effects. Likelihood ratio tests will be performed for this purpose (Elhorst, 2012). If there is joint significance of both effects, the next step is to further see if a SDM is preferred to a SAR or SEM

[3] It is a contiguity matrix—the matrix that considers regions or states with common borders as neighbors. Thus, an element of W_{ij} is one if i and j share a common boundary and zero if they do not. The W_{ij} matrix is row standardized.

[4] The error variable ε_i is identically and independently distributed. It is a multivariate normal variable with zero mean and variance σ^2.

using the Wald test and Likelihood ratio test (Elhorst, 2012).

Consequently, the two hypotheses are (i) H_0: $\theta = 0$ (SDM model can be reduced to SAR model) versus H_1: $\theta \neq 0$ (SDM model is preferred to SAR model) and (ii) H_0: $\theta + \lambda\beta = 0$ (SDM model can be reduced to SEM model) versus H_1: $\theta + \lambda\beta \neq 0$ (SDM model is preferred to SEM model). If the null hypothesis in (i) is not rejected, SAR is the best fitting model, whereas if the null hypothesis in (ii) is not rejected, then SEM is the proper model. If both null hypotheses (i) and (ii) are rejected, SDM is the ideal model for the study (Elhorst, 2012). After selecting the appropriate model, the Hausman (1978) specification test is used to see whether the Spatial Panel Random Effect Model or the Spatial Panel Fixed Effects Model is preferred. If this specification test is rejected, then the fixed effects model is the suitable one for the study.

The final step is to estimate the spatial dependence effect of the explanatory variables on a state's own dependent variable and on its neighboring states' dependent variables (per capita health expenditures). These estimates are known as direct and indirect effects (LeSage & Pace, 2009). The direct effects account for the impact of a change in the explanatory variable X for state A on the dependent variable Y of state A. This also comprises the feedback effect that occurs indirectly—the effect of changes in X for state A on the health spending of the neighboring states may in turn again affect the health spending of state A. The indirect effects measure the changes in the dependent variable of the neighboring states caused by a change in an independent variable of state A. The total effect is calculated as the sum of the indirect and direct effects (LeSage & Pace, 2009).

MATLAB 12 software was used to obtain the results of the spatial analysis. The state-level shape data file acquired from the U.S. Census Bureau (Tiger) report gives the latitudinal and longitudinal values of each state, providing geographic information for each state. This was used to construct the spatial weight matrix needed to perform the spatial panel regression analysis.

6. Results and discussion

Due to the presence of high correlation values between the two health infrastructure variables, hospital beds per 1,000 people and number of hospitals per 1,000 people ($r = 0.74$), three models are considered to perform the empirical analysis. The analyses are: Model I: including hospital beds per 1,000 people and dropping hospitals per 1,000 people; Model II: including number of hospitals per 1,000 people and dropping hospital beds per 1,000 people; and Model III: including the interaction term of both the variables (hospital beds per 1,000 people and number of hospitals per 1,000 people) while dropping the individual variables. The estimation results of the Lagrange Multiplier tests for the four non-spatial panel data models for the above-mentioned three alternatives are presented in Table 3.

Table 3. Classic and Robust LM test for four non-spatial panel data models.

	Model I: Hospital beds per 1,000 people is included				Model II: Number of hospitals per 1,000 people is included				Model III: Interaction term (hospital beds per 1,000 people and number of hospitals per 1,000 people) is included			
	Pooled OLS	Spatial Fixed effects	Time period Fixed effects	Spatial and Time period Fixed effects	Pooled OLS	Spatial Fixed effects	Time period Fixed effects	Spatial and Time period Fixed effects	Pooled OLS	Spatial Fixed effects	Time period Fixed effects	Spatial and Time period Fixed effects
LM test spatial lag	63.693 ***	85.120 ***	13.815 ***	14.818 ***	64.329 ***	101.216 ***	15.864 ***	18.021 ***	63.432 ***	83.623 ***	14.152 ***	15.059 ***
Robust LM test spatial lag	16.253 ***	5.932 ***	17.932 ***	3.194 *	20.067 ***	11.904 ***	23.335 ***	1.173	16.420 ***	5.904 ***	19.138 ***	3.664 ***
LM test spatial error	52.366 ***	144.982 ***	1.117	53.747 ***	46.842 ***	143.969 ***	0.738	48.984 ***	51.790 ***	142.46 ***	0.946	55.939 **
Robust LM test spatial error	4.925 ***	65.794 ***	5.233 ***	42.123 ***	2.579 **	54.658 ***	8.209 ***	32.136 ***	4.778 ***	64.741 ***	5.933 ***	44.544 ***

*The symbols ***, ** and * represent the one, five, and ten percent significance levels.*

Both classic and robust Lagrangian Multiplier (LM) tests were employed to check whether a non-spatial model is preferred over a spatial model. The classic LM test to check for the absence of a spatial lag term in the analysis is rejected at the one percent level of significance in all three types of modeling methods (Elhorst, 2012). For Model II, the robust LM test used to assess for the absence of a spatial lag term is not rejected for the Spatial and Time Period Fixed Effects Model. Further, it can be seen that the classic LM test examining the absence of a spatial error term in the analysis is not rejected only for the Time Period Fixed Effects Model for Models I, II, and III. As a result, the SAR can be considered a better fit than the rest of the non-spatial panel data models for all four types of modeling analyses. As in all four non-spatial models, the specification test (classic LM test) for the hypothesis that there is an absence of a spatial-lagged dependent variable term has been rejected, showing that the model with a spatial lag is a more appropriate method of analysis.

The likelihood ratio tests (Table 4) for all three alternatives indicate joint significance of spatial fixed effects and time period fixed effects. This is because both null hypotheses − that there are no spatial fixed effects and that there are no time period fixed effects − have been rejected at the one percent significance level. Therefore, these tests show that the model considered for the data analysis is a two-way fixed effects model comprised of spatial fixed effects and time period fixed effects (Elhorst, 2012).

Table 4. Likelihood Ratio test for joint significance of spatial fixed effects and time-period fixed effects.

	Model I: Hospital beds per 1,000 people is included	Model II: Number of hospitals per 1,000 people is included	Model III: Interaction term (hospital beds per 1,000 people and number of hospitals per 1,000 people) is included
LR test for joint significance of spatial fixed effects (degrees of freedom)	1049.95*** (49)	1070.19*** (49)	1056.965*** (49)
LR test for joint significance of time period fixed effects (degrees of freedom)	108.65*** (10)	120.01*** (10)	107.240*** (10)

*The symbols ***, ** and * represent the one, five, and ten percent significance levels.*

The estimation results for the SAR and SEM for Models I, II, and III are shown in Table 5. As previously mentioned, the Wald test and the Likelihood Ratio (LR) test presented in Table 6 are used to examine which of the three spatial panel data models is appropriate (Elhorst, 2012). The Wald test result and the LR test result reject the null hypothesis H_0: $\theta = 0$ (SDM model can be reduced to SAR model), proving that the SDM model is preferred over the SAR model for all three modeling frameworks. Further, the Wald test result and the LR test result for Models I, II, and III also suggest rejection of the hypothesis H_0: $\theta + \lambda\beta = 0$ (SDM model can be reduced to SEM model), proving that the SDM model is also preferred over the SEM model. Thus, it can be seen that the SDM is the most appropriate model to be used for the analysis.

Next, Hausman's (1978) specification test (Table 7) is used to find out whether the Spatial Durbin Random Effects or Spatial Durbin Fixed Effects Model is preferred. The results from the three models (I, II, and III) nullify the usage of the Random Effects Model and favor the Fixed Effects Model specification. Thus, it has been demonstrated that the Spatial Durbin Fixed Effect Model is the best-fitting model for the study.

Table 8 provides the SDM coefficients of the explanatory factors that determine the changes in per capita health expenditures across the United States from 2000 to 2009. Results for the direct, indirect, and total coefficients of the explanatory variables for the SDM are provided in Table 9. For all three alternatives, it can be seen from its R-square value that the SDM model captures and explains 97% of the variance in per capita health expenditures. The coefficient of the weighted dependent variable (λ) is positive and significant at the one percent level ($p < 0.01$): a state tends to increase its own health expenditures in response to the rise in health expenditures of its neighboring states. Model III shows the maximum amount of influence on increase in per capita health expenditures on bordering states. Thus, as stated earlier, the expenditure spillover effect and fiscal competition effect describe this positive relationship among the states' per capita health expenses. With respect to the other explanatory variables, a state's GDP is positively associated with its per capita health expenditures. A one unit increase in the

Table 5. Estimation results of spatial panel data models (SAR and SEM) for determinants of real per capita health expenditure.

	Model I: Hospital beds per 1,000 people is included		Model II: Number of hospitals per 1,000 people is included		Model III: Interaction term (hospital beds per 1,000 people and number of hospitals per 1,000 people) is included	
	SAR	SEM	SAR	SEM	SAR	SEM
Percentage in Health Maintenance Organizations	-0.001**	-0.001***	-0.001***	-0.001**	-0.001***	-0.001***
	-2.551	-2.402	-2.616	-2.373	-2.599	-2.285
Log of real Medicaid expenditures	0.062***	0.067***	0.061***	0.066***	0.063***	0.068***
	3.345	4.16	3.328	4.13	3.438	4.208
Active physicians per 100,000 residents	0.001***	0.0003***	0.001***	0.0003**	0.001***	0.000***
	3.749	2.617	3.507	2.546	3.799	2.648
(Hospital beds*number of hospitals) per 1,000 people	-	-	-	-	-0.021	-0.085
	-	-	-	-	-0.234	-1.089
Hospital beds per 1,000 people	0.005	-0.006	-	-	-	-
	0.369	-0.466	-	-	-	-
Log of real Gross Domestic Product	0.569***	0.626***	0.576***	0.625***	0.570***	0.628***
	17.484	21.754	17.83	21.761	17.468	21.843
Poverty rate (%)	0.007***	0.006***	0.0069***	0.006***	0.007***	0.007***
	2.895	2.996	2.863	2.983	2.893	3.079
Percentage of population older than 65	0.024***	0.036***	0.024***	0.036***	0.025***	0.037***
	2.824	4.925	2.903	4.867	2.91	5.045
Percentage of population younger than 17	-0.004**	-0.002*	-0.004**	-0.003**	-0.004**	-0.002**
	-2.201	-1.658	-2.173	-1.684	-2.176	-1.66
Uninsured rate (%)	-0.002**	0	-0.002**	0	-0.002**	0
	-1.687	-0.143	-1.824	-0.145	-1.682	-0.034
Number of hospitals per 1,000 people	-	-	4.885**	0.727	-	-
	-	-	2.434	0.419	-	-
Unemployment Rate (%)	0.008***	0.004	0.007***	0.004	0.008***	0.004**
	2.975	1.635	2.757	1.508	3.059	1.656
Lamda (λ)	0.199***	-	0.215***	-	0.196***	-
	4.073	-	4.336	-	3.975	-
Eta (η)	-	0.483***	-	0.487***	-	0.491***
	-	9.411	-	9.539	-	9.668
σ^2	0.001	0.0008	0.001	0.0008	0.001	0.0008
R^2	0.959	0.956	0.959	0.956	0.959	0.956
Log L	1017.91	1039.65	1020.941	1039.631	1017.866	1040.131
Number of observations	490	490	490	490	490	490

*The symbols ***, ** and * represent the one, five, and ten percent significance levels.*

Table 6. Wald Test and LR test estimation results.

	Model I: Hospital beds per 1,000 people is included				Model II: Number of hospitals per 1,000 people is included				Model III: Interaction term (hospital beds per 1,000 people and number of hospitals per 1,000 people) is included			
	Wald (SAR vs SDM)	Wald (SEM vs SDM	LR (SAR vs SDM)	LR (SEM vs SDM)	Wald (SAR vs SDM)	Wald (SEM vs SDM	LR (SAR vs SDM)	LR (SEM vs SDM)	Wald (SAR vs SDM)	Wald (SEM vs SDM	LR (SAR vs SDM)	LR (SEM vs SDM)
	154.432 ***	103.091 ***	134.804 ***	91.324 ***	132.447 ***	84.989 ***	117.371 ***	79.992 ***	141.086 ***	87.000 ***	124.393 ***	79.863 ***
df	10	10	10	10	10	10	10	10	10	10	10	10

*The symbols ***, ** and * represent the one, five, and ten percent significance levels.*

Table 7. Hausman Specification Test results.

	Model I: Hospital beds per 1,000 people is included	Model II: Number of hospitals per 1,000 people is included	Model III: Interaction term (hospital beds per 1,000 people and number of hospitals per 1,000 people) is included
Hausman Specification Test Value	156.661***	430.884***	461.7441***
Degrees of freedom	21	21	21

*The symbols ***, ** and * represent the one, five, and ten percent significance levels.*

logarithmic value of a state's real GDP increases the per capita health spending by 0.65 (Model I), 0.65 (Model II), and 0.64 (Model III) units, suggesting that the income elasticity of health is less than unity and implying that public health is a normal good. With a rise in GDP, a state increases its spending in all sectors of its economy, including an increase in health spending. Although the direct effect of an increase in GDP is positive, the indirect effect is negative for all three models and notably implies that a state's GDP has a positive influence on its own state and a negative spillover effect on its neighboring states.

The proportion of real Medicaid expenditures (Model III having the maximum influence), people above age 65 (Model II showing the largest variation), and HMO coverage have significant positive effects on per capita health expenditures. An increase in a state's real Medicaid expenditures will boost the cost of health services in the state. It is evident that health costs rise sharply as the population ages because older people fall sick more often and have more health issues due to deteriorating physical conditions (Di Matteo and Di Matteo, 1998). In contrast, a rise in the aged population in state A has a declining effect on the health spending of neighboring states, causing per capita health spending to diminish as a total effect. This is because the elderly population from neighboring states may migrate and settle in state A in search of better and improved health facilities, thereby increasing state A's per capita health expenditures and reducing the adjacent states' per capita health expenses. With the rise in the percentage of people enrolled in HMOs, the total health spending of the state decreases with very small direct, indirect, and total effects.

The total number of active physicians per 100,000 residents also positively influences health expenditures for all three modeling types (I, II, and III); however, the impacts are very small. The increase in supply-side variables, such as the number of doctors or nurses, shows that there is a greater need for hospital staff and health infrastructure as more people are using health facilities. Therefore, an increase in supply-side variables leads to higher per capita health expenditures and also has a significant positive total indirect impact on adjacent states' per capita health expenditures. With an increase in the number of physicians in state A, people from adjacent states that lack proper health staff utilize facilities in state A more often, thereby increasing their own state's health expenditures.

The poverty rate has a very small positive impact on health expenditures. Therefore, an increase in percentage of poor people in a state causes health expenditures to rise, as the number of people accessing emergency and intensive health care services increases due to malnutrition and infectious diseases. Models II and III show that the rise in poverty rate of state A has a negative indirect impact on neighboring states. A rise in poverty level of state A may be viewed as the migrated population from the neighboring states, thereby decreasing the bordering states' per capita health expenditures.

Table 8. Estimation results of spatial panel data models (SDM) for determinants of real per capita health expenditure.

	Model I: Hospital beds per 1,000 people is included	Model II: Number of hospitals per 1,000 people is included	Model III: Interaction term (hospital beds per 1,000 people and number of hospitals per 1,000 people) is included
Percentage in Health Maintenance Organization	-0.001***	-0.001***	-0.001***
	-3.765	-3.542	-3.539
Log of real Medicaid expenditures	0.059***	0.069***	0.073***
	3.826	4.518	4.755
Active physician per 100,000 residents	0.0005***	0.0005***	0.0005***
	3.827	3.794	3.939
(Hospital beds*number of hospitals) per 1,000 people	-	-	0.017
	-	-	0.219
Hospital beds per 1,000 people	0.012	-	-
	0.977	-	-
Log of real Gross Domestic Product	0.652***	0.654***	0.638***
	23.494	22.745	23.014
Poverty rate (%)	0.005***	0.004***	0.005**
	2.513	2.046	2.245
Percentage of Population Older than 65	0.027***	0.037***	0.032***
	3.76	5.227	4.413
Percentage of Population Younger than 17	-0.002	-0.002	-0.002
	-1.489	-1.472	-1.368
Uninsured rate (%)	0	0	0
	-0.099	-0.23	0.2
Number of hospitals per 1,000 people	-	0.884	-
	-	0.498	-
Unemployment Rate (%)	0.003	0.003	0.003
	1.078	1.235	1.082
Lamda (λ)	0.205***	0.228***	0.243***
	3.24	3.639	3.915
W*% in Health Maintenance Organizations	-0.002***	-0.002***	-0.002***
	-2.666	-2.729	-2.975
W*Log of real Medicaid expenditures	-0.084**	-0.021	-0.028
	-2.082	-0.566	-0.736
W*Active physician per 100,000 residents	0.001***	0.001***	0.001***
	4.473	4.184	4.662
W*(Hospital beds*no. of hospitals) per 1,000 people	-	-	0.634***
	-	-	2.925
W*Hospital beds per 1,000 people	0.123***	-	-
	4.349	-	-
W*Log of real Gross Domestic Product	-0.239***	-0.278***	-0.312***
	-3.458	-3.886	-4.649
W*Poverty rate (%)	-0.007	-0.011**	-0.011**
	-1.567	-2.561	-2.527
W* Percentage of population older than 65	-0.101***	-0.068***	-0.084***
	-5.974	-4.428	-5.096
W* Percentage of population younger than 17	-0.002	-0.001	-0.001
	-0.752	-0.387	-0.452
W*Uninsured rate (%)	-0.005**	-0.006**	-0.005***
	-1.797	-2.223	-2.033
W*number of hospitals per 1,000 people	-	12.158***	
	-	2.745	
W*Unemployment Rate (%)	0.015***	0.014***	0.015***
	3.358	3.172	3.256
Sigma2	0.0007	0.0007	0.007
R square	0.969	0.968	0.9684
Log L	1085.312	1079.627	1080.063

*The symbols ***, ** and * represent the one, five, and ten percent significance levels. T-statistics are specified below the coefficients. N = 490.*

Table 9. Results of direct, indirect, and total coefficient estimates of the Spatial Durbin Model.

	Model I: Hospital beds per 1,000 people is included			Model II: Number of hospitals per 1,000 people is included			Model III: Interaction term (hospital beds per 1,000 people and number of hospitals per 1,000 people) is included		
	Direct Coefficient	Indirect Coefficient	Total Coefficient	Direct Coefficient	Indirect Coefficient	Total Coefficient	Direct Coefficient	Indirect Coefficient	Total Coefficient
Percentage in HMOs	-0.001***	-0.003***	-0.004***	-0.001***	-0.003***	-0.004***	-0.001***	-0.003***	-0.004***
	-3.944	-3.009	-3.812	-3.751	-3	-3.727	-3.79	-3.335	-3.993
Log of real Medicaid expenditures	0.057***	-0.085	-0.028	0.070***	-0.008	0.062	0.073***	-0.01	0.063
	3.731	-1.623	-0.483	4.328	-0.163	1.151	4.827	-0.198	1.151
Active physician per 100,000 residents	0.0005***	0.002***	0.0025***	0.0005***	0.002***	0.0025***	0.0005***	0.002***	0.0025***
	4.232	5.166	6.221	4.278	4.856	5.799	4.444	5.455	6.481
(Hospital beds*number of hospitals) per 1,000 people	-	-	-	-	-	-	0.015	0.793***	0.808**
	-	-	-	-	-	-	0.19	2.874	2.628
Hospital beds per 1,000 people	0.017	0.151***	0.168***	-	-	-	-	-	-
	1.384	4.243	4.248	-	-	-	-	-	-
Log of real Gross Domestic Product	0.647***	-0.132**	0.515***	0.649***	-0.163**	0.486***	0.630***	-0.204***	0.426***
	23.79	-1.796	6.454	21.786	-2.105	5.595	23.239	-2.711	5.253
Poverty rate	0.005**	-0.007	-0.002	0.004**	-0.013**	-0.009	0.004***	-0.013***	-0.009
	2.445	-1.368	-0.419	1.812	-2.285	-1.441	2.067	-2.3	-1.416
Percentage of population older than 65	0.024***	-0.116***	-0.092***	0.035***	-0.076***	-0.041**	0.029***	-0.098***	-0.068***
	3.378	-5.375	-3.854	4.981	-4.021	-1.976	4.009	-4.442	-2.806
Percentage of population younger than 17	-0.002	-0.003	-0.005	-0.002	-0.002	-0.004	-0.002	-0.002	-0.004
	-1.535	-0.823	-1.227	-1.473	-0.56	-0.978	-1.392	-0.538	-0.905
Uninsured rate	0	-0.006**	-0.006**	0	-0.007**	-0.008**	0	-0.007***	-0.007***
	-0.334	-1.834	-1.788	-0.457	-2.231	-2.159	-0.088	-2.041	-1.883
Number of hospitals per 1,000 people	-	-	-	0.412	15.158**	15.57**	-	-	-
	-	-	-	0.221	2.644	2.303	-	-	-
Unemployment Rate	0.003	0.019***	0.022***	0.004	0.018***	0.022***	0.003	0.019***	0.023***
	1.308	3.629	4.062	1.53	3.411	3.979	1.367	3.545	3.956
R square	0.969			0.968			0.968		
Lambda (λ)	0.205***			0.228***			0.242***		
	3.24			3.639			3.915		

*The symbols ***, ** and * represent the one, five, and ten percent significance levels. T-statistics are specified below the coefficients. N = 490.*

Model I shows that there is a significant positive indirect effect on the per capita health spending with the rise in the total number of hospital beds per 1,000 people. The Model II results show that a rise in the total number of hospitals per 1,000 people has a significant positive cumulative indirect impact on the neighboring states' per capita health expenditures. Model III shows that the interaction term of hospital beds per 1,000 people and hospitals per 1,000 people also has a significant collective indirect impact on per capita health care expenses. The positive indirect influence shown via these three modeling types can be explained in two ways. First, increases in health infrastructure in state A lead to an increase in the neighboring regions' health infrastructure due to fiscal competition, hence increasing the neighboring states' per capita health costs. Second, as health infrastructure in state A increases, the residents of neighboring states utilize state A's increased facilities more frequently due to lack of proper health infrastructure in their own states, thereby increasing their own per capita health care expenditures.

Both the insignificant direct effect and the significant cumulative indirect effect of the unemployment rate are positive. This leads to a significant positive total effect on health expenditures. As people become unemployed, they are sick more often and have more visits to emergency rooms and intensive care units, which increases the state's total health costs (The White House, 2013). The rate of uninsured people and the proportion of the population below age 17 have no positive or negative influence on the health expenditures.

The preceding model results can be contrasted to Wang (2009), which did not capture the influence of spatial dependence of each variable on the health costs of the states and federal districts of the United States. The cross-sectional and pooled regression method used in Wang's analysis did show how changes in the socio-economic, demographic, or the health care industry variables of a state influence the state's own spending. By showing how a change in any variable of a state has an impact not only on that state's own health expenditures, but also on the neighboring states and districts, this paper is an improvement over previous research. Wang's paper showed that income, aging, urbanization, and the total number of hospital beds are key factors for the changes in health costs. This analysis demonstrates that a state's GDP, aging population, proportion of Medicaid expenditures, and active physicians per 100,000 people also matter. The paper also incorporates three new variables—unemployment level, poverty rate, and number of hospitals per 1,000 people. Of these, the total number of hospitals has a significant positive indirect influence on the variation in health costs, and unemployment and poverty level have positive and smaller direct and indirect impacts.

7. Conclusions and policy implications

The goal of this paper was not only to study the factors explaining health spending, but also to check whether spatial interaction or spatial dependence are present in health spending across states. The factors influencing health costs and rising health expenses in a state cause variation in the living costs of people in that state and its neighbors, and hence have an impact on migration decisions. Several previous empirical studies have tried to find explanatory factors behind the changes in health expenditures or costs of health services. They have employed state-, county-, or regional-level analyses, but none have examined whether there is any spatial panel spillover across a time period of ten years for the states and federal districts of the United States.

Using a Spatial Panel Durbin Model with spatial fixed effects and time period fixed effects, this paper shows that there are positive spillover effects of health expenditures of one state on the welfare of its neighboring states. Thus, it suggests that if one state decides to increase its health spending, neighboring states will take a similar approach to their health spending in response. Consequently, both expenditure spillover effects and fiscal competition effects seem to be explaining the spatial interaction effect of health expenditures among states.

By investigating which economic, demographic, and social factors have caused the health expenditures of the United States to rise over a period of ten years (2000–2009), the empirical results show that a state's GDP, proportion of Medicaid expenditures, percentage of population over age 65, active physicians per 100,000 people, and poverty rate have significant positive direct effects with varied indirect and total effects on its neighbors' health costs. On the other hand, the percentage of residents in HMOs has a negative direct, indirect, and total impact on per capita health expenses. The hospital beds per 1,000 people (Model I), number of hospitals per 1,000 people (Model II), and their interaction term (Model III) also show a significant positive indirect impact on per capita health expenditures. To conclude, any policy-driven decision taken by the government that incorporates these variables would likely limit the growing costs of health care in the United States. This should lead to better allocation and utilization of the resources and funds present while improving the quality of health care. It can also increase standards of living by influencing the cost of living and improving efficiency by releasing resources that could be used to produce other desired goods and services.

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