Differences in Medicare Spending Between States Over Time

Elise Braun, Christine Oscai, and Shae Selix

Abstract

As famously revealed by the Dartmouth Atlas Project, significant variation exists in Medicare spending without consequent improvements in healthcare outcomes. For years, public health professionals have been trying to explain the cause of this variation in order to explore ways to reduce unnecessary healthcare spending. Our project analyzes the association of political affiliation and geographical region on Medicare spending over time. We determined that regional variations, not variations in political affiliation, have impact on Medicare spending variations between states. Further, the region by time interaction variable is also significant. This means that different regions are associated with differences in Medicare spending and different regions respond differently to time in terms of changes in Medicare spending.

Introduction

Representing approximately 20% of national healthcare expenditures and 15% of federal budget outlays, the Medicare program is a highly opportunistic target for cost savings. [12] Despite this, there exists significant regional variations in spending on Medicare that is not justified by differences in health outcomes.[3] The Dartmouth Atlas Project has been one of the most important organizations to shed light on and explore this problem by collecting data on Medicare spending at the regional, state, and hospital level.

Our analysis will add to our current understanding of Medicare spending variations by analyzing spending over time at a broader regional level or by divisions in political affiliation. It would be enlightening to discover how Medicare spending has changed over time based on regional and political differences between states. This knowledge can be used to inform interventions on states where spending on Medicare particularly fast growing.

There are many factors besides prices that have been shown to affect spending on Medicare, including presence of chronic conditions[4], presence of for-profit hospitals[5], and the health of the economy[6]. However, even among these factors, there is limited ability to make predictions about Medicare spending by political affiliation or by region.

The highest burden of chronic illness exists in the Midwest and the South, with the South states tending to vote red and Midwest states tending to have mixed political affiliations.[7] Lower for-profit presence exists in the Northeast region, a geographical area that tends to vote blue, and is mixed for the rest of the region[8]. Finally, blue and red states perform differently on different economic performers.[9] Overall, it is unclear what to expect in terms of Medicare spending.

Our dataset is a combination of Dartmouth Atlas Medicare spending data and information on the political affiliations and geographic regions of states. Specifically, we the age, price, and sex-adjusted data

---

[1] CMS.gov National Health Expenditure Data
[2] CBO Budget and Economic Outlook
[3] Key Issues, Dartmouth Atlas
[4] Keiser Health News
[5] Reschovsky JD, et al. 2011
[6] Mitchell A, 2012
[7] DeVol R, 2007
[8] Kaiser Family Foundation, Hospital by Ownership Type
[9] "Stronger Economy- Blue States or Red States" Econopolitics

on Medicare spending by state from the Dartmouth Atlas Database from 2003 to 2007.[10] We combined this with US region definitions from the Library of Congress and voting information by state from the US Federal Register. That is, Medicare spending changes for each state from year to year but the region and political affiliation information was kept consistent for each state from year to year.

Methods

Before performing more in-depth analysis, we were interested in first exploring the data. We performed a graph of average spending over time by region, average spending over time by political affiliation, and a spaghetti plot of spending over time. Next we conducted ANOVA and LME models in order to further explore the variation in Medicare spending over time that is associated with differences in regions and states. We then use sample variograms to explore the correlations between observations over time. In order to check our assumptions about the specification of the model, the need to transform variables, and the normality of the mean using residual diagnostics and determined the normality of random effects using a histogram. Finally, we used contrast statements to determine an appropriate time trend and the differences between regions.

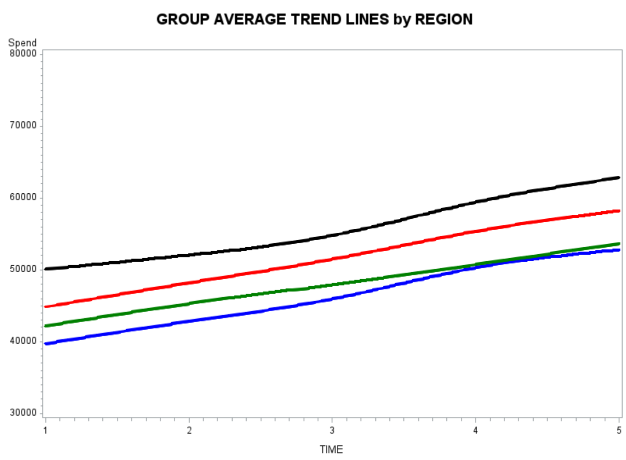
If we were able, we would have used a longer time period for the analysis. It would have been particularly interesting to study the years before and after the implementation of the Patient Protection and Affordable Care Act (ACA), a piece of legislature that had significant implications for Medicare spending. If we had access to this information, we would create a dummy variable for before and after the implementation of the ACA.

Results and Discussion

Data Exploration

By plotting the changes in regional averages in Medicare spending over time, we observe that the spending for each of the regions is increasing over time. Further, there are regional differences in spending as evidenced by the difference in y-intercept creating a distance between each of the four lines. Finally, there are differences in time trends in spending between the West and Midwest regions, as evidenced by the overlap between the lines between time points 4 and 5. This suggests that it would be beneficial to explore the time by region interaction in our ANOVA and LME models to quantify this difference.

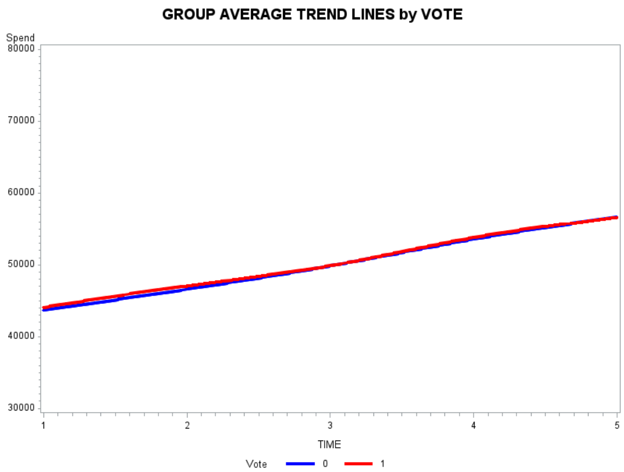
Table 1: Group Average Trend Lines by Region



[10] Medicare Spending Data, Dartmouth Atlas

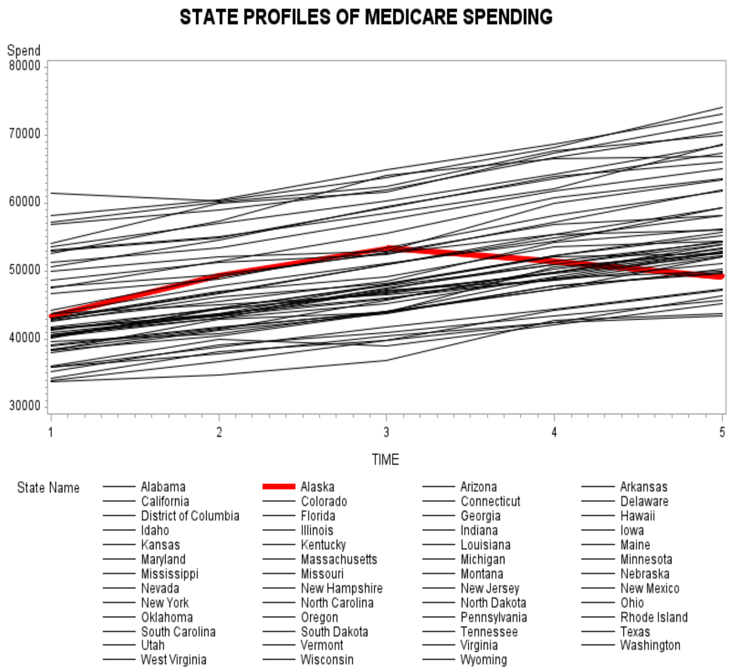
By plotting the changes in average spending by political affiliation over time, there appears to be an upward trend over time in Medicare spending for states with both political affiliations. However, there does not appear to be much difference in spending or in trends in spending over time between states with different political affiliations. Although this is surprising no not see any of these differences, it is possible that there will be differences between political affiliation if the data are stratified by region. Therefore, we will explore a vote by region interaction.

Table 2: Average Spending Trend by Political Affiliation



In order to observe the changes in spending by individual states over time, we created a spaghetti plot of each states' individual profile. Overall, spending appears to be trending upward over time. However, Alaska (ID =2) has a different trend than most of the other states. Rather than generally increasing upward throughout the duration of the time, Alaska's spending peaks at time point 3 (Year 2005) and then decreases.

Table 3: State Profiles of Medicare Spending



ANOVA Model

The results of our ANOVA model indicate that the region, time, and region by time interaction variables are significant. The significance of the region by time variable indicates that the time association with Medicare spending is different by region. In other ANOVA models, the political affiliation and political affiliation by time variables were not shown to be significant.

Table 4: Two-Way ANOVA Model with Time and Region as Factors Predicting Spending

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	66	18601146079	281835547	183.78	<.0001
Error	188	288311193	1533570		
Corrected Total	254	18889457272			

Source	DF	Type III SS	Mean Square	F Value	Pr > F
Region	3	2834032268	944677423	616.00	<.0001
SUBJECT(Region)	47	10392650477	221120223	144.19	<.0001
TIME	4	5044220408	1261055102	822.30	<.0001
Region*TIME	12	47028038	3919003	2.56	0.0037

LME Model

After dropping insignificant variables like vote and the vote by region interaction, the final model includes region and time by region interaction variables.

Table 5: LME Model, Type 3 Tests of Fixed Effects

Type 3 Tests of Fixed Effects				
Effect	Num DF	Den DF	F Value	Pr > F
TIME	4	188	822.34	<.0001
Region	3	188	4.27	0.0060
TIME*Region	12	188	2.56	0.0037

In order to choose the best correlation structure for the LME model, we use a likelihood ratio test to test between simple, compound, Toeplitz, AR(1), exponential, and unstructured correlation structures. As a result of the likelihood ratio test, the unstructured correlation model provides the best fit for the data.[11]

[11] Applendix I

Sample Variograms

In order to assess the correlation between observations over time, sample variograms were conducted for intercept and political affiliation and intercept and region. The correlation between observations seems to be decreasing over time for both. However, the correlation is increasingly decreasing in the intercept and political affiliation sample variogram and decreasingly increasing in the intercept and region sample variogram.

Table 6: Sample Variogram With Intercept and Political Affiliation

Obs	lagtime	semi	pvar
1	1	6053671.99	75113689.91
2	2	23192066.22	75113689.91
3	3	50180231.39	75113689.91
4	4	83435637.25	75113689.91

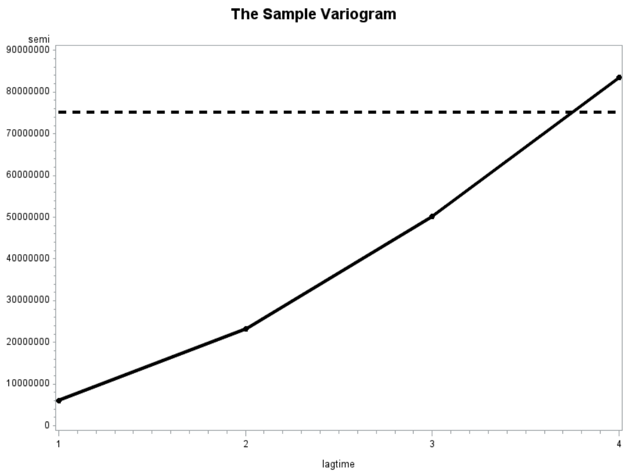
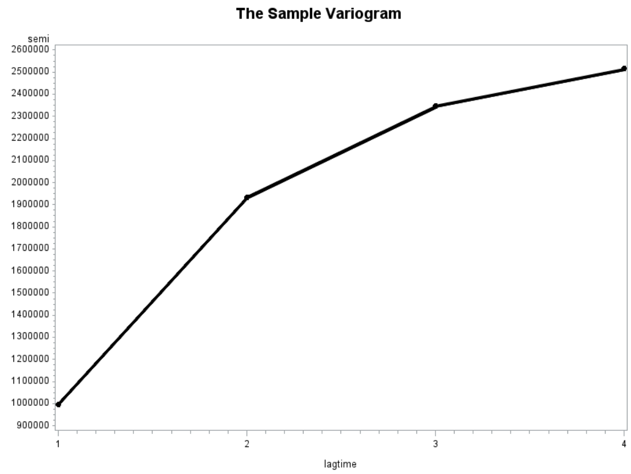


Table 7: Sample Variogram With Intercept and Region

Obs	lagtime	semi	pvar
1	1	996152.66	.
2	2	1932464.60	.
3	3	2346127.74	.
4	4	2515328.12	.

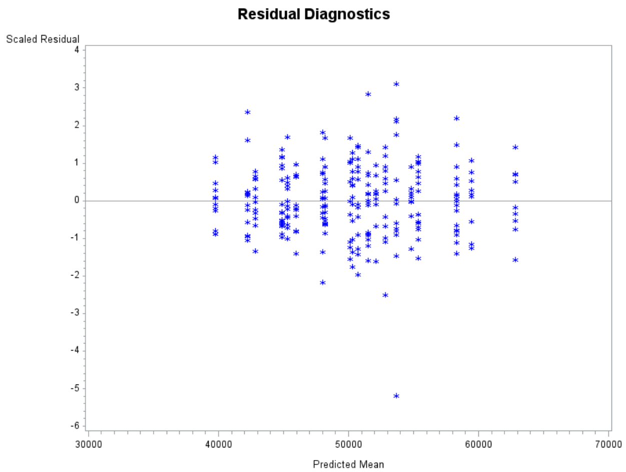


Checking Assumptions: Residual Diagnostics

In order to check whether the model was correctly specified, we check if there are systematic departures by plotting scaled residuals over the predicted mean of response. In a correctly-specified model, there should not be discernable trends in the residuals over predicted mean response plot. However, we will not use this plot to assess constant variance this this is not an assumption that we have.

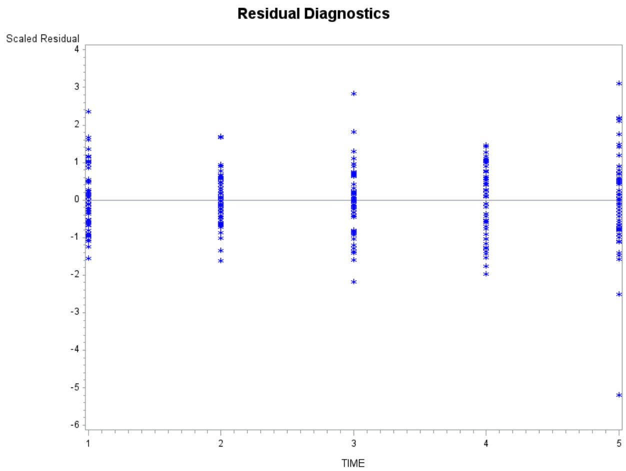
Since there are no discernable trends in the plot of residuals over the predicted mean, we feel confident about the specification of this model. However, we do notice an outlier variable around the -5 residual.

Table 8: Plot Scaled Residuals Over the Predicted Mean



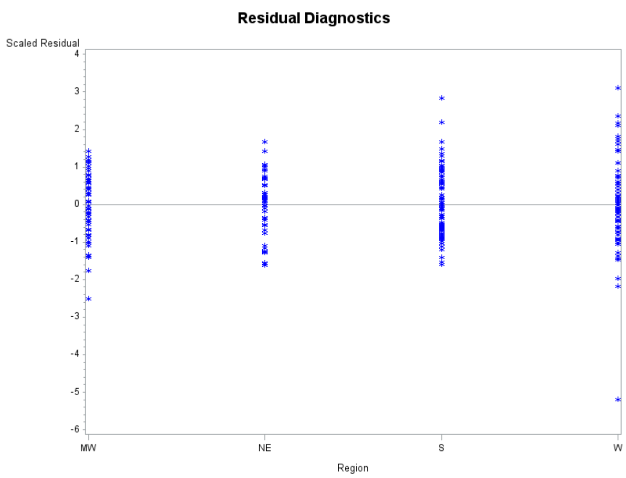
We also analyzed a plot of residuals over the time covariate. Because of the lack of a discernable trend in the scatterplot, there seems to be no reason to transform the time variable. However, we do notice that Alaska appears as an outlier around time = 5 (2007).

Table 9: Plot of Scaled Residuals Over Time



Finally, we analyzed a plot of residuals over the region covariate. Because of the lack of a discernable trend in the scatterplot, there seems to be no reason to transform the region variable. However, there is an outlier in the Western region.

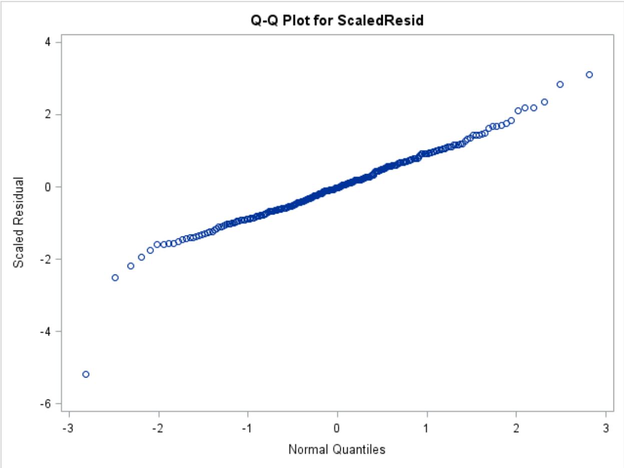
Table 10: Plot of Scaled Residuals Over Region Variable



Checking Assumptions: Assessing Normality of the Mean

In order to assess how many residuals are different from the normal distribution, we use a normal quantile plot (QQ-Plot) to visualize observations that are not close to the reference line. There do not seem to be residuals that depart from the normal distribution.

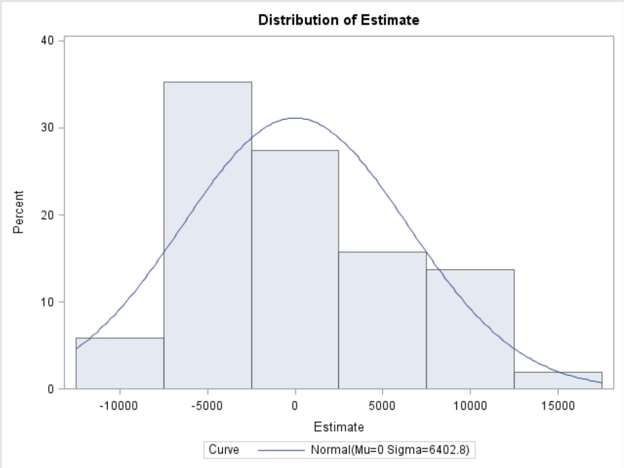
Table 11: Q-Q Plot for Scaled Residuals



Checking Assumptions: Assessing Normality of Random Effects

In order to assess whether the random effects are normally distributed, we will use a histogram to visualize the distribution. It appears that the random effects are approximately normally distributed, as is assumed under ideal conditions.

Table 12: Histogram of the Distribution of Estimates



Contrast Statements

As per our LME and ANOVA models, the time effect is a significant explanatory variable for spending on Medicare. Therefore, it is appropriate to explore which of the follow time trends are most fitting to the data (linear, quadratic, cubic, and quartic). To accomplish this, we produced 4 contrast statements. The results of the contrast statement analysis indicate that the data follow a linear time trend ($p < 0.0001$).

Table 13: Contrast Statements of Time Trends

Contrasts				
Label	Num DF	Den DF	F Value	Pr > F
Linear Trend Contrast	1	188	3279.80	<.0001
Quadratic Trend Contrast	1	188	2.54	0.1125
Cubic Trend Contrast	1	188	3.54	0.0615
Quartic Trend Contrast	1	188	3.50	0.0629

We were also interested in know if there are significant differences in spending trends over time between each region. The results of this contrast statement analysis indicates that there are significant pairwise differences in spending between Regions 1 and 2, Regions 1 and 3, and Regions 2 and 4.

Table 14: Contrast Statements for Contrasting Groups

Region 2 vs. Region 1	1	188	10.55	0.0014
Region 3 vs. Region 1	1	188	4.48	0.0356
Region 4 vs. Region 1	1	188	0.38	0.5366
Region 3 vs. Region 2	1	188	2.36	0.1258
Region 4 vs. Region 3	1	188	2.23	0.1369
Region 4 vs. Region 2	1	188	7.46	0.0069

Conclusion

The results of our analysis indicate that spending on Medicare and spending trends over time differ by geographical region of the United States but not by their political affiliation. For all states except for Alaska, spending on Medicare increases over time. Further research should explore why Alaska's Medicare spending patterns deviates from the trend after 2005. Even more so, further research ought to explore what differences between regions might be associated with different Medicare spending patterns.

Some limitations of our analysis include the lack of clarity in how the Medicare data were age, price, and sex-adjusted by the Dartmouth Atlas, the definition of red or blue state used, and the definition of region used. If we plotted un-adjusted Medicare spending over time per beneficiary, it would increase over time due to the increase in inflation rates and other factors that are not useful to analyze. So the type of adjustment done by the Dartmouth Atlas is very important and the fact that we do not have the adjustment process is a limitation. Further, the use of red/blue state and regional explanatory variables may be associated with each other so it is unclear to see the impact of one or the other. Finally, neither the red/blue state nor regional variables may be the best explanatory variables for this analysis.

Works Cited

Appleby J. "Seven Factors Driving Up your Health Care Costs."

CBO Budget and Economic Outlook, January 2011 (for 1990-2010 data) and May 2013 (for 2020 data). *Kaiser Health News*. 2012. http://www.kaiserhealthnews.org/stories/2012/october/25/health-care-costs.aspx

CMS.gov 2012 data http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/downloads/highlights.pdf

DeVol R and Bedroussian A. "An Unhealthy America: The Economic Burden of Chronic Disease." *The Milken Institute.* October 2007. http://www.milkeninstitute.org/pdf/chronic_disease_report.pdf

"Hospitals by Ownership Type." Kaiser Family Foundation. http://kff.org/other/state-indicator/hospitals-by-ownership/#map

"Medicare Spending" The Dartmouth Atlas of Health Care http://www.dartmouthatlas.org/keyissues/issue.aspx?con=1339

Medicare Spending Data , Dartmouth Atlas http://www.dartmouthatlas.org/tools/downloads.aspx?tab=38

Mitchell A. "Medicaid Financing and Expenditures." *Congressional Research Service.* 30 July 2012. http://www.fas.org/sgp/crs/misc/R42640.pdf

Regions of the United States http://memory.loc.gov/ammem/gmdhtml/rrhtml/regdef.html

Reschovsky JD, et al. "Following the Money: Factors Associated with the Cost of Treating High-Cost Medicare Beneficiaries." *Health Services Research.* 46(4): 9 Feb 2011, 997 – 1021.

"Stronger Economy: Blue States or Red States?" *Econopolitics.* 20 June 2012. http://econopolitics.com/2012/06/20/stronger-economy-blue-states-or-red-states/

US Federal Register http://www.archives.gov/federal-register/electoral-college/votes/2000_2005.html#2004

Appendix 1: Likelihood Ratio Test for Best Correlation Structure

Ho: The model with the simple correlation structure provides a sufficiently good fit to the data.
Ha: The model with the compound symmetry structure provides a better fit to the data.
G2=4298.1-4298.1=0
df=3-2=1
p=0.999
We fail to reject our null hypothesis and conclude that simple structure provides a sufficient fit.

Ho: The model with the simple correlation structure provides a sufficiently good fit to the data.
Ha: The model with the Toeplitz structure provides a better fit to the data.
G2=4375.6-4298.1=77.5
df=6-3=3
p<0.001
We reject our null hypothesis and conclude that Toeplitz structure provides a better fit.

Ho: The model with the Toeplitz correlation structure provides a sufficiently good fit to the data.
Ha: The unstructured model provides a better fit to the data.
G2=4817.4-4375.6=441.8
df=16-6=10
$p<0.001$
We reject our null hypothesis and conclude that unstructured provides a better fit.

Ho: The model with the AR(1) correlation structure provides a sufficiently good fit to the data.
Ha: The unstructured model provides a better fit to the data.
G2=4817.4-4247.3=570.1
df=16-3=13
$p<0.001$
We reject our null hypothesis and conclude that unstructured provides a better fit.

Ho: The model with the exponential correlation structure provides a sufficiently good fit to the data.
Ha: The unstructured model provides a better fit to the data.
G2=4817.4-4247.3=570.1
df=16-3=13
$p<0.001$
We reject our null hypothesis and conclude that unstructured provides a better fit.