Senior Project Department of Economics



# "Diabetes, Complications, and Health Care Expenditure"

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### Abstract

In this paper I research the economic relationship between diabetes and health care expenditure for two age groups, the adult population above and below 65 years of age. I use two models and OLS regression to analyze the interactions of hypertension, diabetes, strokes, and other variables that have been shown to be significant determinants of health care demand. I have found that the interaction of diabetes and hypertension is a significant determinant of Medicare demand. I have found evidence that shows that the benefit of reducing the prevalence of people with both hypertension and diabetes by one percent is an annual \$6.49 per Medicare enrollee

# Introduction

The American Diabetes Association estimated that "1 in 5 health care dollars in the U.S. are spent caring for someone with diagnosed diabetes" (ADA, 2008). Diabetes and other chronic diseases have been shown to be costly. The economic significance of these costs has been the subject of much research. However, deriving meaningful estimations of the cost of diabetes has proven to be difficult. This is because known shortcomings in common research methodologies stem from a fundamental misunderstanding of economic cost. This misunderstanding can lead to estimations that have unclear policy implications.

In this paper I will look at the economic cost of diabetes using a demand based methodology. By using a demand based methodology I hope to derive estimations of the marginal cost of diabetes. Much of the current literature on the aggregate economic cost of diabetes only estimates the benefits of the complete prevention of diabetes. The eradication of diabetes is not yet medically possible and thus, is not yet a viable policy option. Policy makers are more likely to be concerned with the possible marginal benefits and costs of existing programs. Research into the marginal costs of diabetes is pertinent and relevant for informed policy decisions.

# Literature Review

Suhrcke et al (2006) describe three different methods of finding the economic cost of disease, the first of which is the cost of illness method (COI). The COI method is characterized as an estimate of the

total cost of a particular disease; costs associated with paying for the direct costs of treatment, and the indirect costs of loss of productivity and mortality. The other two methods that Suhrcke et al (2006) describe are deemed the "micro" and "macro" approaches. The micro approach looks at the cost of diabetes for individuals and families, while the macro approach looks at the effects of diabetes on macro-economic growth. The cost of illness approach differs significantly from the other two because it is the only method that is used to estimate the total economic cost of a disease.

When COI research is conducted from a public health perspective the possible cost of a disease can be attributed to the disease's existence. "Economists assess the cost of a given situation by comparing it to its next best (and feasible) alternative situation (called the 'counterfactual'). Implicitly, COI studies assume that the counterfactual is the absence of chronic disease, mortality or the risk factor that gives rise to disease." (Suhrcke et al, pg. 19, 2006) The best available alternative may not be the complete eradication of a disease but rather variant levels of prevalence reduction. Thus, a study should include a counterfactual that allows for this.

Alan Shiell, Karen Gerard and Cam Donaldson also discuss some of the limitations of COI research in their paper "Cost of illness studies: an aid to decision-making?" When discussing the possible policy implications of a COI study they write "the total 'cost of illness' can only indicate the benefits of treatment options if an intervention is capable of totally eradicating or entirely preventing the disease in question."(Shiell et al, pg. 320, 1987) They go on to explain that policy makers are usually most interested in the cost and benefits of existing programs. The most appropriate method for answering questions about cost and benefits of existing programs is marginal analysis. COI studies do not provide detailed information about the marginal costs of disease and are therefore, not viable for policy.

In making policy relevant cost of illness research I need to find a methodology that results in estimations of the marginal cost of diabetes. Research by Maureen Cropper et al on the demand for

malaria vaccinations in Ethiopia, has provided me with insight into an alternative method. In their paper "The Demand for a Malaria Vaccine: Evidence from Ethiopia", they measure the monetary value households place on preventing Malaria. They compare cost of illness methodologies with willingness to pay (WTP) methodologies. They note that the COI approach does not reflect all of the possible values of preventing Malaria. The COI approach would ignore the value of lost leisure time, impacts on human capital through reduced child schooling, and the cost of mosquito eradication. "A household's demand for a malaria vaccine that would prevent the disease with certainty should reflect the value household places on preventing all of the consequences of the disease, as it perceives them." (Cropper et al, pg.307, 2003) They use this rationale to justify their use of the willingness to pay methodology.

The willingness to pay (WTP) methodology seeks to find the true value that individuals place on the prevention of a disease by inquiring how much individuals would be willing to pay for disease prevention. A WTP approach seeks to find the summation of individuals' utility functions; i.e. a demand function. Using the WTP approach and the derived demand function a researcher can include some of the costs of a disease that are left out in the COI approach. However, there are other possible benefits of this approach. To understand these benefits we must look closer at the determinants of health care demand.

What are the determinants of health care demand? James W. Henderson depicts four determinant factors of health care demand, "health status (HS), demographic characteristics (DC), economic standing (ES), and Physician factors." (Henderson, pg. 155, 2009) In this paper I am looking at a form of health statues, diabetes, as a determinant of aggregate health care expenditure. How have the determinants of health care demand been used in other research?

The research by Zijun Wang (2009) used state-level data of health care expenditure to estimate the income elasticity of health care demand. Health care expenditure (HCE) data derived from the Center for Medicaid and Medicare Services was the dependent variable. After running a regression

using 11 independent variables only four were statistically significant. The eleven independent variables included, gross state product, price, physician per 100,000 populations, female labor force participation, the amount of uninsured, proportion of the population over 65. The four significant variables were Gross State Product, proportion of the population over 65, degree of urbanization, and number of hospital beds. The goal of this research was to find the degree and sign, either positive or negative, of possible determinants of demand for health care expenditure, and to find evidence of the income elasticity of health care demand. Wang's research has shown evidence of factors that were theorized to be determinants of health care expenditure.

A demand function used in this way also results in parameter estimates. If a dependant variable represents the change in cost due to a change in population, one can derive the marginal cost of that variable using the parameter estimate. This is something that one cannot do using the standard COI methodology. I will use a model like Wang's to estimate the marginal cost of diabetes and its contributing factors. By doing this I hope to find evidence that diabetes is a statistically significant determinant of demand. I also hope to find results that are relevant to health care policy. To do this successfully I need to know the direct and indirect costs of diabetes, and the relationship between diabetes and its complicating medical factors.

The American Diabetes Association (ADA) conducts research on the economic costs of diabetes and makes a detailed estimation of these costs in the article "Economic Costs of Diabetes in the U.S. In 2007" (Dall et.al, 2008). This estimate includes losses from the direct medical costs of caring for diabetes and the indirect costs of diabetes. The direct costs of diabetes are costs associated with increases in medication and health care usage due to diabetes. The indirect costs of diabetes are increases in the risk of getting other diseases, reduced productivity, and increased rates of mortality. Disease types that the ADA attributed to diabetes include neurological, peripheral vascular, cardiovascular, renal, and metabolic. The ADA's aggregate estimated cost of diabetes in 2007 was

\$174 billion (Dall et.al, pg. 596, 2008). This means that diabetes related expenditures were about 1.2% of U.S. gross domestic product in 2007. They also estimated that medical expenditures for diabetics were about 2.3 times higher than people without diabetes. The ADA produces estimates every three years.

I will be using the ADA's research in the formation of my own model.

# Methodology

I will test for the influence of diabetes on aggregate health care expenditure (HCE) using two models. These models are used to test if diabetes and its complicating factors are statistically significant determinants of health care demand. My first model will test for diabetes as a determinant of Medicare expenditure for those over 65. My second model will do the same thing for the remaining adult population. I hypothesize that the consumption behavior of health care differs with different age groups. Therefore, independent variables will have different effects. The ADA has also shown significant differences in consumption behavior between these age groups (ADA, pg.599, 2008) I use two different dependent variables to account for differences in consumption behavior due to age.

I will use different dependent variables in my models. In the first model I will use aggregate Medicare expenditure per-enrollee (MEDHCE). Medicare is reserved for those over 65, and in special cases those who are disabled under the age of 65. I use this variable to determine the aggregate effect of diabetes on HCE for the group who is covered by Medicare. My second dependent variable is aggregate HCE per capita excluding Medicare per capita expenditures (UHCE); I will use this variable to determine the aggregate effect of diabetes for the rest of the adult population.

Both models will include gross state product per capita (GSP). In demand theory income affects demand. In the case of normal goods, and an increase in income results in an increase in quantity demanded. I expect that health care is a normal good. Thus, as GSP increases I expect that health care

expenditure will increase. I expect that GSP will have a positive parameter estimate. Once again, following demand theory and the law of demand, a variable of price of medical care (PRICE) will be tested in both models. An increase in price results in a decrease in the quantity demanded, for most practical and theoretical goods; excluding Giffin goods among others peculiar cases. Thus, I expect that the parameter estimate for price will be negative; indicating that as the price of health care increases the demand for health care will decrease.

The proportion of the population that responded that they had no health insurance, in the Centers for Disease Control's Behavioral Risk Factor Surveillance System survey (BRFSS), will be used in only the model assessing the population under 65 (UNINSURED). I expect that insurance will change consumer expectations. I will only be using this variable in the model testing for those under the age of 65 because Medicare can already be seen as medical coverage. I do not expect that the uninsured will have a huge influence on the expenditures of those covered by Medicare.

The effect of health insurance on HCE is debatable. If we follow the logic of moral hazard, people who do not have health insurance will spend less on health care. This is because people without insurance will have high personal costs of health care, and higher costs theoretically means lower quantity demanded. However, it is also possible that not having health insurance causes more health care expenditure. Theoretically, this is due to the uninsured waiting for treatment until they are at a critical medical point, where they either get treatment or die. Once they reach this critical point, treatment is more costly then it would have been if proper preventive care was pursued. The inability of the uninsured to pay for health care is limited to the time period when they are uninsured. Since I am only looking at one time period, I expect that the amount of the uninsured in this time period will have a negative parameter estimate.

I will also use a variable (PHYSN) which is the amount of physicians per 10,000 populations.

The presence of physicians may cause an increase in the demand for health care. Physicians in these scenarios create a derived demand. The inclusion of this variable in model will take the potential for physician derived demand into account. I expect that as the amount of physicians increases, both (UHCE) and (MEDHCE) will increase. I expect that my variable (PHYSN) will have a positive parameter estimate.

Diabetes may cause other health related complications that result in increased consumption of HCE. The elderly who survive a diabetes related stroke can be expected to increase their consumption of health care significantly due to costs of rehabilitation. I expect that these costs will not be represented as a direct cost of diabetes, but rather an interaction between diabetes and another condition. My interaction variables are restricted by availability of data, and the medical based considerations of contributing factors by the ADA. The ADA researchers used 5 medical factors in their research, neurological, peripheral vascular, cardiovascular, renal, and metabolic. Unfortunately, since these are not diseases but disease types, it is difficult to find macro-economic prevalence data for all five factors. Due to this, I will not be creating interaction terms for all five variables.

For the age group 65 and over I will test the following interaction variables, the first being an interaction variable that is the product of (DIA65) and the proportion of the population that has survived strokes and is above the age of 65 (STROKE65INT). In many cases surviving a stroke results in increases health care expenditures. COI research has shown that \$53.9 billion was spent on treating strokes in 2010 (Heidenreich et al, 2011). Diabetes has also been shown to increase the risk of stroke. "If you have diabetes you are much more likely to have a stroke. In fact 2 out of 3 people with diabetes die from stroke or heart disease." (ADA, 2011) Thus, when a person has diabetes I expect them to have higher risk of stroke. I expect that HCE will increase due to the interaction of stroke and diabetes.

My second interaction variable is the product of (DIA65) and the amount of people with hypertension (HYPER65INT). Hypertension results in cardiovascular conditions which are costly to

care for. Diabetes has been shown to increase the risk of hypertension and other cardiovascular conditions.(Dall et.al, pg.600, 2008) I expect that when a person has diabetes it will increase the risk of hyper tension, which will in turn increase consumption of health care.

I am also interested in finding the direct effect of hypertension and stroke on HCE. I have two other variables for the population over 65, those who have either had a stroke or have hypertension (STROKE65) and (HYPER65). I am interested in the direct effects of these variables because it allows me to separate changes in health care consumption due to these conditions and diabetes related conditions. I expect that these variables are not only affecting health care via diabetes, but also affecting health care expenditure directly.

While it is possible for a person to have a stroke under the age of 65, I do not expect that it will be a significant determinant of health care demand for this age group. Stroke prevalence is lower for this age group. "The prevalence of stroke increased with age: 8.1% of respondents aged  $\geq$ 65 years reported a history of stroke, compared with 0.8% of persons aged 18--44 years." (CDC, 2007) If a disease has low prevalence it will be a less significant determinant of demand. I will test the interaction between diabetes of those under 65 (DIAU) with the prevalence of hypertension for this age group, (HYPERINTU). The direct effect of hypertension will be estimated using the variable (HYPERU). Diabetes has been shown to increase the prevalence of hypertension. Thus, I expect that this interaction will be a significant determinant of health care demand. As diabetes increases I expect that hypertension related HCE will also increase. I will also test the direct effects of hypertension, for this age group, with a variable only representing hypertension (HYPERU).

In 2004 Medicare did not cover medication expenses of diabetes. Thus, I do not expect that direct diabetes (DIA65) will be significant in the over 65 model. However, my health care data for those under 65 does include the cost of over the counter diabetes medications. I expect that a direct variable of diabetes (DIAU) will have significant results for this age group. Diabetes increases the

utilization of medications, such as insulin and test strips; because of this I expect that the variable (DIAU) will have a positive parameter estimation.

I will be testing both models for robustness. Robustness means that the results of my model stay consistent when minor changes are made. I will test for robustness by excluding the direct effects of the interaction terms in some estimations, and then include them in other estimations. With the relationship of these variables and diabetes I expect that they will be correlated. This test for robustness will check for possible changes in my results due to high correlations of these variables. If I found results that were not robust I would expect that my model would produce inaccurate parameter estimations.

# Data

I have obtained data for all states including the District of Columbia. I will exclude Hawaii and Alaska due to their peculiar consumption traits. My data includes 49 observation variables from 2004. Real per capita health care expenditure was taken from The Center for Medicare and Medicaid Service's (CMMS) health care expenditure database. This data has been taken for 2004 and includes nominal aggregate per capita health care consumption by state. The data for HCE has been adjusted and estimated for interstate transfer by the CMMS. Details about this adjustment can be found on the CMMS website (Table 1).

(MEDHCE) was taken from the CMMS's health care expenditure estimates of Medicare per enrollee. The variable (UHCE) was taken from aggregate estimates of HCE by the CMMS. I

subtracted the health care expenditure associated with Medicare, which is within the same data set, from the aggregate. Thus, (UHCE) represents aggregate HCE excluding Medicare. Both of these variables represent annual expenditure. Per-capita state product was obtained from the Bureau of Economic Analysis's regional economic database (GSP). Health care expenditure data was left in its nominal form for the year 2004. Gross state product was collected in nominal terms for the same year.

My variables (DIA65) and (DIAU) are obtained from The Center for Disease Controls Behavioral Risk Factor Surveillance System (BRFSS). BRFSS data are from an annual phone survey which is conducted to obtain data for prevalence rates of unhealthy behaviors and chronic conditions. Since 1995 all states and regions of the US have been participating. The survey is taken by those who are above the age of 18. The BRFSS is a rich source for disease prevalence, socio-economic, and behavioral variables. I collected data from this survey by state on the percentage of people who responded in "yes" when asked: have you been told by a physician that you have diabetes?

Data for (STROKE) and (HYPER) were also obtained from the BRFSS survey. (STROKE) is the proportion of the population which responded yes to: have you ever had a stroke? Hypertension is the proportion of people who responded yes to: Have you ever been told by a physician that you have hypertension. These two variable were broken into age groups based on the respondents declared age.(STROKE65) and (HYPER65) are the proportion of the population over 65 with (STROKE) or (HYPER). (HYPERU) is the percentage of people who responded that they were told that they had hypertension for the age group from 18 to 64.

The data for (INSURANCE) was taken from the BRFSS survey. This data represents those who took the survey and responded in the negative when asked: do you have health care coverage? All data from the BRFSS is in percentage form. Thus, data for (DIAU), (DIA65), and (INSURANCE), (STROKE65) and (HYPERU), are percentages of respondents.

The data for (PHYSN) is the proportion of physicians per 100,000 populations. This data was

taken from the U.S. Department of Health and Human Service's (USDHHS) composite report Health, United States, 2006. This data is derived from medical facility zoning data collected at the state level.

Data for (PRICE) was taken from quarterly cost of index survey data from the American Chamber of Commerce (ACCRA). This index measures price levels for consumer goods for metropolitan areas. The index is based around an average index of 100 for all participating areas. I will use the third quarter as the average for the year; due to infrequent participation of all states in all quarters of 2004. I have taken the indexes for each city in a state and weighted the indexes using population estimates by the US Census Bureau. The weights are created by taking the proportion of a metropolitan population and dividing it by a state population. This gives the population of the area as a percentage of the total population. The indexes of health care price are then multiplied by these weights for all participating areas in the year 2004. The participating regions weighted indexes are then summed together to make the total price index for a state (PRICE).

The interaction terms are the direct effect variables for age groups multiplied by the prevalence rate of diabetes by age group. (STROKE65INT) is the interaction between (STROKE65) and (DIA65). (HYPER65INT) is the interaction between (HYPER65) and (DIA65). The interaction term (HYPERUINT) is the product of (HYPERU) and (DIAU). A statistical summary of the data and sources are provided in table 1.

# Empirical Results

The results are from running four regressions on each model using heteroskedasticity corrected OLS. In the model with dependent variable (MEDHCE) I have found that gross state product (GSP) is a statistically significant determinant of Medicare expenditure per enrollee. The influence of a one dollar increase in GSP per capita is a 3 cent increase in Medicare expenditure. As expected, my results show that increases in income result in increases in Medicare expenditure. A one dollar increase in GSP per

capita causes a three cent increase in Medicare expenditure.

I also found that the variable (PRICE) is statistically significant. An increase in price index by one increases Medicare expenditure by \$18.48. This means that if a state's health care price index was one percent higher than the national average the state would pay \$18.48 more in Medicare expenditure. This variable conflicts with the results of the model for those under 65, which had a negative parameter estimate. The parameter estimate of (PRICE) for those under 65 is -9.36, which indicates as the price index increases by one, medical expenditure decreases by \$9.36. My dependent variable in the over 65 model is the total Medicare expenditure of those over 65. This dependent variable does not reflect changes in co-payments of those on Medicare, only the overall demand for Medicare. Thus, my price variable is a poor indicator of the actual price that Medicare beneficiaries pay for service. I expect that using beneficiaries co-payments, as the price variable, would have shown a more accurate estimation of cost because it would be a closer representation of what consumers are actually paying for Medicare.

Only one interaction term was consistently statistically significant in the (MEDHCE) model. (HYPER65INT) has a parameter estimate of 6.49. (HYPER65) was shown to be either statically significant at the 95% confidence level or very close to being so. The parameter estimate for this variable is \$0.16. This means that a state would pay \$0.16 per percentage of the population that was over 65 and had hypertension. The parameter estimate for (HYPERINT65) is \$6.49. This means that a one percentage increase in those who are 65 and have had both a stroke and diabetes, results in an increase of Medicare expenditure by \$6.49. The interaction term shows that costs associated with hypertension are more costly in the presence of diabetes. The sign of this parameter estimate is positive, and follows my theoretical expectations.

The direct influence of (STROKE65) had high parameter estimates, in comparison to the direct effects of (HYPER). Hypertension itself does not directly lead to high medical expenditure, while strokes do lead to direct medical expenditure, via increases of in-hospital care during rehabilitation.

The differences in the size of the "direct effect" parameter estimates are not surprising. However, the interaction term of stroke and diabetes has a negative parameter estimate. This may be due to increased risk of death from a stroke in the diabetic population over 65. According to the European Stroke Organization diabetes not only increases the risk of having a stroke, but is also responsible for 7% stroke related mortality (ESO, 2011). This parameter estimate could be reflecting a reduction in health care expenditure due to increased mortality. This variable does not have the sign that I predicted, but indicates an interesting interaction between diabetes and stroke.

My second model has the dependent variable (HCEU). There results that suggests that as the amount o physicians per 100,000 increases, health care expenditure also increases by \$48.40. The direction of this parameter estimate matches my theoretical expectations. This variable was statistically significant at the 99% level. The results of this model also show evidence that as price increases by one index point, health care expenditure decreases by \$9.36. The sign for this parameter estimate also agrees with my theoretical predictions for it.

Gross state product was statistically significant at the 95% level; however, the parameter estimate was 0.009, which indicates that as GSP increases by one dollar there is a one penny increase in health care expenditure. About one percent of every dollar created in this nation, in 2004, was spent on non-Medicare health care expenditure. If we include the GSP estimate for the Medicare regression we see that, about 4% of every new dollar produce in 2004 was spent on health care. This estimation agrees with other estimations on the growth rate of per capita health expenditures. For example, the Kaiser Family Foundation reported that the growth rate of health care expenditure per capita was 3.6% in 2003 (Kaiser, 2011). These parameter estimates indicate a change for millions of people and thus, even a few cents per person can have a large economic impact.

The proportion of the population that was not insured (UNINSURED), was shown to be statically significant at the 99% level. As the proportion of the population that was uninsured increases

by 1% heath expenditure decreases by \$41.09. This evidence validates my theoretical position that the uninsured will reduce health care expenditures in the short run. It is both a highly statistically significant and economically significant parameter estimate.

The variable for hypertension (HYPERU) and the indirect influence of diabetes on this term (HYPERINTU), have produced highly negative parameter estimates. The results of the direct influence of hypertension on HCE, has varying statistical significances based on the inclusion of the variable (DIAU). The interaction term (HYPERINTU) also had non-robust statistical significances, due to the inclusion or exclusion of the direct variables, (DIAU) and (HYPERU). Exclusion of the direct effect variables only changes the models predictive power slightly, as seen in the R2 values. All of these variables are shown to be insignificant until all are included into the model. Thus, I expect that increased statistical significance is caused by correlation among the variables. Hypertension, diabetes, and the interaction among the two variables, are not significant determinants of aggregate health care expenditure for those under 65.

Due to the nature of demand and supply functions it is possible that some of my results may be influenced by problems of simultaneity. For example, the variable price could both be influencing health care demand and health care supply. I expect that the parameter estimates for variables (PHYSN) and (PRICE) are biased.

## Discussion

By using two models, representing two different age groups, I have found evidence that suggests that diabetes's influence on consumption behavior is different for both age groups. One of the largest public health policies in the USA is Medicare. Information about diabetes related Medicare expenditure may be significant in determining future policy decisions. For example, the finding that as the percentage of people with both hypertension and diabetes increases by one Medicare expenditure increases by \$6.49,

may be significant in determining the possible benefits of reducing diabetes prevalence in the long run.

The results show that diabetes was not a significant determinant of health care demand for the age group under 65; this indicates there would be very little immediate benefit of reducing diabetes prevalence for this age group. However, as this group ages increases in the prevalence of diabetes does contribute significantly to public expenditures. Thus, while the results may not indicate that there are possible immediate benefits of reducing this age group's diabetes and hypertension prevalence, they indicate that there are significant benefits of reducing prevalence in the long run.

The public benefit of reducing the prevalence of both diabetes and hypertension by one percent is an annual \$6.49 per Medicare beneficiary. It then can be said that any program that reduces the prevalence by one percentage point should be considered as long as the annual marginal cost of that program is \$6.49. Results indicate that programs targeted to the prevention of both hypertension and diabetes may have greater benefits than programs which target diabetes, stroke, or hypertension alone. *Conclusion* 

Cost of diabetes research done in the standard COI methodology does not provide useful information for marginal analysis. In this paper I have presented a methodology to estimate the marginal cost of diabetes and its contributing factors. I have found evidence that shows that the benefit of reducing the prevalence of people with both hypertension and diabetes by one is an annual \$6.49 per Medicare enrollee. A program targeted at preventing these conditions would be preferable as long as the program had an annual marginal cost of \$6.49.

This research was limited by data availability. The policy implications of this research would be more useful if they were up to date. The data I used was from 2004, due to the unavailability of my dependant variable after this year. The Centers for Medicaid and Medicare Services is creating an updated health care expenditure data set, it is expected to be available by the end of the year. Moreover,

the unavailability of macro-data for people with multiple medical factors caused the exclusion of some interaction terms that may have been significant in this research. The BRFFS survey has more medical variables in recent years. Thus, the new CMMS data could benefit this research in at least two ways.

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#### Internet Resources

The American Diabetes Association (ADA), 2011, *Accessed on August 26<sup>th</sup>*, 2007 http://www.diabetes.org/living-with-diabetes/complications/stroke.html

The Centers for Disease Control and Prevention (CDC), 2011, *Accessed on August 26<sup>th</sup>*, 2007 http://www.cdc.gov/chronicdisease/resources/publications/AAG/dhdsp.htm

The Centers for Medicare and Medicaid Services (CMS) Accessed on August 26<sup>th</sup>, 2007 http://www.cms.gov/nationalhealthexpenddata

The European Stroke Oranization, 2011, *Accessed on August 20<sup>th</sup>, 2007* http://www.eso-stroke.org/faq\_04.php?cid=8#q1

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The Kaiser Family Foundation, 2011, *Accessed on August 20<sup>th</sup>*, 2007 http://www.kff.org/insurance/snapshot/chcm010307oth.cfm

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Variables	Model 1.1	Model 1.2	Model 1.3	Model 1.4	
(GSP)	0.031**	0.026**	0.022*	0.017	
	(2.241)	(2.15)	(1,81)	(1.39)	
(PHYSN)	5.5	19.33	14.27	22.23	
	(0.214)	(0.79)	(0.60)	(0.88)	
(PRICE)	18.48**	3.31	17.27**	15.27*	
	(2.119)	(0.36)	(2.07)	(1.79)	
(STROKE65)	329.98			434.24***	
	(1.58)			(6.4)	
(HYPER65)	0.16		0.41***		
	(1.168)		(3.92)		
(STROKE65INT)	-2.02	-1.57*	-6.89	-3.04**	
	(1.28)	(1.7)	(0.53)	(2.64)	
(HYPER65INT)	6.49***	7.07***	4.67***	8.35***	
	(3.37)	(5.3)	(2.93)	(6.49)	
Adj R2	0.64	0.64	0.67	0.74	

 Table 2.1
 Determinants of Health Care Expenditure:
 Model 1 (Dependant variable: MEDHCE)

\*\*\* and \*\*, respectively, denote statistical significance at the 1% and 5% (or better) levels.\* denotes statistical significance at the 10% level.

This model is heteroskedasticity corrected. Values in parenthesis are t-ratios.

Variables	Model 2.1	Model 2.2	Model 2.3	Model 2.4	
(GSP)	0.009**	.009**	0.013***	0.011**	
	(2.261)	(2.025)	(2.75)	(2.294)	
(PHYSN)	48.4***	46.53***	37.05***	44.46***	
· · ·	(5.59)	(4.74)	(3.63)	(4.43)	
(PRICE)	-9.36***	-7.82**	-6.12*	-9.02**	
<b>`</b>	(3.54)	(2.04)	(1.83)	(2.503)	
(UNINSURED)	-41.09***	-47.78***	-52.52***	-41.52***	
、	(3.92)	(4.38)	(4.39)	(3.69)	
(HYPERU)	-104.25***			-15.67	
<b>`</b>	(3.56)			(0.85)	
(HYPERINTU)	-1.29**	-7.99	-6.9	-9.43	
、	(2.58)	(1.31)	(1.09)	(1.56)	
(DIAU)	234.71***		14.85		
	(3.26)		(0.27)		
Adj R2	0.85	0.84	0.81	0.84	

**Table 2.2** Determinants of Health Care Expenditure:
 Model 2 (Dependant variable: UHCE)

\*\*\* and \*\*, respectively, denote statistical significance at the 1% and 5% (or better) levels.\* denotes statistical significance at the 10% level.

This model is heteroskedasticity corrected. Values in parenthesis are t-ratios.

# Table 1:

Variable Definitions Summary statistics and data sources.

Variable	Definition	Source	Variable	Definition
UHCE	Aggregate medical expenditure, minus Medicare, by state. 2004 Mean: 4387 St.dev: 668	Center for Medicare and Medicaid Services http://www.cms.gov/national healthexpenddata	MEDHCE	Annual Medicare expenditure by state. 2004 Mean: 6988 St.dev: 942
DIAU	Proportion of those who respondent "yes" to: Have you ever been told by a doctor that you have diabetes? Also the propotion who responded that they were under 65 years of age. 2004 Mean: 5.5% St.dev: 1.2%	The Center for Disease Control BRFSS http://apps.nccd.cdc.gov/BRF SS	DIA65	Proportion of those who respondent "yes" to: Have you ever been told by a doctor that you have diabetes? Also the propotion who responded that they were over 65 years of age. 2004 Mean: 17% St.dev: 2.1%
STROKE65	Proportion of those who respondent "yes" to: Have you ever had a stroke? The responded also declared themselves over the age of 65 2004 Mean: 2.6% St.dev: 0.54%	The Center for Disease Control BRFSS http://apps.nccd.cdc.gov/BRF SS	STROKE65INT	Proportion of those who respondent "yes" to: Have you ever had a stroke? Multiplied by the variable DIA65. The responded also declared themselves over the age of 65. 2004 Mean: 0.00442 St.dev: 0.00081
HYPER65	Proportion of those who respondent "yes" to: Have you ever been told by a physician that you have hypertension? The responded also declared themselves over	The Center for Disease Control BRFSS http://apps.nccd.cdc.gov/BRF SS	HYPER65INT	Proportion of those who respondent "yes" to: Have you ever been told by a physician that you have hypertension? Multiplied by the variable DIA65. The responded also

	the age of 65. 2004 Mean: 28.1			declared themselves over the age of 65. 2004
	St.dev:3.5			Mean: 0.0476 St.dev: 0.013
PHYSN	Physician per 100,000 population. Mean: 23	The U.S. Department of Health and Human Services. www.cdc.gov/nchs/data/hus/h us06.pdf		
	St.dev:7.5			
HYPERU	Proportion of those who respondent "yes" to: Have you ever been told by a physician that you have hypertension? The responded also declared themselves under the age of 65. 2004	The Center for Disease Control BRFSS http://apps.nccd.cdc.gov/BRF SS	HYPERUINT	Proportion of those who respondent "yes" to: Have you ever been told by a physician that you have hypertension? Multiplied by the variable DIAU. The responded also declared themselves under the age of 65.
	Mean: 19.85 St.dev:2.96			Mean: 0.001045
				St.dev:0.000271
GSP	Real per-capita gross state product. 2004	<i>The Bureau of Economic</i> <i>Analysis</i> http://www.bea.gov/regional/		
	St.dev: 13,914	gsp/		
PRICE	Average weighted index by	The American Chamber of		
	state for price of health care.	Commerce Cost of Living Index		
	Mean: 100 St.dev: 11.8	http://www.coli.org/		