The Relationship Between Poor Health Behaviors and Medicare Costs

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Abstract:
It has been well established that there are negative effects caused by poor health behaviors such as obesity and smoking, generating higher costs of medical care in the long term. In light of the aging baby boom generation as well as rising cost of health care in general, the financial health of Medicare has been under scrutiny in recent years. With negative effects so well known to be associated with poor health behaviors, one would assume that just as most people supplement social security with retirement savings, that there are similar incentives for people to invest in health to prevent poor health outcomes and gain life years. However, individual investments in health are much less than one would expect. This paper firstly quantifies the relationship between Medicare costs and rates of negative health behaviors and secondly explores the reasons that individual do not choose the optimal amount of investments in health.

Keywords: Obesity, Medicare, Health Decisions, Healthcare

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1. Introduction

When Americans were asked, “What would you say is the most urgent health problem facing this country at the present time?” in 1987, the majority (67%) of respondents stated that it was AIDS. However, when asked again in 2003, the greatest number of respondents’ highest concern was Health care/insurance costs (29%). (Gallup, 2003) The rising cost of health care has been the topic of much concern and debate in recent years. Total health care spending has increased from 7% of GDP in 1970 to 14.9% in 2002, and no other country in the OECD spends as much per capita on health care as the United States. (Reinhardt, Hussey, Anderson, 2004) If the same increase in health care spending observed in the last two decades were to continue, the U.S. will be facing health care costs exceeding 28% of GDP by 2025.

One of the most impacted player in the health care market is the Medicare program, which provides in the last and most expensive years of life; those over the age of 65 spend three times as much per year on health care as compared to those 19-65. (Mehrotra, Dudley, Luft, 2003) As life expectancy, cost of health care, and numbers of enrollees has increased over time, the Medicare program has sustained an increased burden in past decades with no prospect of relief in the near future. The Congressional Budget Office projects that annual Medicare expenditures will increase from $207 billion in 1999 to up to $3 trillion by the year 2030.

A major part of the increase in Medicare costs can be attributed to demographic characteristics; Beginning in the year 2011, 77 million Baby Boomers will enter the Medicare program, and by the time the last member of the baby boom generation retires in 2029, one in five U.S. residents will be over the age of 65, and supported by Medicare.
The strain that will be put on the program is not only a population increase problem, but is a deep problem of demographic trends that have significant negative impacts on pay-go programs such as Medicare. In 30 years, there will be a 100% increase in the number of elderly people with only 15% more workers to pay Social Security and Medicare benefits. (Kotlikoff, Smetters, Walliser 2001) Thus, in the face of possible fiscal insolvency for the Medicare program in coming decades, the health of the elderly and any issues relating to the overall costs of Medicare are both timely and have significant impacts on future.

The elderly are a costly cohort not only because they tend to have a greater number of health issues, but also because a greater proportion of new and expensive technological advances are aimed to the elderly population. It is estimated that more than half of research and development in health care is aimed at the elderly population, whose health care is conveniently paid by out of the government’s pocket, and that the greatest culprit of increasing costs in health care advances in technology. (Fuchs, 1996) Studies have found that medical technology contributes to between 15 to 50 percent of health care inflation, and there is fear that “the diffusion of new medical technology may ultimately overwhelm managed care’s attempt to moderate health care costs.” (Neuman, Sandberg, 1998)

However costly, technological advances in health and health care are arguably the most significant contributors to the advancement of Western society in the 19th and 20th centuries. From antibiotics and immunizations to liver transplants and angioplasties, there is no question that health care and medicine have added decades of life to lifespan and decreased the impediment of disease on human growth and development. However,
research and development investments in health care have been landing in an increasingly saturated market, and have been suffering significantly lower returns to investments. There has been a general trend of modern technologies taking center stage by investing in health repair while more old-fashioned ideas of health preservation such as nutrition, exercise, and avoidance of unhealthy habits has taken the sidelines in the production of health.

In fact, there is a general tendency of attributing health status to health care rather than to individual behavioral choices. The effect of medical care and technologies is not the only player in the production of health. Everyday behavioral choices such as choice of activities, occupation, amount of exercise, attention to safety, or diet choices dominate a person’s health far more than the medical care system. Among people aged 15-24, vehicle crash, homicide, suicide, and other accidents constitute more than 75% of cohort deaths, showing that for this age group, the role of medical care is medial, and that behavioral choices are most significant. While the picture appears to be different for people aged over 65, where heart disease, cancer and stroke top the list, (U.S. Department of Health and Human Services, 1999) these diseases are heavily influenced by lifestyle choices made earlier in life. For example, smokers have 2.5 times the risk of nonsmokers for fatal heart attacks, and diets of elevated cholesterol bears 2.4 times the risk of one with normal cholesterol for heart disease. (Phelps, 2003) Behavioral choices are often overlooked but are likely to be much more responsible for health outcomes than the actual provision of health services.

If it is true that the negative effects of health behaviors are well known, why are people willing to invest money in retirement packages but unwilling to invest effort into
investing in health for the long term? The second part of this paper explores the consumer choice element of choosing not to participate in health-enhancing activities.

Despite improvements in technological advances in health care provision, health status in the U.S. has not improved in recent decades, and performs poorly in relation to other OECD countries. It can be hypothesized that poor behavioral trends in the U.S. offset the gains made through technological advances, and individual’s behavioral choices are costing the nation both health and resources. In light of the stress induced by increased health costs and the aging of the baby boom generation, it is important to evaluate all contributors to Medicare costs. It has been consistently shown that negative health behaviors costs society significant resources, and this project aims to seek and quantify the costs of negative health behaviors incurred specifically on the Medicare program.

2. Background

2.1. Obesity

Rising rates of obesity have been well publicized and recently thought to be so serious to be called an epidemic by some media sources. In data collected by the Behavioral Risk Factor Surveillance System (BRFSS), participants self-reported weight and height and other health risk factors. Though self-reported data often understates true BMI, the trend of increasing obesity is still evident, the prevalence of obesity was found to have increased from 12.9% in 1991 to 17.9% in 1998. (Mokdad, et al. 1999) The same survey in 2001 posted nearly a 3% increase over the three-year period, reporting an obesity prevalence of 21.6%. During the nineties, the prevalence of obesity increased in every
single state, from a 24.9% increase in the District of Columbia to a 140.2% increase in New Mexico. While in 1991 no state had an obesity prevalence over 20%, 37 states reached this threshold in 2001. (Ahluwalia, et al. 2003) While the surveys conducted by the BRFSS effectively demonstrates the trend of obesity over time, The National Health and Nutrition Examination Survey (NHANES) program more accurately quantifies the problem of obesity, as this survey physically tracks obesity rates. The NHANES has found that after staying relatively stable from 1960 to 1980, rates of obesity have increased significantly in recent years. NHANES has found that actual obesity rates are significantly higher than the BRFSS data, reporting 22.9% in the 1988-1994 survey, increasing to 30.5% in the 1999-2000 survey, with extreme obesity nearly doubling from 2.9% to 4.7% over the time period. (Flegal, Carroll, Ofden 2002)

In reference to the Medicare population, it has been found that as people age, that they are likely to increase in BMI as well. The trend of obesity among the elderly population has been accelerating growing at an even greater rate than in the general population; for example, obesity rates for males aged 60-74 that were relatively stable at 8.4% in 1960, 10.5% in 1971, have recently skyrocketed to 23.8% in 1988-1994, and most recently to 35.8% in the 1999-2000 survey. (Flegal, Carrol, Ofden 2002). Obesity rates for elderly females have also been increasing, though the increase is not as marked as that of males. For the entire elderly cohort in 1990, 9.9 million Americans over the age of 60 were obese, representing 23.6% of the elderly. Only one decade later, the number of obese elderly Americans rose to 14.6 million, representing over 32% of the age group. Projection estimates predict that the percent of elderly who are obese could climb to up to 39.6% if current trends continue. (Arterburn, Crane, Sullivan 2004)
The trend of obesity has been a significant concern because obesity is involved in a large and increasing number of negative health effects. For example, relative to the non-obese, obese people are found to have 40-60% higher risk of hypertension, 50-60% higher chance of type 2 diabetes mellitus, and there are significant increases in cardiovascular disease risks associated with increasing BMI. (Thompson, et al. 1999) In fact, dose-dependent relationships between obesity and many diseases has been demonstrated; For example, the risk of high blood pressure is nearly 50% higher for overweight people as compared to normal weight people, twice as high for Obesity Class 1 people compared to normal, and nearly three times as high for Obesity Class 3 people compared to normal. (Must, et al. 1999).

The negative health effects caused by obesity are reflected not only in health status, but in economic terms as well; it is estimated obesity causes an increase in average annual medical spending of 37%. (Finkelstein, Fiebelkorn, Wang 2003) In fact, nearly $52 billion in annual expenditures can be attributed to obesity, accounting for 5.7% of all health care costs. (Wolf, Colditz 1998) As compared to the non-obese, mild obesity is expected to increase lifetime medical care costs by 20%, with moderate obesity increasing costs by 50%, and with severe obesity nearly doubling the lifetime medical care costs. (Thompson, et al. 1999)

2.2 Smoking

Unlike obesity, the trend of smoking has been declining in recent years. However, the prevalence of smoking is still high with respect to the population, and as a top-ten contributor to morbidity and mortality, it continues to be a highly significant
negative contributor to health and health care costs. The prevalence of smoking varies across the United States, with prevalence rates in 2001 as low as 13.2% in Utah and as high as 30.9% in Kentucky, according BRFSS. Compared with data a decade earlier in 2001, cigarette smoking decreased slightly, from a median of 24.1% in 1991 to 22.9% in 2001; Most states posted declining rates, with the exception of fifteen Southern and Midwestern states.¹ (Ahluwalia, et al. 2003)

The trend of steady or slight decrease in per capita smokers has been shown to hold true in the elderly population as well. Current smoking prevalence has been found to be twice as high for ‘young-old’ beneficiaries aged 65 to 74 (12.9%) than for those who are aged over 75 (6.1%). Furthermore, higher prevalence of ever smoking in the young-old (52.9%) than the old-old (41.2%) indicates that the higher smoking rate might be affected by sociological influence inherent within the cohort rather than a pure function of aging. (Arday, et al. 2002)

Smoking has had a long-established association with worse health outcomes. In a longitudinal study in Buenos Aires, smoking was found to be significantly associated with higher risks for lung cancer with odds ratio for current smokers of 8.5 and 5.3 for former smokers as compared to non-smokers. (Matons, et al. 1998) Among U.S. veterans, a cohort study of over 200,000 U.S. veterans revealed a strong dose-dependent relationship between smoking and total cancer, declaring over 50% of cancer deaths among current smokers and 23% of cancer deaths among former smokers to be attributable to cigarette smoking. (McLaughlin, et al. 1995) Smoking is well known to be associated with increased risk of coronary heart disease (CHD) and lung cancer, but is

¹ States with increased smoking rates were Georgia, Illinois, Indiana, Iowa, Mississippi, Missouri, Montana, New Mexico, North Dakota, Ohio, Oklahoma, South Carolina, Texas, Virginia, and West VA
also associated with cancers of the esophagus, larynx, oral cavity, bladder, pancreas, and kidney. (Jacobs, et al. 1999) It is estimated that the U.S. has incurred smoking attributable costs of 26 billion dollars due to CHD, 24.9 billion on COPD, and 9 billion on strokes attributed to smoking.

2.3. Physical Inactivity

In contrast to more quantified trends in obesity and smoking, there is little research concerning the prevalence of physical inactivity. However, there is evidence that regular physical activity has been decreasing in all age cohorts, and that physical activity has the potential to be a potentially effective target for health policy reform.

Physical activity is an important indicator of many health factors that are not usually considered in studies considering health behaviors. Aside from the obvious effect of physical activity being a precursor for the prevalence of obesity, physical activity is found to have consistently positive effects on many aspects of health. Regular physical activity is found to be a salient factor in the prevention and rehabilitation of many diseases such as coronary artery disease, hypertension, and diabetes. (Atkins, et al. 1984) Furthermore, in a controlled study, exercise participants were found to exhibit improvements in depression, anxiety, self-concept, and vigor, demonstrating significant psychological benefits to physical activity. (DiLorenzo, et al. 1999) Lastly, several Spanish researchers have gone so far as to deem a schedule of physical activity to be an “anti-aging intervention” that allowed “that person to develop his maximal physical potential while improving his physical and mental health and attenuating the deleterious consequences of aging.” (Garzon, Porcel, Ruiz, 2005) Physical inactivity can be shown
to not only be affecting measures of obesity, but may have spillover effects in psychological health that may also positively contribute to health production.

3. Literature Review

While there has been extensive research concerning obesity and smoking and health effects, there is little documentation evaluating multiple measures of negative health behaviors at the same time. Furthermore, while several studies address the issue of various negative health behaviors on health production, the few studies that do address costs are often limited by specificity to specific outcomes or specific diseases. For example, while specific studies such as documenting the impact of obesity related disease on cardiovascular in-patient costs are relatively common, very few projects address the specific issue of poor health behaviors in general, or thoroughly quantify and compare costs. The following papers represent the most convincing examples of showing the relationship between obesity or smoking and Medicare costs.

3.1. Body Mass Index (BMI) and Medicare Costs

One of the first studies to specifically address the relationship between obesity and Medicare expenses was conducted by Davi glus and colleagues in 2004, relating body mass index (BMI) in young adulthood and middle age to Medicare expenditures in older age. The longitudinal study used BMI data from 39,522 participants of the Chicago Heart Association (CHA) between 1967 and 1973, and obtained Medicare fee-for-service claims for these patients between 1982 and 2002. The study was extremely successfully in tracking the participants, deeming only 0.23% of the participants untraceable. The
study found a significant positive relationship between BMI and Medicare charges, finding overall that total charges were significantly higher for overweight and obese men. Total charges for severely obese men and women were $6192 and $5618 higher (84% and 88%, respectively) than for non-overweight men and women. (Daviglus, et al. 2004) The main strength of this study is that it is the first large-scale, long-term longitudinal study and thus is closer to showing causality. However, as the statistics controlled only for age and race, it is likely that the obesity term is overestimated, as it includes some of the effects of negative health behaviors not specified in the model. Furthermore, while the increase in spending was controlled for the increase in medical prices by adjusting for MCPI, the study does not address changes in the types of treatments over time. The study focuses on cardiovascular disease (CVD) and diabetes, and as these diseases have been of particular concern in recent years, and with the addition of new drugs and procedures, it is possible that MCPI underestimates the cost increases that have been seen in these diseases, thus over attributing some of the inflationary effects specific to these diseases to an increased cost of obesity. Nonetheless, this study is the first to show that obesity in adult life incurs greater costs later in life, and sets a precedent for greater use of longitudinal studies to evaluate obesity in the future.

3.2. Obesity and Medicare Costs

Another study related obesity rates to Medicare costs using the Medicare Expenditure Panel Survey (MEPS) 1998 in conjunction with the 1997 National Health Interview Surveys. The study controlled for sex, race/ethnicity, education, poverty, insurance status, and marital status, and region, and attempts to calculate costs attributable to
obesity by taking the aggregate predicted expenditures for the obese group with a
dichotomous obesity variable of 1 and subtracting the aggregate predicted expenditures
for the obese group with the dichotomous obesity variable set to zero. The study appears
to show very significant impacts on national and Medicare costs, on the order of nearly
$48 billion dollars of annual aggregate medical spending attributable to obesity.
(Finkelstein, Fibelkorn, Wang, 2003) Interestingly, this study fails to address or even
acknowledge the presence of many other negative health behaviors that are correlated
with obesity, such as smoking and inactivity. Thus, it is likely that by including only
obesity the predictive variable, that an over attribution of costs to obesity has occurred.
Furthermore, while the study attempts to recognize regional differences, it uses crude
measures such as Northeast, and South. While this helps to control for different cultural
mentalities in different areas of the United States, it does not address the real problem
associated with geography, which is that differences in costs of living result in different
prices of health labor and thus results in significant geographic variation. It is likely that
the regional specification is too crude and that the regressions suffer omitted variable
bias.

Lastly, there is a problem with using obesity as a predictor at all. While many
studies identify and quantify the diseases that are symptoms of obesity, it is rarely
recognized that obesity is in and of itself a symptom of individual behavioral choices.
While smoking is a behavioral effect, obesity itself is not a behavior, but it is an
intermediate step between observed behaviors and health outcomes. Thus, from a policy
perspective, obesity is difficult to target, and should be considered to be of less
importance than other variables that can be controlled by policy such as physical activity and diet.

3.3. Smoking and Medicare Costs

The first study that directly related the cost of smoking to the Medicare program was conducted by Xiulan Zhang, Leonard Miller, Wendy Max, and Dorothy P. Rice in 1993. This study first estimated smoking attributable expenditures (SAEs), which are the difference between expenditures of smokers and ‘non-smoking’ smokers, who have the same demographic and lifestyle characteristics of smokers except that they do not smoke. Hospital care was the category in which SAE was most pronounced, and the total amount of SAE for Medicare in 1993 was estimated to be just over $14 billion. The study further extrapolated the effect of smoking on total societal costs, which isn’t entirely relevant to the focus of this paper, though it is worth noting that the study estimated that the percent of total smoking costs borne by Medicare to be 19.5%. A more accessible measure of smoking attributable cost used by the study is the smoking attributable fraction (SAF), which is the percentage of smoking-attributable expenses to total Medicare expenses. SAFs by state ranged from as low as 4.6% in Alabama to 15.26% in Montana, with a national average of 9.43% of all Medicare expenses being incurred by smoking. Among specific types of Medicare expenditures, the results showed that while only 5.58% of national ambulatory care could be attributed to smoking, 11.44% of all hospital expenditures could be attributed to the effects of smoking. (Zhang, Miller, Rice 1999) This study improves on the obesity studies previously cited because it attempts to control for all of the other negative health behaviors exhibited by smokers when it makes
the distinction between smokers and non-smoking smokers, thus eliminating some of the
omitted variable bias that the other studies suffered from by failing to include more than
one negative health behavior variable. However, the major weakness of this paper is that
the data comparing the smokers to non-smoking smokers is hypothetically extrapolated
and not experimental, thus does not represent concrete differences.

I intend to improve upon the prior work done in the area in several ways. Firstly,
I utilize three models of varying degrees of specificity to attempt to isolate the effect of
negative health effects on Medicare costs: The historical model, the state specific model,
and the county specific model. Each model has different strengths and shortcomings, and
the use of all three models not only ensures a checks and balances system, but the
differences between the three results has implications about the Medicare system as well.
Secondly, as it is my belief that many of the studies in the past have failed to sufficiently
address the correlation among the different measures of negative health behaviors and
have thus over attributed costs to their problem at hand, I hope to address the problem of
failure to invest in health in general.

4. Methods of Quantifying the Impact of Negative Health Behaviors

Model 1: The Historical Model

A. Methods

The aim of the historical model is to use national data concerning health behaviors during
adulthood to predict Medicare costs incurred later in life. Specifically, the historical
model requires data concerning the negative health behaviors of the 35-45 year old cohort
during the 1960-1970 decade in order to predict the Medicare expenditures of the 65-75 year old cohort during the 1990s and recent years. The time lag of the negative health behaviors is important because in theory, negative health behaviors have cumulative negative effects over time, and thus prevalence of negative health behaviors during adult years should in theory most accurately predict Medicare costs during retirement years.

The dependent variable is the total national cost of Medicare, compiled from cumulative costs from the Federal Budget. The health behavior control variables included on a time lag are obesity, physical inactivity, an smoking. Other control variables incorporated in real time include the Medical Consumer Price Index (MCPI), measuring of the percentage change in medical goods (Ireland, 2001), changes in demographics such as racial composition, urban/rural location preferences, and elderly poverty rates.

\[ \text{Medicare Expenditures} = \beta_0 + \beta_1 \text{negative health behaviors (t-30)} + x\delta \]

The historical model attempts to capture and quantify the changes in Medicare expenditures over time that are associated with the changes in patterns of negative health behaviors during adulthood.

B. Results

In practice, the desired data for the historical model was nearly impossible to find and likely does not exist. The most prominent problem is that data for negative health behaviors has not been consistently recorded for a long enough period of time to accommodate the use of the historical model. One of the two main sources for
information concerning negative health effects is provided by the NHANES, which has only been conducted four times. The first survey was conducted in 1971-1973, which would provide only one data point for the time series model using the 30-year time lag.

The other potential source is the BRFSS, which includes obesity, physical inactivity, as well as other negative health behavior variables, and is relatively consistent and proves desirable for use in the time-series model, but does not go back far enough in time to prove useful in the framework of a 30-year time lag. Using the BFRSS data, the greatest decade-long time lag available would be use 1982-1992 health behavior data lagged on Medicare expenditure data from 1992-2002, which is a time lag of less than ten years, and thus is not representative of the effects of decisions during adulthood on later health. Nonetheless, the historical data is useful for showing trend behavior such as the obesity trends for the elderly cohorts shown in Figure 1.

C. Discussion
While in theory negative adult health behaviors are expected to incur in greater health costs later in life, there are several problems with data and scope that make the historical model unrealistic in practice.

Firstly, although all medical evidence and common sense indicates that obesity is a life-long behavior with long-term consequences, this hypothesis is not reflected in the data. For example, one would expect that high obesity rates in the 65-75 year-old cohort should be reflected in high obesity rates in the 75-85 cohort in the next decade. Though this trend might generally be difficult to detect, one would not expect the result exhibited in Figure 1 in which obesity rates of all elderly cohorts move together. It is extremely
unlikely, for example, that all three cohorts of elderly population experienced mass weight loss between 1996 and 1997, causing an 8% drop in obesity prevalences in every cohort. The similar peaks and dips exhibited amongst all of the elderly cohorts challenges the notion of obesity as a life-long disease, or more likely, shows that there are problems in trends in measuring and self-perception of obesity. Thus, even if the BRFSS data had enough historical volume, the lack of trend adherence to cohort questions its validity as an accurate measure of obesity over time.

Secondly, while the use of national data renders a large scope, it also requires that a great number of factors be controlled for. There are many factors such as legislation and technological differences that affect changes in Medicare expenditures over time, and even if negative health behaviors were accurately recorded in the past, it would be difficult to completely isolate the independent effect of health behaviors and to effectively control for everything else at the national level.

Thus, while the historical model is theoretically the most accurate manifestation of obesity, it is not feasible within the framework of available resources. As society has only become concerned with and quantified negative health behaviors in recent years, a historical model will likely not be feasible for at least another decade.

**Model 2: The State Specific Model**

A. Methods

The State Specific Model uses data compiled from all fifty states and uses differential per capita spending between the states to gauge the effect of differential negative effects among the states. The hope for the state specific model is that differential demographic
characteristics can be controlled for and that spending differences between the states is representative of and can be quantified in terms of negative health habits.

The dependent variable is the 1998 spending per Medicare Beneficiary reported by the Centers for Medicare and Medicaid Services, formally known as the Health Care Financing Administration. In order to control for the many other characteristics that contribute to health care costs, a variety of demographic variables were included, including racial composition, urban/rural distribution, level of poverty, and measures of state government generosity. (See Table 1)

\[
(2) \text{ Per Capita Medicare Expenditures} = \beta_0 + \beta_1 \text{ physical inactivity} + x\delta
\]

Immediately upon examination of the data, the District of Columbia stood out as an outlier. Figure 2 shows the District of Columbia to be a poignant outlier not only in both its high spending per beneficiary as well as its unique racial composition of more than 60% of beneficiaries being black. The District of Columbia was found to be an outlier in nearly every variable; Figure 3 shows the District of Columbia being an outlier in terms of life expectancy. As the District of Columbia lacks state status and has unique circumstances and data that are not consistent with the rest of the fifty states, it was left out of any further results.

The descriptive statistics of the variables with the 50 remaining states are reported in Table 2; Per capita Medicare spending ranged from 3,936 to 7,219, and had a mean of 5,409. Cigarette smoking rate ranged from 12.7% to 32.4% and obesity prevalence ranged from 14% to 26%. Correlations between the variables were also notable. Comparing obesity to beneficiary Medicare costs rendered a weak positive correlation.
Smokers are defined as being those who currently smoke every day or some days and have smoked at least 100 cigarettes in their lifetime, and is obtained from the BRFSS in 2002. Smoking was found to have only a very weak correlation between Medicare per beneficiary costs, shown in Figure 5. Physical inactivity is defined as reporting no leisure time activities that cause increases in heart rate, and the prevalence data is obtained from the Centers for Disease Control and Prevention (CDC). Physical inactivity was found to have the strongest and only statistically significant correlation with Medicare costs, shown in Figure 6.

B. Results
While the inclusion of several measures of negative health behaviors was intended to improve the ability to isolate the effects of each individual behavior, it also introduced the problem of colinearity. For example, physical inactivity was found to be significantly correlated at the 0.01 level with Obesity, Cigarette Smoking, Percent of Black Population, and several other variables. (See Table 3) To gauge the colinearity effect, the predictive ability of the demographic variables on the behavioral variables was tested. It can be seen in Table 4 that more than half of the variation in any of the three behavioral variables can be predicted by the other demographic variables. It is interesting to note that the only variable that consistently does not have predictive power is that of rural residency, but in general, one can conclude that the demographic variables do have predictive power over the behavioral characteristics, and that colinearity cannot be ruled out. Lastly, the effect of colinearity between obesity and physical inactivity is tested in Table 5, which shows that the inclusion of the physical inactivity variable improves
predictability as compared to the obesity variable, and that inclusion of both variables
does not seem to have very much effect compared to having only the physical inactivity
variable. The sign change that occurs in the obesity coefficient when physical inactivity
is added into the regression is suspect of a sign of colinearity, and could explain the
higher variance in the regression containing both physical inactivity and obesity
variables.

Several combinations of the demographic variables were tested, and it was found
that the majority of predictive power was found in the physical inactivity and the rural
population variables. Table 6 shows a number of the combinations of variables that was
tested, and finds the equation below to explain the most variation efficiently.

\[
(3) \text{Per Capita Medicare Expenditures} = 3,625 + 65.46(\text{physical inactivity}) + 15.74
(\text{percent black}) - 21.99(\text{rural population}) + 26.18(\text{elderly poverty rate})
\]

\[n = 50, R^2 = 0.811\]

Through regression (3) on Table 6, all of the coefficients are in the expected
direction. Physical inactivity is shown to have a statistically significant and positive
coeficient ranging from 65 to over 80 dollars per percentage point of physically inactive
populace per state. The only other variable that maintains statistical significance is the
coefficient on rural residency, which ranges from -20 to -22. Percentage of black
beneficiaries has a positive but statistically insignificant beta coefficient, as does the
elderly poverty rate. The addition of further variables fails to add statistical value, and
rouses suspicion firstly because of a decreased adjusted R-squared value, and also because it causes sign changes and increases in variance.

Table 7 shows the result of using only the physical inactivity and rural population variables, suggesting that 64% of variation in Medicare expenditures can be explained by residency and physical inactivity.

Lastly, it is interesting to note that the states that most consistently had the worst negative health behaviors were concentrated in the south and the Midwest while the states with the best health behaviors included Connecticut, Utah, and many coastal states. There are also several states that have paradoxical combinations of variables, such as Massachusetts, which brags the second lowest rate of obesity and correspondingly low prevalences of cigarette smoking and physical inactivity, but has the second highest per capita Medicare expenditures. South Dakota and Nebraska are also both anomalies in that they have two of the lowest per capita Medicare expenditure rates, but have above average rates of negative health behaviors.

B. Discussion

Though the state specific model is unable to discern great detail for reasons discussed in later sections, the importance of physical activity is likely to be valid and economically significant. If one assumes the aforementioned results to be true, $1,650 of per capita Medicare costs are on average attributable to physical inactivity, which spread over 40 million Medicare beneficiaries translates to over 66 billion in annual Medicare costs due to physical inactivity. In fact, it should be no surprise that physical inactivity should be the best predictor of Medicare costs. Not only does physical inactivity contribute
significantly to obesity, but it is intuitive that physical activity would be a better producer of health than simply avoiding smoking or obesity. It is reasonable to believe that the windfall of negative health effects caused by physical inactivity including obesity and the negative health effects of obesity, and negative behavioral and psychological effects have significant effects on Medicare costs. The results from the state specific model suggest that decreasing the prevalence of physical inactivity by only 1% would provide savings of over $63 per year on average for all beneficiaries. Considering that physical activity was defined as having any leisure activity including golf, gardening, or walking as being physically active, such a result is not an unrealistic goal, and could potentially have vast health and financial benefits. For example, the state of Kansas has 297,320 Medicare beneficiaries (Urban Institute and Kaiser Commission, 2004) and a physical inactivity rate of 26%, and if one percent, or slightly less than 3,000 people took up gardening, savings of $65 per beneficiary could be incurred, totaling $19,325,800 in annual savings for the state of Kansas alone. Regardless of the lack of precision of the state-specific model, it does successfully implicate a potentially powerful factor in future health and health care costs.

Though the state-specific model revealed an important predictor of health care costs, there are inherent flaws in the state model that prevent precise results. The underlying problem with the state specific data is that while it does provide a large and sufficient number of easily accessible data points, geographic boundaries in the U.S. are not particularly strict and are do not segment the population into useful groups that control for external effects on health care costs.
Firstly, the fluidity of state boundaries is a problem causing inaccuracies in per beneficiary spending. For example; the underlying reason for dropping the District of Columbia was not entirely because it lacked the infrastructure of a state, but because of its small population but large number of prestigious hospitals. In the densely populated east coast, it would not be unheard of, in fact it would be absurd for those in neighboring states not to travel to the District of Columbia for higher quality medical care. For example, while the larger and more populated neighboring state of Virginia has no hospitals ranked by U.S. News and World Report in any category while the District of Columbia touts four hospitals ranked nationally in seven categories, including the Medicare-heavy heart and heart surgery category. While Washington D.C. was dropped from the dataset, its effect on the dataset was not eliminated entirely as the per capita costs of neighboring states are likely to be consequently underestimated. Furthermore, the trend of state border hopping for medical care is not limited to Washington D.C; States all over the east coast are small, accessible, and have varying ranges and qualities of health care services, and with cheap air travel it is not unreasonable to expect that some people even travel nationwide to obtain health care, deeming per capita state Medicare beneficiary statistics to be less than perfect.

Secondly, the arbitrary geographic bounds of states and the lack of uniformity within states make it difficult to control for differential input prices. While the cost of medical equipment and products does not vary much across states and regions, labor is one of the most costly inputs and the cost of labor varies widely across metropolitan and non-metropolitan areas. Unfortunately, using state boundaries denies the prospect of being able to control input price by discriminating between different degrees of
metropolitan areas. As states have varying amounts, and levels of metropolitan areas, it is nearly impossible to control for labor input prices in the framework of state bounds, and it is likely necessary to identify specific metropolitan or non-metropolitan areas rather than state bounds.

The effect of physician labor input is clearly a significant part of differential Medicare per capita costs, and it is in fact the likely reason for the significance found in the rural residential population variable. While the rural residential population variable was initially included under the hypothesis that those who lived in rural areas were less likely to be in close proximity to medical care and thus utilize it less. However, as labor inputs have not been explicitly controlled, one can assume that the effect of labor input prices is factored into the rural residency term, as states with higher percentages of rural residences by definition have proportionally less metropolitan areas, and thus on average have lower wages and lower prices for health care professional labor.

The state-specific data is unable to produce great detail because of the crude nature of geographic boundaries, but is useful in providing direction and a framework for the other models.

**Model 3: The County Specific Model**

A. Methods
The county specific model aims to alleviate some of the problems created by the crude geography of the state specific model by focusing on the county unit, which usually contains a population much more uniform in population density, demographic, and quality of living than the state unit. Particularly important is the fact that division by
counties ensures that cities are contained in urban counties, while rural areas are excluded from the averages, thus alleviating the problem of cost of living differences between rural and urban populations that haunted the state specific model.

Specifically, West Virginia and its fifty-five counties was selected as a good candidate for the county specific model for several reasons. Firstly, West Virginia has nearly as many counties as California with only a fraction of the population and thus has the benefit of great representative specificity. Secondly, West Virginia has a very homogeneous population; 96% of West Virginians are white, and 90% of the population earns less than $75,000. (U.S. Census Bureau, 2000) Thirdly, data concerning obesity and other negative health behaviors in West Virginia has been made widely and thoroughly available, and shows a significant amount of variation between counties.

The dependent variable in the county specific model is the monthly Medicare per capita rate of each county. Independent demographic variables include per capita income, racial composition, and population density. Like the state specific model, the negative health behavior variables include measures such as physical inactivity, obesity, smoking, and binge drinking prevalences. Like the state specific model, the county specific model estimates that the per capita Medicare rate in each county can be predicted by the negative health behavior variables as well as demographic variables, but it is expected that the demographic variables will be less important,

\[
\text{(4) Per Capita Medicare Rate} = \beta_0 + \beta_1 \text{ negative health behaviors} + E
\]

The variables and respective sources are listed in Table 8. The descriptive statistics for the county specific model illustrates the likely advantage it has over the state specific
model, as the demographic variables such as per capita income and racial background show much less variance than similar variables in the state specific model, while the negative health behavior variables appear to maintain variation among the counties (See Table 9).

B. Results

In light of the potential multicollinearity problem that was noted amongst the negative health behavior variables in the state specific model, physical inactivity, black population, and obesity were tested for multicollinearity, shown in Table 10. As compared to the state specific model, multicollinearity appeared to be less of a problem, although the negative health behaviors were still found to be related, as shown in Figure 8.

As shown in Table 11, the negative health behavior variables were much more likely to be significant contributors to Medicare rates. In particular, when either obesity or physical inactivity was included by itself in a regression, it was consistently found to be significant, and with a positive and economically significant coefficient. Similarly to the state specific model, cigarette smoking shows a mixed result, as it bears little economic or statistical importance in nearly all of the regressions. Binge drinking, a variable not included in the state specific model, is also not found to be consistently significant.

Population density is included to parallel the inclusion of rural percentage in the state specific model, but proves to play a drastically different role. While population density shows to be statistically significant in several of the regressions, the beta coefficients are consistently under 0.5 and thus population density in the county specific
model is not shown to be as economically significant as it is in the state specific model. Similarly, per capita income is included but not found to be statistically or economically significant. The only demographic variable that bears significance in the county specific model is that of black population, which is not only consistently proves to be statistically significant, but also has a large coefficient, suggesting economic significance as well.

Equation (4) of Table 8 is featured as an example of an interpretation of the results of the county specific model below.

\[
(5) \text{Per Capita Medicare Rate}= 156.58 + 1.30 \text{ (Physical Inactivity)} + 3.63 \text{ (Obesity Prevalence)} + 0.58 \text{ (Cigarette Smoking Rate)} + 3.96 \text{ (Binge Drinking Prevalence)} + 8.36 \text{ (Percent Black)}
\]

\[n=55, R^2=0.520\]

The literal interpretation of Equation (5) is that 16% of differences in the Medicare rate can be attributed to rates of physical inactivity, and that 21%, 4%, and 22% of Medicare rates can be attributed to obesity, cigarette smoking, and binge drinking, respectively.

C. Discussion

The greater propensity for negative health behaviors to show statistically and economically significant results combined with the lessened propensity for demographic characteristics to show significant results suggests that the county specific data inherently controls for some of the demographic characteristics that were included as independent variables in the state specific model. In particular, the results of the county specific
model suggest that the problem of cost of living differences between urban and rural areas that were problematic in the state specific model were likely to have been controlled for by using the county geographic borders instead.

Taken at face value, the results from the county specific model indicate that each individual hour of exercise or additional pound lost can have significant and costly impacts on an individual’s health expenditures. However, it is important to note that the data represents only a subset of time. It is not likely that negative health behaviors have a simple linear relationship to health outcomes; there are likely complicated time-lag and accumulation factors that are not accounted for in this model and aggravate the difficulty of isolating the specific effects of negative health behaviors.

Furthermore, while the predictive quality of the negative health behavior variables was improved in the county specific model, the overall predictive power was not. The state specific model had R-squared values to indicate that the model was able to predict over 60% of the variation in Medicare expenditures while the county specific model explained only around 40% of the variation. This is likely the result of the fact that the more specific county data has less variation than the state county data, reducing the total amount of variation to be explained. Thus, the lower R-squared value does not necessarily indicate predictive inferiority.

While narrowing the geographic scope proved to help control some differences, there are many other variables that are factored into individual health and expenditures that are not accounted for even in the improved model. For example, it is intuitive that ones individual health expenditures should be a function of ones age, genetics, and
environmental factors in addition to negative health factors. The effects of many similar variables are lost in the process of averaging.

Furthermore, even if one does accept the model to provide an estimation of the effects of negative health variables, the issue of causation limits the applicability of the estimation. Not only is it difficult to accurately assign health characteristics to specific choices in behaviors, but that there are also many health conditions that are not caused by negative health behaviors that may cause the appearance of negative health. A common example of reverse causation might be the fact that diabetes often causes excessive weight gain and thus the origin of the negative health characteristics may not be accurately perceived.

Lastly, while it may in fact be true that negative health behaviors do cause higher health expenditures, these results may not be revealed in Medicare costs, or even in total lifetime health expenditures because of the negative effect on lifespan that negative health behaviors exhibit. People who consistently have negative health behaviors tend to have shorter lifespans, and thus likely confound averaged Medicare data. In fact, it is possible that due to premature death, negative health behaviors are actually cost saving to the Medicare program. For example, while it is well established that at any given time in life, the average annual medical expenses of smokers exceeds that of non-smokers, the lifespan of smokers is known to be significantly shorter than that of non-smokers. Smokers might in fact lower Medicare costs by thwarting more expensive ways of dying by dying early, or they might die before they reach 65 and not burden the Medicare program at all. Similarly in the case of obesity, while the obese incur higher medical care costs during life, differential mortalities might result in little difference in overall costs.
It has been suggested that if obesity were eliminated, health care costs would be lower during each year of life from 20 to 79. However, after the age of 79, as a greater number of people would live to exceed this age, costs would be higher than they if obesity were not eliminated. (Allison, Xannolli, Narayan 1999) Though one might assume that premature death does not affect the data presented higher costs incurred during life are reflected in per capita Medicare expenditures at any given time, unfortunately averaging across those with health and unhealthy habits dilutes this effect. As those who have negative health habits are on a shorter trajectory of life, they incur costs earlier in life when other young beneficiaries are incurring relatively low costs that offset each other in an average per capita expenditure survey. In order to completely understand the complete effect of negative health behaviors on Medicare, one would have to conduct a longitudinal study of individuals or have more detailed data that catalogues Medicare expenditure data by specific health behaviors.

In fact, in order for one to be able to ascertain and quantify the effects of negative health behaviors confidently, one would have to conduct a detailed, long-term longitudinal study documenting a wide variety of patients’ health status, environment, life span, as well as health behaviors. As negative health behaviors and their effects have recently come to be at the forefront of public health concerns, there is no doubt that such studies will emerge in the near future.

Though the results produced in the previous pages are not necessarily the most accurate or econometrically sound, they do support the medical evidence and provide a framework within which society might start thinking about negative health behaviors as
being decisions that have long-term consequences not solely confined to the individual but affecting society as well.

5. Exploring the Choice of Not Investing in Health

It might seem a natural transition that people who are saving money to finance retirement or college might also invest in health in order to gain life years in decades to come. However, the same mentality for investing in the future does not exist for physical health as it does for financial health. In fact, if the goal is to maximize societal life span, then the current investment in health enhancing activities is far from optimal, and that greater investment could render vast health and perhaps financial benefits. If the answer is not myopia and people are willing to invest in the future financially then why are not willing to do so for their health? The two most plausible explanations to this problem are that consumers have or perceive incomplete information, or that consumers have time preference and risk aversion patterns that heavily discount the future and cause consumers to invest little in health.

5.1. Information

Though it is generally well known in the populace what behaviors are health enhancing and what activities are not, it may be that the magnitude of the action is underestimated. For example, though there is little difference in the harmful effects of light cigarettes as compared to regular cigarettes, it has been found that many people favor light cigarettes because they perceive them to lower their risks of developing cancer. (Etter, Kozlowsky, Perneger, 2003) Another study examined perceived risks of
heart attack, cancer and stroke between smokers and nonsmokers and found that while smokers accurately perceived their health risks to be greater than nonsmokers, that they were still underestimating their risks. (Strecher, Kreuter, Kobrin, 1995) Thus, there is evidence that there is an incomplete understanding of the true risks of smoking, and that greater information might be helpful in allowing people to make efficient decisions.

While there is little literature concerning other negative health factors, from becoming unable to pay their bills, or to misplacing valuable things, there is a vast literature showing that in general, people tend to underestimate the probability of being unable to control bad things happening to them.

While it makes sense in theory that people have incomplete information and thus are unable to make intelligent decisions concerning negative health behaviors, there is some interesting evidence to suggest that even when consumers do have complete information, that it does not always significantly affect the decision making process. For example, a study examined risk perception of smoking among teenagers to gauge firstly how much risk was perceived, and secondly, how much the risk actually affected individual actions. The study found that both smokers and non-smokers over-estimated the risk of lung cancer, and that while individuals with higher perceived risks were less likely to smoke at all, that perceived risk was not correlated with the degree of smoking. (Lundborg, Lindgren, 2004) This study is particularly interesting for two reasons: It contrasts from previous studies concerning adults in that the adolescent participants tend to overestimate their health risks rather than to underestimate the risks. While one cannot be certain why this is true, it can be hypothesized that the targeting of youth in anti-smoking campaigns may be resulting in an over-awareness of the risks of smoking.
However, before leaping to the conclusion that education programs concerning smoking are effective, the second result showing that the level of information had little effect on smoking quantity reduces the societal benefit of the information, and might indicate that information is not necessarily the most important player in determining behavioral choices.

Though the literature is not always consistent or conclusive, it is clear that the relationship between information and behaviors is complicated and unpredictable, but the relevance of complete information in making behavioral decisions is worth considering.

5.2. Discounting

If one assumes that there is complete knowledge of associating behaviors with risks concerning health outcomes and that individuals are able to make choices that alter these risks and outcomes, one might attribute low investment to health to be a rational result of discounting, which would involve a function of several factors, such as risk aversion and time preferences.

One of the first studies specifically addressing the differences between financial and health investments used three different experiments to show that for hypothetical amounts of future health and money, some similar patterns of discounting were found, they exhibited domain independence; Although participants were reliable in their discount rates within a domain, they were not highly correlated in discount rates between domains, indicating that decision makers use different discount rates for different domains. Specifically, in each experiment participants compared an immediate amount of money or full health with a delayed but large amount of money or longer duration of
full health, but showed with different discount rates that domain independence resulted from different utility functions for health and money. (Chapman, 1996)

There is some literature that attempts to isolate the effect of risk aversion on health choices. For example, several studies have evaluated patient choices to receive pain relief from chronic conditions such as cancer and have shown that individuals show properties of risk aversion, preferring the expected relief of a 50:50 outcome to taking a 50:50 chance of receiving complete relief or no relief. (Gafni, Torrance, 1984)

In addition to risk aversion, there are several other factors that play a role in future discounting. A ‘quantity effect’ has also been identified, in which individuals value each additional day in a chronic dysfunctional state less and that patients, for example, value health in the first day of being bed-ridden higher than they value health in the 100th day of being bed-ridden. This result can be extrapolated to imply that individuals become accustomed to suffering the consequences of heavy smoking or obesity and thus face decreasing marginal costs for each additional pound or cigarette.

In addition to risk aversion and quantity effect, additional discounting can occur because of differences in time preferences. For example, there is evidence that people of different ages value risk and life at different costs, and that people value health at different ages differentially.

All of these factors cause the future to be worth drastically less than the present and likely contribute to discounting that might cause individuals to rationally invest little into preservation of health.

5.3. Health Insurance
Another element contributing to underinvestment in health is the presence of health insurance and the guarantee of Medicare health insurance late in life. Health insurance alleviates the financial costs that might be incurred by negative health behaviors, and thus creates moral hazard for potential beneficiaries and reduces incentives to participate in health enhancing activities.

6. Conclusions

Though the effect of poor health behaviors on individual health has been a common public concern, there has been little attention paid to consequences of negative health behaviors beyond the effect on the individual. In reality, individual health choices do have an effect on society at large, and as greater proportion of the population enters the Medicare program and the Medicare program becomes more generous, the costs incurred by negative health behaviors become increasingly significant and of increasing societal concern. The econometric data suggests that the financial burden of negative health behaviors on Medicare costs could potentially near 40% of Medicare costs, and though these results are not numerically perfect, they do confirm individual health behaviors have consequences extending beyond the immediate individual’s health.

The problem of underinvestment in personal health is the inevitable result of the combination of uncertainty, imperfect information, heavy discounting, and the moral hazard provided by the Medicare subsidy. Thus from a policy perspective, improving the incentives to invest in health can come from any number of sources such as improving consumer information or reducing moral hazard, while disincentives to invest can be worsened by increased uncertainty or increased subsidies. In terms of current policy
proposals, while the Bush Administration’s suggestion of Health Savings Accounts might increase accountability over health costs in retirement years and thus reduce moral hazard, the passage of the Bush Administration’s Medicare Modernization Act of 2008 extends Medicare coverage to include prescription drugs, and thus worsens the problem of moral hazard.

While policy makers are likely aware of the relationship between negative health behaviors, production of health, and ultimate costs incurred, the importance of negative health behaviors does not appear to be reflected in policy decision making. Though the focus of this project has been on Medicare costs, the financial burdens of behaviors are not the only reason that individuals should be concerned with their behaviors; in fact the benefits of an improvement in American health behaviors affect both individual and society, health and economy, happiness and productivity. For these and many other reasons, there would be great and far-reaching benefits to incorporating the goal of improving American health behaviors into policy making in the future.
**APPENDIX**

**Table 1: State Specific Variable Descriptions (United States)**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per capita Medicare spending</td>
<td>Per Capita spending per Medicare beneficiary, by state as reported in the 1998 State Health Expenditure Accounts from the Centers for Medicare and Medicaid Services</td>
</tr>
<tr>
<td>Percent of Black Medicare Population</td>
<td>Percent of Medicare beneficiaries who are black according to the Urban Institute and Kaiser Commission based on pooled 2002 and 2003 Current Population Surveys (CPS)</td>
</tr>
<tr>
<td>Per Capita State Expenditures</td>
<td>State Expenditures per dollar of taxes collected in 2002, according to the U.S. Census</td>
</tr>
<tr>
<td>Rural Residency</td>
<td>Percent of Population that does not live in a Metropolitan Statistical Area, which must include at least one city of 50,000 or more inhabitants according to the 2002 and 2003 CPS</td>
</tr>
<tr>
<td>Cigarette Smoking Rate</td>
<td>Percentage of population that currently smokes every day or some days and have smoked at least 100 cigarettes in their life time, reported by the Behavioral Risk Factor Surveillance System Survey Data, 2002</td>
</tr>
<tr>
<td>Obesity Prevalence</td>
<td>Percent of Population with a body mass index greater than or equal to 30.0 kg/meters sq. reported by the BRFSS, 1991-2001</td>
</tr>
<tr>
<td>Elderly Poverty Rate</td>
<td>Percentage of the 65+ population who make less than 100% of the Federal Poverty Level (FPL), which in 2002 was $14,348 for a family of three, based on the 2002 and 2003 CPS.</td>
</tr>
<tr>
<td>Percent of Population on Medicare</td>
<td>Percentage of population enrolled in the Medicare program based on data from the Medicare State Enrollment in 2003</td>
</tr>
</tbody>
</table>

**Table 2: State Specific Summary Statistics (United States)**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per capita Medicare spending</td>
<td>5049.28</td>
<td>808.165</td>
<td>3936</td>
<td>7219</td>
</tr>
<tr>
<td>Percent of Black Medicare Population</td>
<td>6.34</td>
<td>6.268</td>
<td>0</td>
<td>21</td>
</tr>
<tr>
<td>Prevalence of Physical Inactivity</td>
<td>25.22</td>
<td>4.65</td>
<td>17</td>
<td>36</td>
</tr>
<tr>
<td>Per Capita State Expenditures</td>
<td>1.1824</td>
<td>0.37239</td>
<td>0.57</td>
<td>1.99</td>
</tr>
<tr>
<td>Rural Residency</td>
<td>30.240</td>
<td>21.622</td>
<td>0.00</td>
<td>75.00</td>
</tr>
<tr>
<td>Cigarette Smoking Rate</td>
<td>23.310</td>
<td>3.3214</td>
<td>12.7</td>
<td>32.4</td>
</tr>
<tr>
<td>Obesity Prevalence</td>
<td>20.50</td>
<td>2.452</td>
<td>14</td>
<td>26</td>
</tr>
<tr>
<td>Elderly Poverty Rate</td>
<td>12.920</td>
<td>3.469</td>
<td>5.00</td>
<td>22.00</td>
</tr>
<tr>
<td>Percent of Population on Medicare</td>
<td>14.18</td>
<td>2.154</td>
<td>7</td>
<td>19</td>
</tr>
</tbody>
</table>
## Table 3: State Specific Multicolinearity Among the Independent Variables

<table>
<thead>
<tr>
<th></th>
<th>Physical Inactivity</th>
<th>Percent of Black Beneficiaries</th>
<th>Obesity Prevalence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Inactivity</td>
<td>1</td>
<td>0.554 (0.000)</td>
<td>0.643 (0.000)</td>
</tr>
<tr>
<td>Percent of Black Beneficiaries</td>
<td>0.554 (0.000)</td>
<td>1 (-----)</td>
<td>0.491 (0.000)</td>
</tr>
<tr>
<td>Obesity Prevalence</td>
<td>0.643 (0.000)</td>
<td>0.491 (0.000)</td>
<td>1 (-----)</td>
</tr>
</tbody>
</table>

## Table 4: Colinearity between the Independent Variables

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Dependent: Obesity</th>
<th>Dependent: Physical Inactivity</th>
<th>Dependent: Smoking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Inactivity</td>
<td>9.390 (2.007)</td>
<td>-----------------------------</td>
<td>0.184 (0.115)</td>
</tr>
<tr>
<td>Percent Black Beneficiaries</td>
<td>0.112 (0.053)</td>
<td>0.143 (0.106)</td>
<td>0.02744 (0.085)</td>
</tr>
<tr>
<td>Rural Residency</td>
<td>0.01985 (0.13)</td>
<td>0.00066 (0.026)</td>
<td>0.03097 (0.020)</td>
</tr>
<tr>
<td>Cigarette Smoking Rate</td>
<td>0.254 (0.90)</td>
<td>0.298 (0.187)</td>
<td>--</td>
</tr>
<tr>
<td>Obesity Prevalence</td>
<td>--</td>
<td>0.629 (0.279)</td>
<td>0.598 (0.213)</td>
</tr>
<tr>
<td>Elderly Poverty Rate</td>
<td>0.02140 (0.084)</td>
<td>0.358 (.0156)</td>
<td>-0.117 (0.129)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.767</td>
<td>0.751</td>
<td>0.687</td>
</tr>
<tr>
<td>Adjusted R-Squared</td>
<td>0.542</td>
<td>0.514</td>
<td>0.412</td>
</tr>
</tbody>
</table>
Table 5: Comparing the Effectiveness of the Obesity and Physical Inactivity Variables in the State Specific Model

*Dependent Variable is per capita Medicare Costs*

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Inactivity</td>
<td>-----------</td>
<td>69.244</td>
<td>72.271</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(21.906)</td>
<td>(23.363)</td>
</tr>
<tr>
<td>Obesity Prevalence</td>
<td>27.140</td>
<td>-----------</td>
<td>-18.352</td>
</tr>
<tr>
<td></td>
<td>(47.230)</td>
<td></td>
<td>(45.644)</td>
</tr>
<tr>
<td>Cigarette Smoking Rate</td>
<td>29.435</td>
<td>-11.383</td>
<td>-6.726</td>
</tr>
<tr>
<td></td>
<td>(17.970)</td>
<td>(27.126)</td>
<td>(29.737)</td>
</tr>
<tr>
<td>Percent of Black Beneficiaries</td>
<td>29.435</td>
<td>17.012</td>
<td>19.074</td>
</tr>
<tr>
<td></td>
<td>(17.970)</td>
<td>(15.822)</td>
<td>(16.778)</td>
</tr>
<tr>
<td>Elderly Poverty Rate</td>
<td>49.951</td>
<td>24.440</td>
<td>24.057</td>
</tr>
<tr>
<td></td>
<td>(26.426)</td>
<td>(25.332)</td>
<td>(25.586)</td>
</tr>
<tr>
<td></td>
<td>(4.351)</td>
<td>(3.839)</td>
<td>(3.981)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.765</td>
<td>0.812</td>
<td>0.813</td>
</tr>
<tr>
<td>Adjusted R-Squared</td>
<td>0.538</td>
<td>0.621</td>
<td>0.613</td>
</tr>
</tbody>
</table>
Table 6: Regression Results Utilizing Prevalence of Obesity, Prevalence of Physical Inactivity, or both as Predictor Variable in the State Specific Model

**Dependent Variable is per capita Medicare Costs**

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Inactivity</td>
<td>82.173</td>
<td>87.383</td>
<td>65.455</td>
<td>76.173</td>
<td>72.271</td>
<td>76.207</td>
<td>81.214</td>
</tr>
<tr>
<td></td>
<td>(22.090)</td>
<td>(15.33)</td>
<td>(19.775)</td>
<td>(17.927)</td>
<td>(23.363)</td>
<td>(23.701)</td>
<td>(25.584)</td>
</tr>
<tr>
<td>Percent Black Beneficiaries</td>
<td>---------</td>
<td>---------</td>
<td>15.742</td>
<td>---------</td>
<td>19.074</td>
<td>13.987</td>
<td>16.937</td>
</tr>
<tr>
<td></td>
<td>---------</td>
<td>---------</td>
<td>(15.387)</td>
<td>---------</td>
<td>(16.778)</td>
<td>(16.346)</td>
<td>(17.342)</td>
</tr>
<tr>
<td>State Expenditures per dollar of taxes</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>-136.70</td>
<td>---------</td>
<td>---------</td>
<td>-164.702</td>
</tr>
<tr>
<td></td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>(252.52)</td>
<td>---------</td>
<td>---------</td>
<td>(260.72)</td>
</tr>
<tr>
<td></td>
<td>(3.299)</td>
<td>(3.553)</td>
<td>(4.124)</td>
<td>(3.981)</td>
<td>(3.862)</td>
<td>(4.773)</td>
<td></td>
</tr>
<tr>
<td>Cigarette Smoking Rate</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>-6.726</td>
<td>-9.057</td>
<td>-1.371</td>
</tr>
<tr>
<td></td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>(29.737)</td>
<td>(27.402)</td>
<td>(30.510)</td>
</tr>
<tr>
<td></td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>(45.644)</td>
<td>---------</td>
<td>(46.352)</td>
</tr>
<tr>
<td>Elderly Poverty Rate</td>
<td>---------</td>
<td>26.184</td>
<td>37.789</td>
<td>24.047</td>
<td>22.290</td>
<td>27.131</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(24.749)</td>
<td>(25.06)</td>
<td>(25.586)</td>
<td>(25.504)</td>
<td>(27.022)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent of State on Medicare</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>-30.016</td>
<td>-32.844</td>
</tr>
<tr>
<td></td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>(38.013)</td>
<td>(38.842)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.473</td>
<td>0.797</td>
<td>0.811</td>
<td>0.808</td>
<td>0.813</td>
<td>0.815</td>
<td>0.818</td>
</tr>
<tr>
<td>Adjusted R-Squared</td>
<td>0.208</td>
<td>0.619</td>
<td>0.628</td>
<td>0.621</td>
<td>0.613</td>
<td>0.617</td>
<td>0.605</td>
</tr>
</tbody>
</table>
Table 7: Using only Rural Residential Status and Prevalence of Physical Inactivity as Predictors of per capita Medicare Beneficiary Costs in the State Specific Model

**Dependent Variable is per capita Medicare Costs**

<table>
<thead>
<tr>
<th></th>
<th>β</th>
<th>t-Statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prevalence of Physical Inactivity</td>
<td>87.383</td>
<td>5.700</td>
<td>0.000</td>
</tr>
<tr>
<td>Rural Residential Status</td>
<td>-23.987</td>
<td>-7.272</td>
<td>0.000</td>
</tr>
</tbody>
</table>

The R-squared Value is 0.635.

Table 8: County Specific Variables and Explanations (West Virginia, n=55)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent of Population Black or African American</td>
<td>United States Census, State Fact Finder <a href="http://factfinder.census.gov">http://factfinder.census.gov</a></td>
</tr>
<tr>
<td>Per Capita Personal Income, Percent of US</td>
<td>Regional Economic Information System, Bureau of Economic Analysis; Table CA1-3, April 2005 <a href="http://www.bea.gov/bea/regional/reis/drill.cfm">http://www.bea.gov/bea/regional/reis/drill.cfm</a></td>
</tr>
<tr>
<td>Prevalence of Obesity</td>
<td>West Virginia Health Statistics Center, same as above</td>
</tr>
<tr>
<td>Prevalence of Binge Drinking</td>
<td>West Virginia Health Statistics Center, same as above</td>
</tr>
<tr>
<td>Prevalence of Cigarette Smoking</td>
<td>West Virginia Health Statistics Center, same as above</td>
</tr>
</tbody>
</table>
Table 9: County Specific Descriptive Statistics (West Virginia, n=55)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly Per Capita Medicare Rate</td>
<td>360.84</td>
<td>43.32</td>
<td>328.96</td>
<td>503.97</td>
</tr>
<tr>
<td>Population Density</td>
<td>43.807</td>
<td>45.27</td>
<td>7.3</td>
<td>208.8</td>
</tr>
<tr>
<td>Percent of Population Black or African American</td>
<td>1.93</td>
<td>2.48</td>
<td>0.01</td>
<td>11.98</td>
</tr>
<tr>
<td>Per Capita Income as a percentage of United States Average</td>
<td>66.22</td>
<td>17.42</td>
<td>15</td>
<td>104</td>
</tr>
<tr>
<td>Percent of Population over the age of 65</td>
<td>15.12</td>
<td>2.58</td>
<td>9.19</td>
<td>20.47</td>
</tr>
<tr>
<td>Prevalence of Physical Inactivity</td>
<td>45.01</td>
<td>8.69</td>
<td>22.4</td>
<td>63.2</td>
</tr>
<tr>
<td>Prevalence of Obesity</td>
<td>21.39</td>
<td>5.50</td>
<td>8.9</td>
<td>38.9</td>
</tr>
<tr>
<td>Prevalence of Cigarette Smoking</td>
<td>26.38</td>
<td>5.50</td>
<td>8.9</td>
<td>38.90</td>
</tr>
<tr>
<td>Prevalence of Binge Drinking</td>
<td>9.31</td>
<td>3.91</td>
<td>.50</td>
<td>22.90</td>
</tr>
</tbody>
</table>

Table 9: County Specific Multicolinearity

<table>
<thead>
<tr>
<th></th>
<th>Physical Inactivity</th>
<th>Percent of Black Beneficiaries</th>
<th>Obesity Prevalence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Inactivity (Pearson Correlation, Significance (2-tailed))</td>
<td>1 -0.122 (0.377)</td>
<td>0.563 (0.000)</td>
<td></td>
</tr>
<tr>
<td>Percent of Black Beneficiaries (Pearson Correlation, Significance (2-tailed))</td>
<td>-0.122 (0.377)</td>
<td>1 -0.132 (0.337)</td>
<td></td>
</tr>
<tr>
<td>Obesity Prevalence (Pearson Correlation, Significance (2-tailed))</td>
<td>0.563 (0.000)</td>
<td>-0.132 (0.337)</td>
<td>1 -0.132 (0.337)</td>
</tr>
</tbody>
</table>
Table 11: County Specific  
Dependent Variable: Per Capita Medicare Spending

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical Inactivity</td>
<td>---------</td>
<td>2.594</td>
<td>0.064</td>
<td>1.300</td>
<td>1.716</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.572)</td>
<td>(0.903)</td>
<td>(0.811)</td>
<td>(0.840)</td>
</tr>
<tr>
<td>Obesity</td>
<td>5.206</td>
<td></td>
<td>4.924</td>
<td>3.633</td>
<td>3.669</td>
</tr>
<tr>
<td></td>
<td>(1.235)</td>
<td></td>
<td>(1.624)</td>
<td>(1.403)</td>
<td>(1.389)</td>
</tr>
<tr>
<td>Cigarette Smoking</td>
<td>---------</td>
<td>---------</td>
<td>1.817</td>
<td>0.583</td>
<td>0.212</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(1.281)</td>
<td>(1.117)</td>
<td>(1.131)</td>
</tr>
<tr>
<td>Binge Drinking</td>
<td>---------</td>
<td>---------</td>
<td>3.446</td>
<td>3.986</td>
<td>2.348</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(1.486)</td>
<td>(1.263)</td>
<td>(1.548)</td>
</tr>
<tr>
<td>Population Density</td>
<td>0.299</td>
<td>0.378</td>
<td></td>
<td></td>
<td>0.281</td>
</tr>
<tr>
<td></td>
<td>(0.114)</td>
<td>(0.139)</td>
<td></td>
<td></td>
<td>(0.165)</td>
</tr>
<tr>
<td>Percent Black</td>
<td>5.483</td>
<td>7.355</td>
<td></td>
<td>8.364</td>
<td>6.972</td>
</tr>
<tr>
<td></td>
<td>(1.987)</td>
<td>(1.901)</td>
<td></td>
<td>(1.864)</td>
<td>(1.998)</td>
</tr>
<tr>
<td>Per Capita Income</td>
<td>-0.107</td>
<td></td>
<td></td>
<td></td>
<td>-0.128</td>
</tr>
<tr>
<td></td>
<td>(0.324)</td>
<td></td>
<td></td>
<td></td>
<td>(0.311)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>54</td>
<td>54</td>
<td>54</td>
<td>54</td>
<td>54</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.447</td>
<td>0.471</td>
<td>0.316</td>
<td>0.520</td>
<td>0.550</td>
</tr>
<tr>
<td>Rbar-Squared</td>
<td>0.414</td>
<td>0.429</td>
<td>0.261</td>
<td>0.471</td>
<td>0.483</td>
</tr>
</tbody>
</table>
Figure 1: Trends in Obesity Rates Over Time
Figure 2: The Association Between Spending per Medicare Beneficiary and the Percent of Beneficiaries who are Black for the Fifty States and the District of Columbia.

Figure 3: The Association Between Spending per Medicare Beneficiary and Female Life Expectancy for the Fifty States and the District of Columbia.
Figure 4: The Association Between Spending per Beneficiary and the Prevalence of Obesity (p=0.208)

![Graph showing association between spending per beneficiary and obesity prevalence.](image)

Figure 5: The Association Between Spending per Beneficiary and Rate of Smoking (p=0.779)

![Graph showing association between spending per beneficiary and smoking rate.](image)
Figure 6: The Association Between Spending per Beneficiary and Prevalence of Physical Inactivity (p=0.001)
Figure 7: Spending and Negative Health Behavior Patterns of the Fifty States

- Spending
- Physical Inactivity
- Smoking
- Obesity
Figure 8: Negative Health Behavior Patterns in West Virginia Counties

[Graph showing data on physical inactivity, obesity, and cigarette smoking.]
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