APPLYING DIFFERENCE-IN-DIFFERENCES TO MEASURE THE EFFECT OF MEDICARE PREVENTIVE MEDICINE POLICY

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Abstract

In this study I examine the effectiveness of the Medicare Modernization Act's inclusion of preventive cholesterol screenings with no copay or deductible to Medicare Part B beneficiaries. The screenings were included in the MMA to increase usage of cholesterol screenings among Medicare beneficiaries. Using data from the Medical Expenditure Panel Survey, I employ a difference-in-differences model to isolate the change in screening rate among Medicare beneficiaries. Using individuals not covered by Medicare as a baseline, I find that in three age restricted samples the rate of screening among Medicare beneficiaries either decrease or keep a constant screening rate, relative to the control group. Overall, the MMA's cholesterol screening policies are not effective in increasing the rate of cholesterol screenings utilized.

KEYWORDS: Medicare, Preventive Medicine, Difference-in-Differences, Cholesterol

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1. INTRODUCTION

On July 30, 1965, President Lyndon B. Johnson signed Medicare into law, providing medical insurance to those aged 65, as well as to older and younger persons with some disabilities or health problems. Medicare provided coverage to many individuals who previously struggled to gain private health insurance. For these individuals, before Medicare the costs of their health care would fall entirely on themselves or on their families whenever they required any sort of medical care (Stanton, 2012). Upon its creation, Medicare was divided into two parts: Part A, which covers hospital insurance, and optional Part B, which covers outpatient care, doctors' services and other medical services, such as preventive screenings (Medicare Parts A and B, 2012).

Until 2010, when President Barack Obama signed into law the Patient Protection and Affordable Care Act (PPACA), the biggest reform to Medicare came in 2003 with the Medicare Modernization Act (MMA), signed into law by President George Bush. This law set in place Medicare Part D, a prescription drug coverage program, and also expanded the range of preventive medicinal procedures covered (Prescription Drug Coverage for Medicare Beneficiaries: A Summary of the Medicare Prescription Drug, Improvement, and Modernization Act of 2003, 2003).

The inclusion of preventive procedures in the MMA furthers efforts to change the focus of Medicare to improve the health of Americans by changing Medicare to a prevention-based system. The Center for Medicare & Medicaid Services acknowledges that Americans die in the hundreds of thousands each year due to diseases that are preventable through early detection from preventive screenings.

Though the MMA has made other broad reforms to Medicare, this study focuses on preventive medicinal aspects covered by the law, specifically cholesterol screenings. Under the MMA, Medicare Part B beneficiaries will now be allowed to undergo one cardiovascular screening to check cholesterol levels every five years without any copay or deductible, effective starting January 1, 2005 (The Guide to Medicare Preventive Services for Physicians, Providers, Suppliers, and Other Health Care Professionals, 2005). By decreasing up-front costs in the form of copays or deductibles, the MMA made it more likely that Medicare beneficiaries should receive a cholesterol screening. Using a difference in differences model, I will attempt to measure the MMA's effectiveness in increasing the rate of cholesterol screenings among Medicare beneficiaries.

Previous studies link preventive medicine usage with a variety of patient characteristics. I intend to test the effect of the policy altogether, not only the specific characteristics that affect usage. In doing so, I will use a variety of these characteristics to control for omitted variable bias. Studies that measure the effects of these characteristics and their results are described below.

Ettner (1996) tests the effect of a patient maintaining a usual source of care on that patient's preventive medicine usage. Ettner (1996) updates previous studies on having a usual source of care's effect by using instrumental variables to eliminate possible feedback effects from the data. Ettner (1996) confirms, to a degree, the previous assumption that being able to name a usual source of care increases preventive medicine usage. Some services, contrary to this assumption, are relatively unaffected by ability to name a usual source of care. In more recent studies, ability to name a usual source of care occurs as a control while testing other characteristics' effects on preventive medicine usage (Carrasquillo, Lantigua, & Shea, 2001; McAlpine & Sambamoorthi, 2003).

Bao et al (2007) investigates differences in cancer screening rates among racial and socioeconomic groups. They examine two different issues: difference in cancer screening rates between whites and minorities with different doctors, and differences in rates among whites and minorities with the same doctor. Edlund et al (1999) also tests for differences in types of preventive cancer screenings used by different racial and gender groups. Similarly, McApline and Sambamoorthi (2003) look for differences in preventive medicine screening rates for a variety of services among racial, ethnic and socioeconomic groups.

Both Bao et al (2007) and Edlund et al (1999) find that significant disparities exist between racial groups in their cancer screening rates. However, they do not identify a specific pattern among these disparities. For example, Bao et al (2007) observes different rates of mammography among black and white women, while whites and Asians experience disparities in usage for types of colorectal cancer screenings. Edlund et al (1999), similarly, finds differences in the patterns of types of colorectal cancer screenings among blacks and whites. Blacks are found to receive a higher rate of barium enemas, while whites receive colonoscopies with higher rates. McAlpine and Sambamoorthi (2003) find similar results when applied to a variety of services; different racial groups maintain varied screening rates with no unifying pattern.

Along with racial differences, Edlund et al (1999) finds differences in colorectal cancer screening rates and gender groups. In the three types of screenings tested, there exists no unifying trend between women and males. Although they could not identify a unifying trend, they demonstrated significant differences exist between male and female patients in preventive screening trends.

Bao et al (2007) also shows significant differences in screening among individuals with different education levels. Examining trends “within-physician” groups (different individuals with the same doctor), they conclude that the same doctor will interact with individuals differently based on the patient’s level of education. These different interactions indicate a positive relationship between education and preventive screening rates.

Schone and Weinick (1998) examine marriage’s effect on health care usage and health-related behaviors among the elderly. Previous studies show that marriage increases healthy behavior, but those studies do not focus on an elderly population. Schone and Weinick show, similar to a younger population, that marriage among elderly individuals also increases the probability of preventive medicine usage, as well as overall healthier behaviors.

Buist et al (2008) attempt to determine how income affects mammogram use among women. Their results show that lower-income women are less likely to receive a mammogram than higher income women covered by similar health insurance. The data also showed that retired women are more likely to receive a mammogram than unemployed women, but employed women are more likely to receive a mammogram than both retired and unemployed women.

Adamache and Rosenbach (1995) examine how access to care is affected by “medical need.” Medical need is measured by a combination of self-reported health status and level of dependency. They conclude there is a strong relationship between use of health services and health status; those who report worse health reported using more services.

Carrasquillo et al (2001) observes the relationship between preventive medicine usage among Medicare beneficiaries with no or a variety of supplemental insurance options. Previous studies show that Medicare beneficiaries with private supplemental insurance are 50% more likely to receive preventive cancer screenings than those without such coverage, and Medicare beneficiaries belonging to a health maintenance organization (HMO) are 10% more likely to receive the same services that those with private supplemental insurance. Carrasquillo et al (2001) updates these studies with more recent data. Dellenbaugh et al (2007) test preventive screening usage among elderly, male veterans. Dellenbaugh et al (2007) consider supplemental coverage plans from the Veterans Health Administration (VHA), Medicare Fee-for-Service plans (FFS), and Medicare HMOs. Both Carrasquillo et al (2001) and Dellenbaugh et al (2007) conclude that supplemental coverage increases rates of preventive medicine usage. Dellenbaugh et al (2007) further state that the well-organized structure of the VHA is the most effective for delivering preventive Medicinal care.

Difference-in-differences framework has also been applied to health care related issues. Similarly, I apply the same methodology to measure the effect of the MMA's cholesterol screening provision. This methodology has been used to analyze similar health care policies. For example, Finkelstein (2002) employs DID framework to measure the effect of tax subsidies on employer-provided supplemental health insurance. Subsidies for providing supplemental care to employees were cut in Canada's Quebec

Province, while the other Provinces and Canadian government kept the same subsidies in place. Finkelstein (2002) concludes that the removing the subsidy decreased employer-provided supplemental coverage by 13% in Quebec relative to the other Provinces in Canada.

Foote et al (2008) also uses DID framework to measure the effectiveness Medicare policies providing for a variety of health care services. Medicare allows for contractors to issue local coverage determinations (LCDs). LCDs are coverage regulations that apply to a certain policy in the contractor's jurisdiction. These LCDs must follow procedures for implementation and formatting, but can regulate the coverage of new technologies and procedures. Foote et al (2008) observes the reaction to a LCD policy change in eight case studies. Foote et al (2008) find that in only one of the eight case studies they examined did utilization vary significantly, overall, concluding there is no systematic evidence that the policies affect utilization.

I apply a DID framework to evaluate the effect of providing preventive cholesterol screenings to those covered by Medicare Part B, as allowed by the MMA. I use information from the Medical Expenditure Panel Survey to examine three different groups of people: those aged older than 35, those aged older than 55, and those between the ages of 60 and 70. I find that in both the group older than 35 and the group older than 50, screening rates among those covered by Medicare decrease relative to those not covered by Medicare after the MMA's cholesterol screening provision takes place. The Medicare-covered and non-Medicare-covered populations in the group between the ages of 60 and 70 do not significantly change after January 1, 2005, the effective date of the MMA.

2. MODEL

The study seeks to determine the impact of a change in Medicare policy on beneficiary behavior. Specifically, the study examines if Medicare beneficiaries became more likely to undergo preventive cholesterol screenings after Medicare began covering them with no copay or deductible. In other words, does the extension of Medicare coverage, which reduces the price to consumers of preventive health care screening, change consumer behavior? This study employs a difference-in-differences model to determine the impact of the policy.

The difference-in-difference model acts in a quasi-experimental format, testing the resulting effect of a shock to a system relative to a control group (Cameron & Trivedi, 2005). A DID model examines two groups and their relationship to some outcome during two time periods. The first group is a control group. These individuals are not affected by whatever change the DID seeks to measure. The second group is the treated group. These individuals are affected by the change in policy. The model estimates both populations before the change occurs, and finds the difference in outcome, then estimates both populations after the change occurs and finds that difference in outcome. The DID is calculated by subtracting the difference in outcome from the pre-change group from the difference in outcome from the post-change group.

2.1 APPLICATION OF DIFFERENCE-IN-DIFFERENCES

A famous example of the DID methodology is David Card and Alan Krueger's study on minimum wages and employment in fast food restaurants. Card and Krueger's study tests the theory that increasing the minimum wage would cause perfectly competitive employers to decrease employment, creating the opposite effect of what policy makers intended. Card and Krueger examine an increase in the minimum wage of New Jersey, using the neighboring state of Pennsylvania to act as a baseline to estimate the natural change in unemployment that may have occurred without a policy change. They survey employment data from a variety of fast food restaurants in both states, choosing the fast food industry due to its role as a leading minimum wage employer and its compliance with minimum wage requirements, the relative homogeneity of products across different restaurants, and the ease of constructing a sample (Card & Krueger, 1994).

Card and Krueger collect their first round of data by surveying restaurants in late February and early March of 1992, before the law changing the New Jersey minimum wage took effect on April 1, 1992. They administer follow-up surveys in November and December of the same year. Card and Krueger implement a DID model to examine the effect the new minimum wage law had on employment, relative to the natural change in employment over the same period. In their experimental design, the systematic shock is the increase in New Jersey minimum wage. New Jersey fast food restaurants are the treated group, and Pennsylvania fast food restaurants are the control group (Card & Krueger, 1994).

In their study, Card and Krueger find that from the pre- to post-treatment periods, employment increased in New Jersey, while actually decreasing in Pennsylvania. Average full-time employment in New Jersey fast food restaurants rises from 20.44 employees to 21.03 per store, a difference of .59 employees. In Pennsylvania, full time employment decreases from 23.33 to 21.17 employees per store, a difference of -2.16 employees. The changes results in a difference-in-difference of 2.76, meaning that the study concluded the policy had the effect of increasing employment by 2.76 employees per store relative to what would have been expected to happen if left untreated. Card and Krueger present a variety of additional scenarios that could have resulted in the observed increase in employment, but none of the additional tests contradict the original DID. They conclude that, contrary to the traditional theoretical model of minimum wage, the increase in minimum wage increased employment (Card & Krueger, 1994).

2.2 DIFFERENCE-IN-DIFFERENCES AND CURRENT FRAMEWORK

Similar to Card and Krueger's study, a DID estimation can be applied to measuring the effect of a Medicare policy change on the utilization of preventive medicineprocedures by covered patients. Effective January 1, 2005, Medicare covers, without any deductible or copay, cardiovascular screenings to detect high cholesterol and other risk factors for cardiovascular disease and stroke (The Guide to Medicare Preventive Services for Physicians, Providers, Suppliers, and Other Health Care Professionals, 2005). This reform to Medicare's preventive service policy allows for all beneficiaries to undergo one blood screening once every five years. By removing up-front costs in the form of copay and deductible, demand for cholesterol screenings should rise, barring a change in supply of these screenings.

DID can be applied to test whether Medicare beneficiaries increased their frequency of cholesterol screenings, post-2005, against a control group. Measuring only the increase in Medicare beneficiaries' utilization does not fully measure the impact of the change in policy. After all, utilization of these preventative measures could changed over the time period for reasons unrelated to the change in policy. DID provides a baseline against which to test the new policy's effect, by comparing the change due to the policy against what occurred naturally. Doing so shows whether the policy changed the outcome more than would have been expected in a natural occurrence.

Similar to Card and Krueger's study on minimum wage law and employment, measuring the increase in utilization by Medicare beneficiaries against a control group better isolates the effect of the policy. DID provides a comparison, using all non-Medicare MEPS respondents as a control group. Drawing further analogies to Card and Krueger's study, individuals not covered by Medicare play the role of the Pennsylvania fast food restaurants, while Medicare beneficiaries take the place of New Jersey's restaurants. The first round interviews conducted by Card and Krueger are replaced with MEPS data from the surveys from 2001 to 2004, while the second round is replaced with MEPS data from 2005 to 2010.

The DID estimation is computed as such:

$$Y_{ist} = \gamma_s + \lambda_t + \delta D_{st} + \Omega\text{'X} + \epsilon_{ist} \tag{2.2.1}$$

where

$$E(\epsilon_{ist}|s,t) = 0; V(\epsilon_{ist}|s,t) = \sigma^2 \tag{2.2.2}$$

Y_{ist} is the outcome variable "chol." The subscript "s" refers to a dummy variable indicating the group of the observation. The subscripts "s" and "t" refer to the group and time period. The treated group is the population of people whose behavior the policy change may affect, while the untreated group includes those individuals for whom nothing changes. In this study, the treated group includes Medicare beneficiaries eligible for a cholesterol screening post-January 1, 2005. Medicare beneficiaries are deemed eligible if they have not had a cholesterol screening in the past five years. These individuals are represented when s = 1. The untreated group includes those individuals not covered by Medicare, represented when s = 0. This study utilizes two time periods, before and after the January 1, 2005, effective date of the policy change. All observations before this date are part of the pre-treatment period, and represented when t = 0. All observations after this date are included in the post-treatment period, represented when t = 1.

The parameter λ_t represents the time of the policy's implementation effect on the outcome variable "chol". In this study, λ_t is measured by dummy variable "EL" with the pre-treatment period, λ_0, being coded to equal 0. Variable "EL" is coded to equal 1 if an observation is in the post-treatment period, meaning any year 2005 or later, and if the individual is eligible for a cholesterol screening, that is, they have not had a screening in the past five years. The parameter γ_s is the effect of being in a particular group; either belonging to the untreated group, those individuals not covered by Medicare, γ_0, or the treated group, the set of individuals covered by Medicare, γ_1.

The variable D_{st} is a dummy variable that equals 1 if subscripts *s* and *t* both equal 1. Applied to this study's model, D_{st} will equal 1 if, and only if, an individual is a Medicare Beneficiary who is eligible for a cholesterol test in the post-treatment period of post-January 1, 2005. An eligible Medicare beneficiary before this date is in the pretreated period, and though eligible for screening, has a D_{st} value of 0. Any individual not covered by Medicare either in the pre- or post-treatment periods is part of the untreated control group, and also has a D_{st} value of 0.

When D_{st} is equal to zero, the term δD_{st} will also equal zero and drop out of equation 3.1.1. The change in Medicare policy has no effect on this person, and the outcome variable is calculated. However, when D_{st} is equal to 1, the treatment does have an effect on the outcome variable. The coefficient corresponding to D_{st}, δ, determines the magnitude of the treatment's effect. For example, consider two individuals in the sample, identical in every way except treatment period: the first individual is from the pre-treatment sample, and the second individual is from the post-treatment sample. Both individuals are covered by Medicare and eligible for a cholesterol screening. The equations estimating the outcome variable will be identical, except the second individual's equation will have the term δD_{st} in it. The only different trait between the two is treatment; the term δD_{st} will capture the effect of the policy change. Since D_{st} is equal to 1, the coefficient δ will measure the treatment's effect on likelihood to receive a cholesterol screening.

The DID, represented by δ, is computed by first finding the differences in outcome between the two groups, treated and non-treated, as time moves from pre- to post-treatment. The difference between time periods for the control group is calculated as such: $E[Y\_ist \mid s = 0, t = 1] - E[Y\_ist \mid s = 0, t = 0] = \lambda_1 - \lambda_0$. The difference between time periods for the Medicare group is calculated as such: $E[Y\_ist \mid s = 1, t = 1] - E[Y\_ist \mid s = 1, t = 0] = \lambda_1 - \lambda_0 + \delta$. The DID is calculated by finding the difference between these two differences, hence: $\delta = \{E[Y\_ist \mid s = 1, t = 1] - E[Y\_ist \mid s = 1, t = 0]\} - \{E[Y\_ist \mid s = 0, t = 1] - E[Y\_ist \mid s = 0, t = 0]\}$.

In the model tested in this study, Ω'X is the set of controls, and their respective coefficients. These are included in the model to decrease the possibility of omitted variable bias. The controls are listed and explained in the data section.

To ensure the groups will be compared similarly, sample age is restricted. The MEPS question used to determine the variable "chol" is asked to everyone 18 years old and up. However, 18 and 65 year olds are not expected to behave similarly. Comparing cholesterol screening patterns in a range of ages this wide would not likely be very insightful. Three versions of the model will be tested. One model includes those older than 35, the age that the United States Preventive Services Task Force (USPSTF) recommends cholesterol screening for men. The USPSTF recommends women start cholesterol screening at 45, however, for a model not separated by sex, it seems more appropriate to start with the lower age (Screening for Lipid Disorders in Adults, 2008). Another model will include those who are older than 50. This will further restrict the range of ages; individuals of a smaller range of ages should behave increasingly similar. Lastly, those between the ages of 60 and 70 will be tested. This is the smallest range of ages, and though it will not capture as broad and nationally representative a population, the population it does compare will more characteristically similar.

3. DATA

Data used in the study are from the Medical Expenditure Panel Survey, or MEPS. MEPS is published yearly since 1996. MEPS surveys families, individuals, and employers across the United States, and collects data on what health care services are utilized, how frequently, and the method of payment utilized. MEPS also collects information on the cost and scope of health insurance held and available to workers in the U.S. (Survey Background, 2009). The Full Year Consolidated files from years 2001 through 2010 are used in this study. These files contain the responses to all questions surveyed.

The MEPS survey collects information on a household over a span of two years, in a set of five rounds. Households are surveyed, with each household being assigned its own dwelling unit identification number (DUID). Each individual within the household receives a personal identification number (PID) that identifies the individual within his or her specific dwelling unit. The DUID and PID combine to create an individualized identification number (DUPERSID) that is employed to track the individual through the entire survey (MEPS HC-138 2010 Full Year Consolidated Data File, 2012). A household that enters the survey in 2002 will be included in the 2002 and 2003 results, and the survey collects data from each included household for two years. The household and its members retain the same identification numbers during their time in the study, allowing MEPS to track how an individual's medical utilization, expenditures, and health insurance status change over the duration of the study.

MEPS classifies variables by the round of survey interviewing in which the question was asked. The same questions are asked around the same time of a year, to avoid seasonal variation, but will correspond to different rounds of interviews for different panels. For example, a question asked in round three for a household new to MEPS corresponds to the same question being asked to a different household in its second year of MEPS participation in round five. These variables are labeled with a "53" suffix to denote the when they were asked (MEPS HC-138 2010 Full Year Consolidated Data File, 2012).

Each individual in MEPS is included in two output files, the first being the file corresponding to the year they entered the survey, and the second being the next year when they left the survey. To eliminate individuals being counted twice in the data set, each person's information is used in this study from only the later of the two years. For example, an individual who entered MEPS in 2009 is featured in the 2009 and 2010 data file. For the purpose of creating an appropriate sample, only the later year's data is included; the 2009 information on this individual is removed from the data set. To eliminate individuals being counted in both the pre-and post-treatment groups, all information from the year 2005 is removed from the sample. Individuals who entered into MEPS in 2004 and left in 2005 are included in the pre-treatment population.

3.1 VARIABLES

This paper uses variables taken from the 2nd, 3rd, 4th, and 5th rounds of MEPS. The second and fourth round interviews occur throughout most of the year, starting around halfway through the first quarter of the year and lasting through about halfway through the fourth quarter. The third and fifth round interviews begin about halfway through the third quarter and run until the end of the year (MEPS-HC Panel Design and Data Collection Process). In these rounds, preventive medicinal usage, insurance status, demographics, and pre-existing condition data are queried.

3.1.1 DEPENDENT VARIABLE

The dependent variable "chol" is a qualitative variable measuring the time since an individual's last cholesterol check. MEPS determines the amount of time since the respondent's last cholesterol check. MEPS permits a respondent to state: within the past year, within the past two years, within the past three years, within the past five years, more than five years, never, don't know, refused, not ascertained, or inapplicable. The question is asked of both men and women over the age of seventeen (MEPS HC-138 2010 Full Year Consolidated Data File, 2012).

The change to Medicare Part B's policy in 2005 allows for coverage of a cholesterol check every five years. The outcome variable "chol" is coded differently depending on the year of the observation. For all years, those who refused to answer, those for whom the question did not apply, and those for whom an answer was not ascertained, are removed from the sample due to the inability to determine whether a 1 or 0 is appropriate. For the pre-treatment period, 2004 and earlier, "chol" is coded to equal 1 if the respondent reported he or she received a cholesterol check within the past five years, and 0 if he or she reported more than five years or never. For the post-treatment years, 2006 through 2010, "chol" is coded depending on how many years have passed the policy's effective date.

Each year is coded differently to eliminate the possibility of including someone who is in a post-treatment year but ineligible to receive a cholesterol screening. For example, an in individual from the 2006 survey who responded that he or she had received a screening within the past three years may have received the screening before the policy, and therefore should not be counted as receiving the treatment after the screening. To correct this problem "chol" is coded as such: in 2006, equal to 1 if the participant received a cholesterol screening within the past year, equal to 0 otherwise; in 2007, equal to 1 if the participant responded they had received a screening within the past one or two years, equal to 0 otherwise; in 2008, equal to one if the participant received a screening within the past one, two, or three years, equal to 0 otherwise; in 2009, "chol" i coded the same as 2008, due to the fact that the survey did not permit respondents to state they had received a screening within the past four years; and in 2010, equal to 1 if the respondent reported receiving a screening within the past one, two, three, or five years, and equal to 0 otherwise.

3.1.2 DIFFERENCE-IN-DIFFERENCES VARIABLES

The difference-in-difference model requires variables differentiating between the treated and control groups, as well as a time variable to denote the pre- and post-treatment periods. The treated group includes those individuals who were covered by Medicare, and represented by in the data set by variable "medicare." This variable determines if a respondent was covered by Medicare in each month of the year in which the survey was conducted (MEPS HC-138 2010 Full Year Consolidated Data File, 2012). Those who covered by Medicare are coded to equal 1; all others are coded to equal zero.

The variable “EL” addresses eligibility for coverage, and represents the pre- and post-treatments periods. Variable “EL” is equal to 0 for all observations pre-2005. However, in the post-treatment period, “EL” does not only represent time. It also represents that an individual is eligible for a cholesterol screening. If an individual received a cholesterol treatment in 2004, he or she is not eligible to receive one for another five years. Due to their inability to take part in the treatment, ineligible individuals are removed from the sample. Similar to the outcome variable “chol,” “EL” is coded differently each year: in 2006, it is set equal to 1 if the respondent reported receiving a treatment within the past year, if the respondent reported his or her last screening was more than five years ago, or the respondent never underwent a screening, it is set equal to 0 otherwise; in 2007, it is set equal to 1 if the respondent reported his or her last screening was within one or two years, more than five years ago, or reported he or she never received one, it is set equal to 0 otherwise; in 2008, it is set equal to 1 if the respondent reported his or her last screening within the past one, two, or three years, more than five years ago, or reported he or she never received a screening, it is set equal to 0 otherwise; in 2009, “EL” is coded the same as 2008, due to the lack of a within the past four years option; and in 2010, it is set equal to 1 if the respondent reported receiving a screening within the past one, two, three, or five years, his or her last screening being more than five years ago, or never having received one, leaving no options to be equal to zero.

A variable “elxmedicare” is the dummy variable D_{st} from equation 2.2.1, created by multiplying variables “medicare” and “EL” together. A value of 1 for “elxmedicare” implies a Medicare beneficiary, post-2005, who is eligible for treatment. A value of 0 implies the individual is not covered by Medicare, either pre- or post-treatment, or an individual is covered by Medicare but the policy has not taken effect yet. A missing value for “elxmedicare” implies that the individual is ineligible for a cholesterol screening post-January 1, 2005.

3.1.3 CONTROLS

This model controls for the following variables that may affect a patient’s use of preventative services: monthly premium for Medicare Part B in the current year, race, years of education, marital status, smoking status, employment, sex, reported perceived health, the ability to name a usual source of care, and medical history of diabetes, myocardial infarction, stroke, asthma, and year effects dummy variables.

The change in cholesterol screening policy under the MMA affected those with Medicare Part B, an optional service; in 2010, Part B covers 43.8 million of the 47.5 million, or 92.2% total Medicare enrollees (Fast Facts About Medicare, 2012). However, MEPS does not provide information on which Medicare enrollees Part B covers until 2009. The variable “prtbprm” is created in an attempt to correct for the lack of information on enrollment and also to control for the price of Part B. This variable is the monthly premium for Medicare Part B enrollment. The premium changes yearly: for in 2001, the monthly premium was $50.00 per month; in 2002, $54.00; in 2003, $66.60; in 2004, $66.60; in 2006, $88.50; in 2007, $93.50; in 2008, $96.40, in 2009; $96.40; and in 2010: $110.50 (Medicare: A Timeline of Key Developments, 2013; Graham, 2008; Part B Premium: Who Pays What and Why?). I expect premium to have a negative relationship with the outcome variable. As price for the service increases, people should be less willing to use it, and therefore decrease enrollment and utilization of cholesterol screenings.

Race is determined from a combination of MEPS variables and coded into five dummy variables "white," "black," "hispanic," "asian," and "other." MEPS participants are able to select one or more of the first four listed options. If a participant identified with an available racial group, the variable corresponding to that race in this model is coded to equal 1. If they did not identify with a specific race, the variable is coded to equal 0. If a participant identifies with none of the options presented, variable "other" is coded to equal 1. For example, if the respondent reports being white, and no other races, the variable "white" was coded to equal 1, while variables "black," "hispanic," "asian," and "other" are all coded to equal 0. The variable "white," however, is not used in the regression; it was excluded as the reference group. Similarly to the theories and results of Bao et al (2007) and McAlpine and Sambamoorthi's (2003), I expect a lower rate of screening among non-white minorities. This will make the coefficients on the variables corresponding to these minority races negative, representing a decreased rate of screening relative to the reference group.

The variable "educ," denoting years of education, is determined from MEPS variable EDUCYR. MEPS asks survey participants how many years of education they have received at the time of survey. The possible responses for the survey participants are the number of finished years of school, ranging from 0 through 17 or more years. Bao et al (2007) hypothesizes and shows there is a strong relationship between education and preventive screenings, implying less educated individuals are less likely to receive preventive services. I expect a similar relationship between education and the specific cholesterol screening.

Variable "married" is determined from MEPS variable MARRY53X. In MEPS, respondents are able to report a variety of marital status options, including single, married, divorced, separated, and widowed. For the purposes of this study, "married" is coded to equal 1 if marriage was reported, and 0 if the respondent was not married for any reason. Consistent with Schone and Weinick (1998), I expect marriage to increase the likelihood of receiving a cholesterol screening. Their study tests the idea that marriage increases positive health behaviors, extending previous studies by examining an elderly population.

Smoking status is coded from MEPS variable ADSMOK42. Smoking status is represented by the variable "smoke," and is coded to equal 1 if the respondent currently smokes. McAlpine and Sambamoorthi (2003) acknowledge a variety of factors that they failed to control for, one being smoking. To eliminate this potential error, I include smoker status in as a control. I expect smokers to be less likely to receive preventive treatments; smoking signifies a lower level of interest in maintaining one's health.

Sex is coded to equal 1 if the respondent reported being male, and 0 otherwise. Edlund et al (1999) shows there are significant differences in screening rate between sexes. They study a variety of screenings and did not find a specific trend among men and women; men and women prefer certain screenings. The fact that significant differences between sexes were found leads me to believe that sex will be a significant determinant in cholesterol screening.

Variable “employed” identifies an individual’s employment status. This variable is coded to equal 1 if the respondent reported employment in the fifth or third round when the question was asked, and to equal 0 if they are not employed for any reason. I expect employment to affect this data set in a similar manner as is shown in Buist et al (2008).

The respondent’s perceived health is asked in MEPS, and included in this model. In MEPS, respondents have a choice of answers: poor, fair, good, very good, and excellent. Perceived health is represented by variable “perhealth”. It is coded to equal 1 if a respondent perceived him or herself to be in good health, that is, the respondent responded with either good, very good, or excellent. Otherwise, this variable is coded to equal 0. Adamache and Rosenbach (1995) show a relationship between poor health and high rate of health care utilization. I expect a similar result.

The variable “usc” is determined from MEPS variable HAVEUS42. This information in MEPS addressed whether the respondent has a specific provider they usually turn to for care. The MEPS variable does not specify between the type of caregiver; the response options were yes or no. This variable is coded to equal 1 if the respondent answered yes, 0 if the respondent did not. Ettner (1995) aims to confirm or reject the assumption that having a usual source of care is positively related to increased preventive procedures by correcting previous studies’ methodological errors. Her study upholds the assumption, but only to a degree, stating that having a usual source of care increases the likelihood of receiving some services, but not all. Due to her findings, I expect either a positive or close to zero relationship between ability to name a usual source of care and cholesterol screenings.

Information on preexisting conditions and medical history are also included. The conditions used as controls are: diabetes, myocardial infarction, stroke, asthma, coronary heart disease, angina, other heart disease and high blood pressure. These variables have been named as such: “diabetes,” “myocardial,” “stroke,” “asthma,” “coronary,” “angina,” “otherhd,” and “highbp.” Each is coded to equal 1 if the respondent reported a diagnosis of the condition in the past. Otherwise, the variables are coded to be 0. Medical history of diabetes, myocardial infarction, stroke and asthma are included due to their inclusion in Dellenbaugh et al (2007).

Other medical history variables “coronary,” “angina,” “otherhd,” and “highbp” are included due to the relationship between cholesterol and heart disease. High cholesterol levels increase risk of heart disease (Mayo Clinic Staff, 2012). I expect individuals that have experienced types of cardiovascular diseases in the past will be more vigilant in monitoring their risk factors, one being cholesterol. These variables are expected to have positive coefficients, meaning experiencing a diagnosis will increase your likelihood to receive a preventive cholesterol screening.

Time effect dummy variables are included to control for year-to-year fluctuations in cholesterol screening trends. These variables control for the possibility of an outlier year throwing off the data. The variables correspond to year as such: time_1 corresponds to 2001; time_2 to 2002: time_3 to 2003; time_4 to 2004: time_5 to 2006; time_6 to 2007; time_7 to 2008; time_8 to 2009; and time_9 to 2010. In the estimation of the model, time_1 was excluded.

3.2 DESCRIPTIVE STATISTICS

Descriptive statistics are given below, summarized in four separate tables. Each table corresponds to a certain group, Medicare or non-Medicare, at a certain time, pre- or post-treatment. Each table describes the data set used for the three different models. First, it summarizes the data for those older than 35, then the data for those older than 50, and then the data for those between the ages of 60 and 70.

TABLE 3.1

MEDICARE GROUP, PRE-TREATMENT

	Age > 35		Age > 50		60 < Age <70	
	% Sample	% Screened	% Sample	% Screened	% Sample	% Screened
All		94.25%		94.69%		94.55%
Usual Source						
USC	93.09	95.92	93.40	96.25	92.08	96.30
No USC	6.91	71.70	6.60	72.64	7.92	74.16
Demographics						
Male	41.99	78.71	41.40	94.05	45.00	93.35
Female	58.01	94.90	58.60	95.14	55.00	95.52
White	83.42	94.26	83.81	94.70	82.46	94.44
Black	13.51	94.70	13.07	95.15	13.90	95.10
Hispanic	12.52	91.50	12.45	92.06	14.92	91.88
Asian	2.31	92.04	2.41	91.96	2.88	92.11
Other	0.79	92.21	0.75	95.71	0.72	94.72
Married	50.61	94.94	51.42	95.17	63.18	94.72
Employed	3.56	93.68	3.53	93.90	6.59	93.10
Perceived Health						
Good	68.18	93.45	69.31	93.90	72.92	94.13
Poor	31.82	95.95	30.69	96.46	27.08	95.66
Medicare History						
Smoker	12.77	99.28	13.16	99.26	10.38	98.91
Coronary	8.36	98.65	8.54	98.61	6.86	97.79
Angina	11.50	98.58	11.83	98.64	8.94	97.46
Myocardial	15.59	97.44	15.89	97.50	12.84	98.23
Other HD	10.37	97.73	10.56	97.96	7.42	98.96
Stroke	60.95	97.55	62.03	97.63	57.69	97.64
High BP	20.40	98.14	20.61	98.17	20.95	98.37
Diabetes	10.68	95.88	10.16	96.08	10.27	96.68
Asthma	0	0	0	0	0	0
Mean Age		71.63		73.01		66.55
Mean Education		13.15		13.17		13.40
Observations		9767		9302		2640

Pre-treatment, both groups experience high cholesterol screening rates, with Medicare beneficiaries holding the higher of the two pre-treatment groups. Screening rates in the pre-treatment control group, however, increase to similar levels as those covered by Medicare as age becomes restricted and average age increases. As time moves from the pre- to post-treatment period, overall rate of screening decreases. The same patterns between the control and Medicare groups exist in the post-treatment sample. Overall, the post-January 1, 2005 group has a higher rate of screening across all age groups. As age becomes more restricted in the post-treatment control group, however, rates rise closer to that of the post-treatment Medicare group.

TABLE 3.2

CONTROL GROUP, PRE-TREATMENT

	Age > 35		Age > 50		60 < Age <70	
	% Sample	% Screened	% Sample	% Screened	% Sample	% Screened
All		81.09		89.23		91.26
Usual Source						
USC	78.22	86.65	84.11	93.21	85.56	95.07
No USC	21.78	61.14	15.89	68.16	14.44	68.63
Demographics						
Male	45.98	77.52	45.68	87.30	44.98	90.53
Female	54.02	84.13	54.32	90.85	55.02	91.85
White	80.93	80.68	81.89	89.08	81.17	91.60
Black	14.06	83.51	13.28	90.59	14.22	90.54
Hispanic	20.63	74.77	16.40	83.56	14.62	87.73
Asian	4.07	81.89	4.13	87.71	3.81	85.88
Other	0.93	79.92	0.70	90.28	0.72	93.75
Married	68.16	82.46	68.73	90.34	67.58	91.90
Employed	17.65	79.99	15.80	88.88	12.47	90.29
Perceived Health						
Good	85.36	80.51	81.80	88.92	79.78	91.12
Poor	14.64	84.50	18.20	90.61	20.22	91.80
Medicare History						
Smoker	2.01	98.29	3.92	98.00	5.56	97.58
Coronary	1.57	95.15	2.89	97.30	3.95	100
Angina	2.10	95.99	3.83	96.43	5.38	98.33
Myocardial	4.88	92.33	7.35	96.15	8.79	94.39
Other HD	1.68	95.24	2.84	97.25	3.68	97.78
Stroke	26.58	92.81	39.87	95.42	48.61	96.22
High BP	7.85	96.20	12.53	97.66	14.98	97.60
Diabetes	8.71	86.28	9.54	92.63	9.33	95.19
Asthma	0	0	0	0	0	0
Mean Age		48.33		56.79		62.50
Mean Education		13.79		13.79		13.49
Observations		26181		10239		2230

Post-treatment rates of screening, in general, are lower than pre-treatment rates across all groups. Examining only the Medicare groups, screening rates decrease across all age groups. The same pattern occurs with the control groups.

TABLE 3.3

MEDICARE GROUP, POST-TREATMENT

	Age > 35		Age > 50		60 < Age <70	
	% Sample	% Screened	% Sample	% Screened	% Sample	% Screened
All		86.97		87.19		87.16
Usual Source						
USC	75.87	97.41	76.04	97.69	75.16	97.32
No USC	24.13	54.14	23.96	53.88	24.84	56.44
Demographics						
Male	43.18	86.59	43.00	86.91	45.45	86.56
Female	56.82	87.25	57.00	87.41	54.55	87.66
White	75.73	86.62	76.33	86.79	75.54	86.22
Black	18.38	87.16	17.69	87.60	18.74	90.03
Hispanic	12.44	85.85	12.38	85.85	12.84	84.99
Asian	5.08	90.99	5.18	91.46	4.57	90.91
Other	0.88	90.00	0.86	89.25	1.25	88.10
Married	50.83	87.69	51.88	87.69	61.19	97.98
Employed	3.77	58.64	3.77	58.44	6.67	56.44
Perceived Health						
Good	70.48	87.05	71.65	87.28	76.19	86.93
Poor	29.52	86.76	28.35	86.96	23.81	87.92
Medicare History						
Smoker	12.07	84.76	11.19	85.09	14.08	82.32
Coronary	18.02	93.07	18.47	93.21	12.02	92.39
Angina	8.93	90.64	9.05	90.63	7.29	89.43
Myocardial	12.03	90.78	12.27	90.92	9.96	93.15
Other HD	22.71	92.13	23.10	92.10	18.44	91.00
Stroke	12.12	88.96	12.30	89.06	8.75	89.83
High BP	69.57	88.96	70.50	88.92	66.77	89.79
Diabetes	24.56	90.22	24.71	90.07	25.88	91.41
Asthma	11.02	86.02	10.51	86.68	11.47	85.56
Mean Age		71.38		72.65		66.51
Mean Education		12.98		13.01		13.26
Observations		11362		10852		3373

In both time periods, those covered by Medicare are more able to name a usual source of care than those not covered by Medicare. A similar trend exists in the pre- and post- control groups. As determined by Ettner (1996), the individuals with a usual source of care will be more likely to receive preventive screenings. This pattern is reflected in all four groups. Overall, there is a decrease in proportion of individuals with a usual source of care, and within the sample of those with a usual source of care, there is a decrease in screening rates.

TABLE 3.4
CONTROL GROUP, POST-TREATMENT

	Age > 35		Age > 50		60 < Age <70	
	% Sample	% Screened	% Sample	% Screened	% Sample	% Screened
All	28998	78.41	12636	83.74	2955	85.82
Usual Source						
USC	63.41	90.45	68.50	94.99	71.68	96.13
No USC	36.59	57.53	31.50	59.27	28.32	59.74
Demographics						
Male	45.81	75.75	46.44	82.12	47.55	84.77
Female	54.19	80.65	53.56	85.14	52.45	86.77
White	74.39	77.34	75.14	83.21	77.77	86.25
Black	18.24	81.13	17.86	85.16	15.74	86.24
Hispanic	23.78	74.94	18.65	81.41	15.53	82.79
Asian	6.63	83.20	6.43	85.96	5.89	79.89
Other	0.76	76.02	0.72	79.12	0.88	84.62
Married	65.91	8.27	66.18	18.89	66.09	80.90
Employed	15.74	52.51	14.28	53.91	12.32	59.07
Perceived Health						
Good	85.59	77.94	82.73	83.65	82.81	85.62
Poor	14.41	81.16	17.27	84.14	17.19	86.81
Medicare History						
Smoker	17.87	70.72	17.04	76.82	14.28	79.15
Coronary	3.53	91.30	5.92	91.84	8.53	95.24
Angina	1.99	89.97	3.05	91.69	4.16	94.31
Myocardial	2.62	88.14	4.42	88.89	5.96	89.20
Other HD	7.47	88.97	10.65	91.38	13.10	93.80
Stroke	2.36	87.45	3.66	89.63	5.28	92.95
High BP	34.86	86.86	48.21	88.53	55.43	90.60
Diabetes	10.69	89.16	15.62	89.46	18.61	90.19
Asthma	8.41	81.87	8.78	85.32	8.46	88.00
Mean Age		49.14		57.04		62.04
Mean Education		13.69		13.72		13.76
Observations		28998		12636		2995

Consistent with Adamache and Rosenbach (1995), individuals who self-report worse health also report higher rates of screening in the pre-treatment period. However, in the post-treatment period, this result disappears. Individuals with who deem themselves to be in good health also report higher rates of screening in some age groups. The controls mentioned follow similar patterns as described for the two traits mentioned. Medicare groups routinely receive higher screening rates than the control group, but post-January 1, 2005, rates in both groups are less than the rates experienced in the same groups pre-treatment.

4. RESULTS AND DISCUSSION

The results show that for the age groups older than 35 and older than 50, cholesterol screening among those covered by Medicare decreased relative to the control group once the MMA took effect. There is no significant decrease or increase in rate of screening among Medicare beneficiaries relative to the control in the group aged between 60 and 70. As shown in the tables 4.1 and 4.2, the groups aged above 35 and above 50 have a DID that is both negative and significant. The group between the ages of 60 and 70 also shows a negative DID; however that result is not statistically significant. The sign of the coefficients corresponding to the controls are generally consistent with the literature discussed previously, with the exception of perceived health which was predicted to be negative, yet was sometimes positive (Adamache & Rosenbach, 1995).

TABLE 4.1

DIFFERENCE-IN-DIFFERENCES RESULTS

	Pre-Treatment			Post-January 1, 2005			
	Non-Medicare	Medicare	Diff	Non-Medicare	Medicare	Diff	DID
Age > 35							
chol	.507	.57	.065***	.506	.527	.022***	-.043***
observations	25861	9581	35442	25975	10316	36291	
Age > 50							
chol	.61	.632	.022***	.61	.614	.004	-.018***
observations	10127	9124	19251	11395	9861	21256	
70 > Age > 60							
chol	.596	.608	.012	.596	.597	.001	-.011
observations	2198	2600	4798	2697	3085	5782	

*** p < .01
** p < .05
* p < .1

TABLE 4.2

LINEAR REGRESSION RESULTS

Chol	Age > 35	Age > 50	60 < Age < 70
elxmedicare	-.0428***	-.0176***	-.0107
Medicare	.0645***	.0219***	.0116
EL[1]	---	---	---
prtbprm	.0014***	.0001***	.0010***
usc	.2299***	.2276***	.2247***
Male	-.0330***	-.0189***	-.0126**
Black	.0099***	.0004	-.0037
hispanic	-.0188***	-.0158***	-.0150*
asian	.0176***	.0074	-.0250*
other	-.0175	-.0057	.0143
married	.0337***	.0252***	.0214***
perhealth	.0027	.0043	.0065
employed	.0067	.0113	-.0047
smoke	-.0448***	-.0230***	-.0357***
coronary	.0172***	.0147***	.0249***
angina	.0264***	.0156***	.0090
myocardial	.0202***	.0122***	.0044
otherhd	.0137***	.0111***	.0022
stroke	.0776***	.0463***	.0449***
highbp	.0680***	.0426***	.0537***
Constant	.5056***	.6098***	.5963***
time effects	yes[2]	yes[3]	yes[4]
Observations	71733	40507	10580
F	472.02***	214.40***	54.06***
R^2	.1861	.2447	.2562

*** $p < .01$
** $p < .05$
* $p < .1$

[1] "EL" omitted in all models due to collinearity
[2] Only 2002, 2006 and 2007 significant, corresponding coefficients: .0165***, -.0339***, and -.2235***. 2009 omitted due to collinearity
[3] Only 2002, 2006 and 2007 significant, corresponding coefficients: .0135**, -.0137**, and -.2732***. 2009 omitted due to collinearity
[4] Only 2002 and 2007 significant, corresponding coefficients: .0363*** and -.2573***. 2009 omitted due to collinearity

These results suggest the MMA policy change seems to be ineffective in its goal of increasing the amount of cholesterol screenings undertaken for all age groups. Those covered by Medicare over 35 and 50 decreased in their rates of screening while the control groups of the same age maintain the same rates. The DID pertaining to the group between ages 60 and 70, though negative, is insignificant, implying the Medicare group's screening rate, post-January 1, 2005, does not change relative to the control group.

These results are somewhat consistent with Foote et al's (2008) findings. Foote and his colleagues examine the effects of local coverage policies on usage of the following procedures: heliobacter pylori breath test, deep brain stimulation, ocular photodynamic therapy, transesophageal echocardiography, abdominal and pelvic CT and MRI scans, epotin α, toenail debridement, and chest x-rays. They find that in seven out of these eight services, there is no significant change in usage. That is, the DID calculated for these services is not significantly different from zero, similar to the results of the DID calculations for the age group between 60 and 70. In the one case Foote et al (2008) do find significant, that of transesophageal echocardiography, has a negative DID, similar to the DID of the models restricted to those over 35 and those over 50. The Foote study concludes that there is no evidence, regardless of type of service covered, that coverage policies affect procedure usage. This study has shown a similar result, although two groups actually have a negative DID.

A negative DID could also be, in part, due to a change in supplemental insurance coverage, assuming there is no change in Medicare Part B participation rates over the same period. Carrasquillo et al (2001) and Dellenbaugh et al (2007) both show that supplemental health insurance, either in the form of an HMO, coverage from the VHA, or simply extra private insurance, can increase the rate of preventive screening. Even without a preventive screening being completely covered by Medicare, a beneficiary with supplemental coverage can have the remainder of the cost of the service covered (Carrasquillo, Lantigua, & Shea, 2001). In the pre-treatment Medicare group, 76.15% of individuals reported being covered by another source besides Medicare. Post-treatment, 57.61% of Medicare covered individuals reported being covered by another, non-Medicare source. With Part B enrollment held constant, the decrease in supplemental coverage could explain the decrease in screening rates. However, there is no point for comparison, as the data set does not include information on the nature of the supplemental forms of coverage for those not covered by Medicare.

Also, between 2004 and 2006, the monthly premium for Medicare Part B increased from $66.60 to $88.50, and increase of 32.88 percentage points. An increase in price of Part B over the time periods could lead to a decrease in Part B participation. Decreasing participation would decrease the number of eligible beneficiaries. However, MEPS does not provide information on whether an individual has opted in to Part B, so there is no way to examine this effect from the data set.

Future studies could examine the effect of changes in supplemental coverage patterns. From pre- to post-treatment, rates of supplemental coverage dropped by 18.54 percentage points. The significant positive relationship between supplemental coverage and preventive medicine screenings could shed some light on why the MMA policy change did not meet its desired effect. To examine this, supplemental insurance status could be included as a control, or run as a difference-in-difference-in-differences (DIDID). The DIDID option would measure the change in usage among those with supplemental insurance. Also, the opposite could be tested, measuring the change among only those without supplemental insurance.

Similar to supplemental insurance status, it would be interesting to run DIDID models on the controls for gender, and usual source of care. Edlund et al (1999) find significant differences in preventive procedure utilization between genders. Running DIDID models for both men and women could examine how whether men and only women react to changes in policy in different ways. If trends can be identified between the two groups, policy makers could try to tailor policies that would even disparities in screening rates among genders.

The same analysis could also be performed for those with the ability to name a usual source of care. As shown in tables 3.1 and 3.2, before 2005, Medicare beneficiaries with a usual source of care had a higher rate of screening than their control group counterparts. A similar effect, though not as pronounced, exists in the post-treatment sample. If there exists a significant difference in utilization rates pre- to post- among those only with a usual source of health care, further studies could attempt to identify what factors changed. In addition future policies could try to increase use of preventative services by encouraging patients to develop relationships with providers. Buist et al (2008) show preventive screening rates depend on physician-patient interactions. Combining their results with a DIDID could prompt a study on how physician-patient interactions have changed, either for the worse or better. Knowledge of interactions that are associated with higher screening rates could be useful information to provide to physicians and those looking to increase screening rates.

Also, this study could be improved by use of functional status as a control. Functional status measures disability; how mobile a person is and if they need assistance in daily tasks (Dellenbaugh, Hebert, Keyhani, Penrod, Ross, & Siu, 2007). Medicare populations, as shown in tables 3.1 through 3.4, have a higher average age than the control groups used. Assuming an older population is more likely to have functional restrictions and disabilities, it may be harder for a larger proportion of a Medicare group to receive treatment. Their physical condition could put physical barriers to, and decrease rates of preventive screenings regardless of policy.

5. CONCLUSIONS

Pre- to post-treatment, the inclusion of cholesterol screenings without copay or deductible under Medicare does not reach the desired end. Two of the three models show Medicare beneficiaries decrease their screening rate relative to the control group, while the third shows no increase or significant difference between the Medicare and control groups.

As discussed previously, further studies on this subject could test the effects of functional status and a variety of difference-in-difference-in-differences models. Identifying patterns between sexes or between those with and without usual sources of care could provide insight that would allow policy makers to form better policies to increase rates of screening. Similarly, identifying the effects of supplemental coverage could provide policy makers information to create more effective reforms. Two last issues that could be analyzed are the inability to specify between Medicare Part B beneficiaries and those not covered, and the reliability of self-reporting to MEPS. Medicare Part B is also an optional service. For the purposes of correctly placing individuals in to the appropriate group, it would be important to know if an individual is covered by Part B and therefore eligible. However, MEPS does not begin to specify if a person is covered by Part B or not until 2009. This specification was not used, so even though Part B utilization is high, there may be individuals in the treatment group who were, in fact, not eligible for treatment. Increased knowledge on Part B participation could increase the accuracy of the sample and potentially change the results.

Finally, there lies the issue of MEPS data being self-reported. With self-reported data, there is potential for innate inaccuracies in the data set. Olin and Zuvekas (2009) examines the amount of error in MEPS by comparing information Medicare beneficiaries reported to MEPS with their Medicare claims. The results show that Medicare beneficiaries underreport medical office visits. This could decrease the number of cholesterol screenings reported to MEPS and could play a role in the calculation of a negative DID.

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