ABSTRACT

Title of dissertation: THE IMPACT OF HEALTH INSURANCE ON CANCER PREVENTION: *EX ANTE* AND *EX POST* MORAL HAZARDS

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The classic model of moral hazard suggests that health insurance may reduce preventive care because the insurer will pay for part of the treatment in case of disease. However, if health insurance covers preventive care as well, the reduced cost of preventive care will encourage the insured to consume more preventive care. These two countervailing effects are referred to as *ex ante* and *ex post* moral hazards (Zweifel & Manning 2000). Most studies do not distinguish the two effects, leading to a potentially wrong characterization of moral hazard.

Using Medicare coverage as an example, this thesis identifies *ex ante* and *ex post* moral hazard effects of health insurance on cancer prevention. As we know, Medicare eligibility rules increase health insurance coverage at age 65. However, some preventive screenings were not covered in Medicare until recently. The different timing of Medicare eligibility and Medicare expansion of preventive care allows me to use a difference-in-differences framework to separate *ex ante* and *ex post* moral hazards.

I focus on female uptake of breast cancer screening and male uptake of prostate cancer screening, using the Medical Expenditure Panel Survey (MEPS) and the National Health Interview Survey (NHIS). In both datasets, I find evidence in support of *ex ante* and *ex post* moral hazards. No evidence shows that people try to delay screening until it has been covered by Medicare. Moreover, the level of prevention and responsiveness to insurance changes vary with demographics, with larger effects among whites and the better-educated.

Then I take a second look at the moral hazard problem in the health insurance market using the Health and Retirement Study (HRS). Compared with MEPS or NHIS, the panel nature of HRS allows me to control for individual fixed effects and therefore provides a more stringent test. The major findings on female uptake of breast cancer screening are consistent. I find strong *ex ante* and *ex post* moral hazard effects in female uptake of breast cancer screening, and individual reactions to Medicare enrollment and Medicare's preventive care coverage vary by factors such as race and income. However, moral hazards on male uptake of prostate cancer screening is not found, mainly due to poor quality of data.

THE IMPACT OF HEALTH INSURANCE ON CANCER PREVENTION: *EX ANTE* AND *EX POST* MORAL HAZARDS

by

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It is impossible to remember all, and I apologize to those I've inadvertently left out.

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List of Abbreviations

ACS	American Cancer Society
BBA	Balanced Budget Act of 1997
CDC	Centers for Disease Control and Prevention
DD	Difference-in-differences
DI	Social Security Disability Insurance
FIML	Full Information Maximum Likelihood
HRS	Health and Retirement Study
LIML	Limited Information Maximum Likelihood
MEPS	Medical Expenditure Panel Survey
ML	Maximum Likelihood
NHIS	National Health Interview Survey
PPACA	Patient Protection and Affordable Care Act
OLS	Ordinary Least Square
PSA	Prostate-specific antigen
RD	Regression Discontinuity
TFL	TRICARE for Life

Chapter 1

Introduction & Background

1.1 Introduction

The classic model of moral hazard suggests that health insurance may reduce the incentive for prevention because it lowers out-of-pocket medical cost in case of disease. The reduced incentive may result in an increase in unhealthy behaviors and a decrease in the usage of preventive care. While this moral hazard problem is always mentioned as a reason for too little prevention in health care, the empirical evidence of its existence is limited. In comparison, researchers have found a significant moral hazard effect in other insurance contexts [1].

There are at least two arguments for why moral hazard may not be an important problem in health insurance. The first is that the moral hazard effect is neutralized by risk aversion (Zweifel and Manning, 2000). Alternatively, moral hazard may be solved by the fact that health insurance covers the financial but not the health loss of a serious illness (Kenkel, 2000).

However, both arguments fail to explain why we observe little moral hazard in health insurance but a significant amount in other contexts, such as workers' com-

[1] For discussion on workers' compensation, please refer to Ruser, 1985, 1991; Kaestner and Carroll, 1997; and Fortin and Lanoie, 2000. For discussion on automobile insurance, please refer to Cummins and Tennyson, 1996; and Dionne et al., 2004.

pensation and automobile insurance. Lack of prevention can result in severe health events in all three insurance contexts. But none of them address the health loss. For example, skipping routine cancer screening exams may not detect cancer in a timely manner and lose the precious time for treatment in early stage; less precaution at work place increases the probability of getting in serious accident; aggressive driving may lead to fatal accident. Health insurance, workers' compensation, and automobile insurance all cover part or all of the insurees in medical costs, but not health loss.

This thesis aims to solve this puzzle by investigating two types of moral hazard in health insurance. On the one hand, health insurance may reduce preventive care because the insurer will pay for part of the treatment in case of disease. This is the classic moral hazard. On the other hand, if health insurance covers preventive care as well, the preventive coverage will encourage the insured to consume more preventive care. These two countervailing effects are referred to as *ex ante* and *ex post* moral hazards[2] (Zweifel and Manning, 2000). Failure to distinguish the two may lead to a conclusion of non-existence because the two moral hazard effects may cancel one another out.

Using Medicare coverage as an example, I use a difference-in-differences (DD) approach to separate *ex ante* and *ex post* moral hazards. More specifically, Medicare eligibility rule increases health insurance coverage at age 65, which allows me to identify *ex ante* moral hazard (*i.e.*, reduced prevention due to medical care coverage) by comparing preventive behaviors among people just before and just after

[2]For definitions of *ex ante* and *ex post* moral hazards, the reader is referred to Section 1.3.1.

65. The same identification strategy has been used to study the impact of Medicare enrollment on preventive behavior and health care utilization in several papers (McWilliams et al., 2003; Decker et al., 2006; Dave and Kaestner, 2006; Card et al., 2004, 2007).

To estimate *ex post* moral hazard (*i.e.*, increased prevention due to preventive care coverage), I use two policy changes that expanded Medicare preventive care coverage in recent years. Medicare covers annual breast cancer screening for female beneficiaries since 1998 and covers annual prostate cancer screening for male beneficiaries since 2000. The transition of breast cancer screening from no coverage to full coverage occurred in 1998. It happened right after the passage of the act that enacted the change, which makes the transition unlikely to be anticipated. It affects Medicare female beneficiaries directly but not the younger female cohorts (age 55-64) who are not eligible for Medicare. The transition of prostate cancer screening is somewhat anticipated. Later on I examine the anticipation effect explicitly.

The DD approach has several appealing features. First, using the DD framework, I can differentiate *ex post* moral hazard from *ex ante* moral hazard. If we do not separate them, the estimate based on the Medicare eligibility alone will capture the net sum of the two moral hazards.

The second advantage of the research design is that it solves the endogeneity problem arising from insurance coverage because the age threshold for Medicare eligibility provides an exogenous variation in insurance status. Figure 2.1 shows that Medicare coverage rate jumps from about 10% to 90% at age 65. The expansion of Medicare preventive coverage offers a second exogenous source of variation focusing on the insurance coverage of preventive care.

Another favorable feature of this study is the choice of prostate cancer and breast cancer. The reason is that they are less heavily influenced by behavioral factors than most other chronic diseases. Age, gene mutation, and a personal or family history of breast cancer are the most important factors affecting female breast cancer risk; age, race/ethnicity, and family history of the disease are well-established risk factors of prostate cancer(ACS, 2008). The research design would not work as well for conditions like heart attach or hip fracture.

The empirical analysis employs three data sets, the Medical Expenditure Panel Survey (MEPS), the National Health Interview Survey (NHIS), and the Health and Retirement Study (HRS). They are national interviews and survey a broad range of health and healthcare related questions. The first two are cross-sectional, and have large sample sizes, while the third is longitudinal, and contains fewer observations. They all have pros and cons in terms of quality of data and use for estimation, and they complement each other's shortcomings.

I find evidence on both types of moral hazards. From the MEPS, *ex ante* moral hazard is found to decrease male uptake rate of prostate cancer screening by 6.5% and *ex post* moral hazard is found to increase it by 9.8%. With the MEPS and NHIS combined, the study shows that *ex ante* moral hazard decreases female uptake rate of breast cancer screening by 5.8%, and *ex post* moral hazard increases it by 7.1%.

In the extreme case, if the estimated moral hazard effects are solely driven by the uninsured before age 65, *ex ante* and *ex post* moral hazards affect male PSA testing by 12.5% and 18.9%, and female mammogram screening by 17.1% and 21.0% respectively. It is plausible that it is bigger for the uninsured as it is a bigger change for them and they may be more sensitive to copays.

Using the HRS, I find stronger evidence in support of two moral hazards on female uptake of breast cancer screening. *Ex ante* and *ex post* moral hazards are found to change the rate of breast cancer screening by -7.4% and 9.8% respectively. They are statistically significant, and larger than the corresponding numbers in the MEPS and NHIS data (-5.9% and 7.1%). As I discuss below, estimation on male uptake of prostate cancer screening using the HRS is problematic due to poor quality of data.

Another interesting finding is that the two countervailing effects, *ex ante* and *ex post* moral hazards, are of similar magnitudes, and cancel off each other if combined. This may help to explain why previous literature has not found evidence on *ex ante* moral hazard upon Medicare enrollment. The magnitude of the two effects varies with demographics, such as race/ethnicity, marital status, education and income/wealth. Higher education is associated with higher level of screening and larger effects of *ex ante* and *ex post* moral hazards.

Several robustness tests are done to verify the validity of the empirical approach using the MEPS and NHIS. First, I test whether people delay taking screenings around the time of policy change and around age 65. Delaying screenings would invalidate my research design and bias the estimates on *ex ante* and *ex post* moral hazards. I find no evidence that supports the delay hypothesis. Second, I conduct falsification tests to investigate whether the discontinuity found in the year of the policy change can be found in other years. Test results confirm the research design and validates the assumptions that the study rely on. Due to data limitation, the robustness tests are not carried out with the HRS.

Understanding the effect of health insurance on the uptake of preventive care has important policy implications. CDC (2003) estimates that chronic diseases account for roughly 75% of the $1 trillion spend on health care costs each year, and that more than 125 million Americans live with chronic conditions. The focus of our health care system over the past century has not been on prevention, but on treatment. If people get sick, they get care. But little is spent to keep people healthy in the first place and detect disease in early stage when it is most curable.

With the passage of the new health care law, the situation may change. Congress approved a set of wide-ranging health promotion initiatives to prevent disease and encourage healthy behavior. Health reform made covering prevention mandatory. Health insurance companies will soon have to cover all recommended screenings, preventive care and vaccines, without charging co-payment or deductibles.

H.R. 3590 - the Patient Protection and Affordable Care Act (PPACA), which was signed into law on March 23, 2010, aims to promote preventive health care and improve the public health. Prevention provisions in the PPACA are summarized in Appendix A. According to the Implementation Timeline of PPACA, all new group health plans and plans in the individual market must provide full coverage for preventive services without co-pay and deductibles in 2010. And all health plans will be forced to comply by 2018. For Medicare beneficiaries, a free, annual wellness visit and personalized prevention plan services will be provided, and cost-sharing for preventive services will be eliminated since 2011.

This study suggests that changes will increase the use of preventive care. *Ex ante* moral hazard is found to cause reduction in preventive care, and *ex post* moral hazard can help offset that negative effect. With the removal of financial barriers to preventive care, more people are expected to use regular preventive care. According to the Annual Estimate of the Resident Population by U.S. Census Bureau, 26.8 million men and 50.7 million women fall into the recommended age group for prostate cancer screening and breast cancer screening and are not eligible for Medicare yet in 2008. This study estimates that each year 710 thousand more men and 1,582 to 1,901 thousand more women would use regular prostate cancer screening and breast cancer screening respectively. Although it may not stop the medical cost from growing in the short run, people will be having better quality of life and social welfare will be improved.

1.2 Outline of Thesis

The rest of Chapter 1 first reviews current theoretical and empirical papers on the effect of health insurance on preventive care and the debate on the existence of moral hazard in health insurance. It explores the reason why current empirical evidence does not offer support for moral hazard by introducing another effect of health insurance on preventive care utilization, *ex post* moral hazard.

Then some background information is offered. This thesis studies Medicare and its preventive care coverage, focusing on two types of cancers, breast cancer and prostate cancer, and their corresponding screening tests. Facts on Medicare and its preventive care coverage are presented and recent studies on cancers and medical guidelines on preventive screenings are discussed.

At the end of Chapter 1, a theoretical model is presented to study *ex ante* and *ex post* moral hazards caused by insurance coverage on preventive care. The focus is on the Medicare expansion and its impact on the elderly uptake of preventive care. According the model, obtaining Medicare at age 65 has two potentially offsetting effects on prevention. On one hand, getting Medicare may reduce prevention because it lowers the cost of medical care in case of disease, which is *ex ante* moral hazard. On the other hand, Medicare coverage of preventive services reduces the cost of preventive care, and the financial incentive may increase prevention, which is *ex post* moral hazard.

Chapter 2 empirically studies *ex ante* and *ex post* moral hazards using the MEPS and NHIS. The following question is asked - how to identify *ex ante* and *ex post* moral hazards? An empirical framework is developed, validity of the design is verified, and estimation issues are discussed. To analyze changes in male uptake of prostate cancer screening, I use survey data from the pooled 1998-2005 MEPS. For female uptake of breast cancer screening, I supplement these data with pooled 1993-1994 NHIS which provides pre-1998 data on breast cancer screening.

The estimation indicates that both types of moral hazards exist, and that they are of similar magnitudes and cancel off each other if combined. That helps explain why previous literature did not find evidence on *ex ante* moral hazard upon

Medicare enrollment. The magnitude of the two effects varies with demographics, with larger effects among white and more educated people. Robustness tests are done and confirm the research design.

Chapter 3 use the HRS data to evaluate *ex ante* and *ex post* moral hazards. First, the pro's and con's of MEPS/NHIS and HRS are discussed. To complement the shortcomings of the MEPS and NHIS data, HRS is used to control individual effect. Empirical framework and data are described in details, as also are the estimation results. It is found that evidence on *ex ante* and *ex post* moral hazards on female uptake of breast cancer screening is stronger and that the estimated effects are larger than those from the MEPS and NHIS. They are significant in all model specifications. However, estimation on male uptake of prostate cancer screening using the HRS is problematic due to poor quality of data.

1.3 Background

1.3.1 Two Moral Hazards

Ex ante moral hazard refers to the possibility that health insurance for curative care reduces incentives for prevention (Ehrlich and Becker, 1972; Pauly, 1986). It is "*ex ante*" because it concerns the effect of insurance on the actions that an individual takes before the possible health event and the provision of medical care (Zweifel and Breyer, 1997). If the market price of health insurance is actuarially fair and reflects preventive activities, the insured has the correct incentives to spend on prevention because it lowers the price of insurance. But if the insurer can not observe some of the actions of the insured and therefore the price of insurance does not reflect individuals' cost of prevention, the purchase of market insurance decreases the demand for prevention and creates *ex ante* moral hazard. In short, *ex ante* moral hazard problem stems from an informational asymmetry.

In contrast, *ex post* moral hazard refers to the possibility that health insurance increases incentive for medical care consumption because health insurance reduces the net price of medical care. It is not caused by asymmetric information and has nothing to do with morality. It is essentially a price effect (Pauly, 1968). The problem of *ex post* moral hazard has received a great deal of attention in health economics, but few works have been done to analyze the *ex post* moral hazard problem in preventive care as it is often thought as an insignificant problem (Cutler and Zeckhauser, 2000; Kenkel, 2000). This thesis shows that *ex post* moral hazard problem is important and it helps identify the "pure" *ex ante* moral hazard.

There are theoretical reasons to believe the existence of *ex ante* moral hazard in health insurance market, but there is very limited empirical evidence on it. Researchers have mixing views on this dilemma. For example, some researchers support the *ex ante* moral hazard hypothesis. Klick and Stratmann (2007) find that mandated health insurance coverage for the treatment of diabetes does generate a moral hazard problem with diabetics exhibiting higher BMIs after the adoption of the mandates. In contrast, other researchers do not find any *ex ante* moral hazard effect. Newhouse and the Insurance Experiment Group (1993) find that less generous insurance had no significant effect on health behavior such as smoking, drinking, and exercise. Courbage and Coulon (2004) show that purchasing private health insurance in Britain does not significantly affect the probability of exercising, physical check-ups and smoking.

Using the Medicare eligibility rule of age 65, several researchers have studied *ex ante* moral hazard problem and found no positive evidence for its existence. McWilliams et al. (2003) and Decker et al. (2006) estimate that obtaining Medicare at age 65 significantly increased the uptake rates of breast cancer screening and prostate cancer screening; Dave and Kaestner (2006) find no significant increase in unhealthy behaviors (less exercise, smoking and alcohol use) among elderly persons; Card et al. (2004) find that Medicare coverage is not strongly associated with the increased use of breast or prostate cancer screenings.

One explanation for the conflict between theoretical prediction and empirical findings is that previous empirical works do not isolate *ex post* moral hazard from *ex ante* moral hazard. Since health insurance reduces the net price of both preventive services and curative cares, the use of both services will go up. In other words, while the insurance coverage of curative care may reduce prevention due to *ex ante* moral hazard, the coverage of preventive services may increase prevention due to *ex post* moral hazard. The failure to distinguish the two effects will lead to a potential cancellation of the two moral hazards. For papers listed above which use Medicare eligibility rule to study the use of cancer screenings, their data covers the period over which Medicare covers cancer screenings, and therefore their estimates do not reflect the pure *ex ante* moral hazard effect. Rather, they capture the sum of *ex ante* and *ex post* moral hazards.

1.3.2 Too Little Prevention?

With the objective of improving health, public health professionals commonly emphasize the importance of prevention and encourage greater use. According to an estimate of total spending on prevention in the U.S. by the Centers for Disease Control and Prevention (CDC, 1992), prevention is not being used at levels recommended by major professional organizations such as the U.S. Preventive Services Task Force and the American Cancer Society.

However, economists tend to approach the question of what is the optimal level of prevention and what level represents an appropriate balance between prevention and cure differently than do public health professionals. In economics, an optimal level of prevention is reached where the marginal benefits equals the marginal costs. This approach in prevention study is somewhat foreign and even controversial (Kenkel 2000).

Another way to study whether there is enough prevention is to look at social welfare and economic efficiency. One question needs to be answered is whether there are relevant market failures, like *ex ante* moral hazard caused by insurance coverage. My thesis focuses on the moral hazard problem.

Externalities are important market failures as well. Phelps (1992) introduces the concept of "herd immunity" where an individual's chances of getting an infectious disease fall when others in the society are immune because of previous vaccinations. Since societal marginal benefits of a vaccination exceed private marginal benefits, private vaccination decisions will result in a vaccination rate that is less than the socially optimal rate. This provide a ground for government involvement in prevention.

Health economics researchers also have done study on the link between lack of consumer information and demand of prevention. Because consumers lack information about the health consequences of their choices, they will fail to make optimal personal prevention choices. Kenkel (1991a) finds that people knew a great deal but not everything about the health effects of smoking and that people knew less about drinking and exercise. Viscusi (1990) and Kenkel (1991b) show that information is an important determinant of cigarette demand.

1.3.3 Medicare and Preventive Care Coverage

Medicare is a health insurance program for the elderly, which covers nearly 40 million Americans. In general, individuals are eligible for Medicare if they are 65 years or older and they or their spouses have worked for at least 10 years in Medicare-covered employment[3]. Medicare coverage begins on the first day of the month in which they turn 65. Younger people might also qualify for coverage if they have a disability or an End-Stage Renal disease.

Medicare beneficiaries are automatically enrolled in Medicare Part A (hospital insurance) free of charge, which helps pay for the health care services delivered in a hospital and skilled nursing facility, home health care, and hospice care. Medicare beneficiaries may choose whether or not to accept Part B (medical insurance), which

[3]Individuals who do not quality may still enroll in Medicare at age 65 by paying monthly premiums for both Part A and Part B.

helps pay for doctor visits, outpatient hospital care, and other medical services. The monthly premium for Part B is \$96.40 in 2008. Part B is optional and may be deferred if the beneficiary or their spouse is still actively working. There is a lifetime penalty (10% per year) imposed for not enrolling in Part B unless actively working.

Figure 2.1 shows the effects of reaching age 65 on Medicare coverage and any coverage for male and female respectively. Medicare coverage jumps from 10% at age 64 to 90% at age 65, and the jump for female sample is larger than that of the male sample. There is an increase for any coverage at age 65 as well due to Medicare coverage, and after age 65 the fraction of any coverage remains stable.

Although Medicare program started in 1965, it did not cover a number of clinical preventive services until recently. The Balanced Budget Act of 1997 (BBA) expanded coverage of preventive care. First, effective January 1, 1998, Medicare covers an annual screening mammogram for all women over age 39, and waives the Part B deductible for screening mammogram. Second, effective January 1, 2000, Medicare provides coverage for annual prostate cancer screening for men over age 50, and no Part B deductible for the PSA test. A prostate-specific antigen (PSA) blood screening is included.

This change significantly brings down the cost of screenings of breast cancer and prostate cancer for Medicare beneficiaries. For one without health insurance, the average cost of mammogram is about \$100, and may cost up to \$400. And a PSA test costs \$70 to \$400 without insurance. Under Medicare coverage, eligible women are only responsible for the Part B 20% coinsurance amount for an annual mammogram and eligible men pays no coinsurance for an annual PSA test.

Is financial incentive enough for Medicare beneficiaries to respond? Neuman et al. (2009) find that health care spending is a heavy financial burden among Medicare beneficiaries. In 2006, out-of-pocket health care spending comprised a larger share of total expenditures for Medicare households (14.1%) than non-Medicare households (4.3%). And, top quartile of Medicare households spends on average 32.9% of total expenditures on health care. Thus, the difference in the cost of screenings with and without Medicare is a financial incentive for Medicare beneficiaries to utilize those screenings.

1.3.4 Cancers and Preventive Screenings

Cancer is one of the most severe chronic diseases. In the U.S., nearly 20% of adults aged 65 and older have cancer (CDC, 2004), and it is the second most common cause of death, accounting for 1 of every 4 deaths (ACS, 2008). According to the estimate by National Institutes of Health, the overall costs of cancer in 2007 are $219.2 billion, including health expenditures, lost productivity due to illness, and lost productivity due to premature death (ACS, 2008).

Breast cancer and prostate cancer are two common types of cancer among women and men. Breast cancer is the most frequently diagnosed cancer in women, excluding skin cancer, and ranks second as a cause of cancer death in women after lung cancer. Prostate cancer is the most frequently diagnosed cancer in men, and is a leading cause of cancer death in men.

This thesis focuses on prostate cancer and breast cancer for two reasons. Firstly, they are less affected by behavioral factors than many other cancers. According to ACS, important factors affecting female breast cancer risk are age, gene mutation, a personal or family history of breast cancer, and previous chest radiation. Cigarette smoking and diet are not found to be associated with breast cancer in most studies, but excessive alcohol use is linked to an increased risk of developing breast cancer. Although recent studies find that physical exercise reduces breast cancer risk, the question how much exercise is needed remains open (ACS, 2008).

For prostate cancer, age is the strongest risk factor, and race/ethnicity and family history of the disease are important risk factors as well. The exact role of diet in prostate cancer is not clear, and being obese and physical exercise are not linked with risk of getting prostate cancer in most studies (ACS, 2008). It is not associated with cigarette smoking either (Lumey et al., 1997).

Secondly, prostate cancer and breast cancer can be detected at an early stage and early detection can greatly increase the chances of survival. The ACS recommends yearly mammogram for women beginning at age 40. Research has shown that annual mammograms lead to early detection of breast cancers, when they are most curable and breast-conservation therapies are available. Currently, 61% of breast cancers in the U.S. are diagnosed at a localized stage (malignant cancer that has not spread to lymph nodes or other locations outside the breast), for which the 5-year survival rate is 98% (ACS, 2007). Prostate-specific antigen (PSA) tests measure the level of PSA in the blood, which may be increased by prostate cancer. The ACS recommends that the PSA test should be offered annually to men at average risk beginning at age 50 [4]. More than 90% of all prostate cancers are discovered in the local and regional stages, for which the 5-year survival rate approaches 100% (ACS, 2008).

There are other screening tools for breast cancer, such as digital mammogram, Magnetic Resonance Imagine of the breast, clinical breast examination and self-examination of the breast, and for prostate cancer, such as digital rectal examination. However, so far mammogram and PSA test are the most recommended screening tools for breast cancer and prostate cancer respectively. According U.S. Preventive Service Task Force, for breast cancer screening, there is lack of evidence on the benefits of digital mammography and Magnetic Resonance Imaging of the breast as substitutes for film mammogram; there is inadequate evidence of Clinical Breast Examination's additional benefit, beyond mammography; and adequate evidence suggests that Breast Self-Examination does not reduce breast cancer mortality. For prostate cancer screening, the prostate-specific antigen (PSA) test is more sensitive than the digital rectal examination (DRE).

[4] The most recent recommendation of the American Cancer Society does not support routine testing for prostate cancer at this time. The ACS suggest that health care professionals should discuss the potential benefits and limitations of prostate cancer early detection testing with men before any testing begins. This discussion should include an offer for testing with the prostate-specific antigen (PSA) blood test and digital rectal exam (DRE) yearly, beginning at age 50, to men who are at average risk of prostate cancer and have at least a 10-year life expectancy.

1.4 A Theoretical Model

The theoretical model is based on Ehrlich and Becker (1972) model of market insurance which only covers treatment care, self-protection and self-insurance. Self-protection, also called primary prevention, means behaviors that reduce the probability of a loss. For example, staying physically active, limiting alcohol and eating right. Self-insurance, also called secondary prevention, means behaviors that reduce the size of a loss. For example, screening mammogram can detect early breast cancers in women who experience no symptoms and thus reduces the medical cost from late-stage treatment and loss from diminished quality of life.

A main improvement of this model is that health insurance may include preventive care besides curative care and thus *ex ante* moral hazard can be differentiated from *ex post* moral hazard. Mammograms and prostate-specific antigen (PSA) tests can reduce the size of loss from cancers but cannot reduce the probability of getting cancer. Therefore, those screening tests are ways to self-insure. The model below only includes self-insurance because it is the kind of prevention discussed later in the empirical part.

An individual is assumed to face only two states of the world (ill, healthy) with probabilities p and $1 - p$. He has a utility function $U()$ which depends exclusively on income. His income in healthy state is given with certainty by I and in the case of illness he faces a sick loss L which includes income loss of not being able to work, medical expenditure, and disutility of being sick. The sick loss is determined by the nature of the disease but he can reduce the size of the sick loss by spending c on self-insurance, with $L'(c) < 0$ and $L''(c) := \partial^2 L/\partial c^2 > 0$. The expenditure on self-insurance (c) is assumed to not affect the probability of being sick (p).For example, screening for cancer, cardiovascular disease, diabetes and other chronic illnesses allows early detection and treatment thus reducing the health consequences of these illnesses but they cannot change the risk of getting cancer.

Besides self-insurance, the individual can insure himself against the sick loss by purchasing health insurance with the amount of coverage for curative care s when insurance is available. The price per dollar of insurance coverage is π. Due to an informational asymmetry, the insurer cannot observe the insuree's preventive effort and thereby the price of health insurance is assumed to be independent of the amount of self-insurance. If health insurance also covers preventive services, the out-of-pocket expenditure on preventive services is reduced to $\theta(c)$, with $\theta(c) < c$ and $\theta'(c) < 1$.

Discussion will be carried out under three scenarios:

(1) there is no health insurance available and the individual can only choose the level of self-insurance to maximize the expected utility,

(2) health insurance coverage of curative care is available but coverage of preventive care is unavailable,

(3) both coverage of curative care and preventive care are available.

We will compare individual's choice of taking preventive care under the three scenarios. Let c_1, c_2 and c_3 be the optimal expenditure on preventive care (self-insurance) under three scenarios respectively. Then by definition, $c_2 - c_1$ is *ex ante* moral hazard and $c_3 - c_2$ is *ex post* moral hazard.

1.4.1 No Insurance

When health insurance is unavailable, the individual's utility in healthy state is $U(h_1) = U(I - c)$ and the utility in ill state is $U(i_1) = U(I - L(c) - c)$. Thus, the objective would be to maximize

$$\begin{aligned} EU &= (1-p)U(h_1) + pU(i_1) \\ &= (1-p)U(I - c_1) + pU(I - L(c_1) - c_1) \qquad (1.1) \end{aligned}$$

The first order conditions are[5]:

$$-L'(c_1)pU'(i_1) = (1-p)U'(h_1) + pU'(i_1) \qquad (1.2)$$

On the left-hand side of (1.2) is the expected marginal benefit of prevention and on the right-hand side is the marginal cost of prevention, given by the decreased utility associated with additional prevention in both states.

1.4.2 Insurance Covers Curative Treatment

When health insurance which covers curative treatment is available, the individual's expected utility becomes

$$\begin{aligned} EU &= (1-p)U(h_2) + pU(i_2) \\ &= (1-p)U(I - c_2 - \pi s_2) + pU(I - L(c_2) - c_2 - \pi s_2 + s_2) \qquad (1.3) \end{aligned}$$

[5]The second order conditions are satisfied.

The first order conditions are:

$$-L'(c_2)pU'(i_2) = (1-p)U'(h_2) + pU'(i_2) \tag{1.4}$$

$$pU'(i) = \pi[(1-p)U'(h) + pU'(i_2)] \tag{1.5}$$

Similar to scenario one, on the left-hand side of (1.4) is the expected marginal return of prevention and on the right-hand side is the expected cost. One the left-hand side of (1.5) is the expected return of health insurance, given by the probability of being sick timing the increased utility in ill state associated with additional health insurance coverage. On the right-hand side is the expected cost of health insurance.

1.4.3 Insurance Covers Curative Treatment and Preventive Care

When health insurance covers both curative treatment and preventive services, the individual's objective would be to maximize

$$\begin{aligned} EU &= (1-p)U(h_3) + pU(i_3) \\ &= (1-p)U(I - \theta(c_3) - \pi s_3) + pU(I - L(c_3) - \theta(c_3) - \pi s_3 + s_3) \end{aligned} \tag{1.6}$$

The first order conditions are:

$$-L'(c_3)pU'(i_3) = \theta'(c_3)[(1-p)U'(h_3) + pU'(i_3)] \tag{1.7}$$

$$pU'(i_3) = \pi[(1-p)U'(h_3) + pU'(i_3)] \tag{1.8}$$

On the left-hand side of the first order conditions are the expected marginal returns in regard to prevention and health insurance respectively and on the right-hand side are the expected costs respectively.

1.4.4 Discussion

Combining equation (1.4) and (1.5) yields

$$L'(c_2) = \frac{-1}{\pi} \tag{1.9}$$

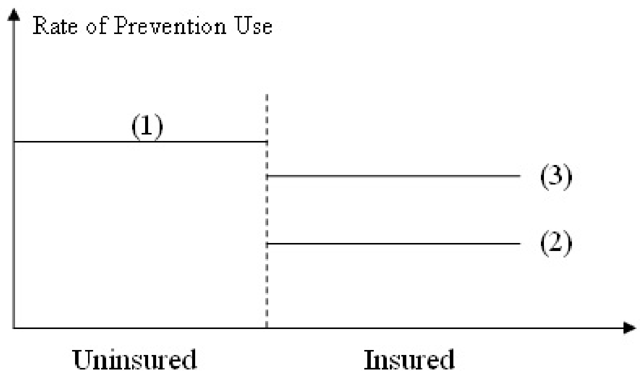
Combining equation (1.7) and (1.8) yields

$$L'(c_3) = \frac{-\theta'(c_3)}{\pi} \tag{1.10}$$

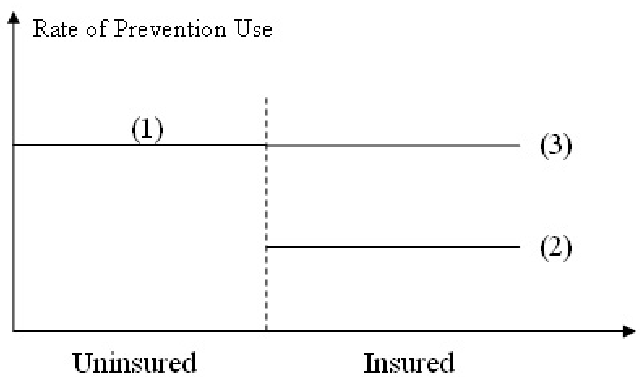
Since $\theta'(c) < 1$, the right-hand side of (1.10) is greater than the right-hand side of (1.9) and thus $L'(c_3) > L'(c_2)$. Since $L''(c) > 0$, $c_3 > c_2$. Therefore, when preventive services are covered, the demand for preventive services increases due to reduced effective price of preventive services. Thus *ex post* moral hazard exists. Ehrlich and Becker (1972) in their paper show that $c_1 > c_2$, meaning when medical cost is covered in case of disease, demand for prevention decreases. That is *ex ante* moral hazard. Thus this model shows that *ex ante* and *ex post* moral hazards exists in the health insurance market.

Ex ante moral hazard may induce decreased demand for preventive care and *ex post* moral hazard may induce increase demand for preventive care. When taking the two effects together, the total effect of health insurance on uptake of preventive care is ambiguous. Figure 1.1 illustrates this. If *ex ante* moral hazard effect is great than the *ex post* one, there is reduced use of preventive care when individual gets covered; if the *ex ante* one equals the *ex post* one, there is no change in the use of preventive care; if the *ex ante* one is less than the *ex post* one, increased use of preventive care is observed.

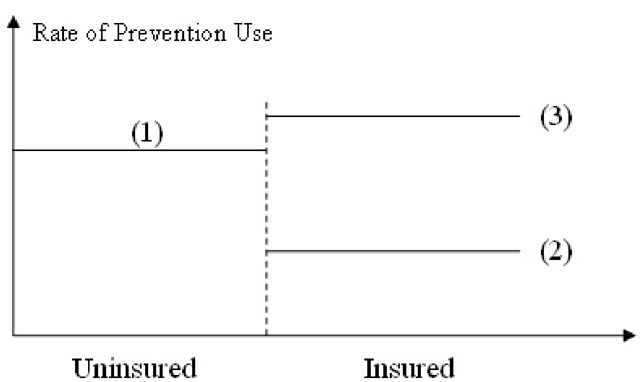
Individuals who are either age 65 and over, or who meet other special criteria are eligible for Medicare. The theoretical model above indicates that Medicare has an ambiguous impact on use of screening procedures, depending on which effect is larger, *ex ante* or *ex post* moral hazard.



Case 1: *Ex Ante* Moral Hazard Effect > *Ex Post* Moral Hazard Effect



Case 2: *Ex Ante* Moral Hazard Effect = *Ex Post* Moral Hazard Effect



Case 3: *Ex Ante* Moral Hazard Effect < *Ex Post* Moral Hazard Effect

Figure 1.1: *Ex Ante* and *Ex Post* Moral Hazards

Chapter 2

Evidence from MEPS & NHIS

2.1 Empirical Framework & Data

2.1.1 Empirical Framework

Health insurance may have an ambiguous impact on the use of cancer screenings because *ex ante* and *ex post* moral hazards coexist. This section discusses the empirical framework that identifies the two moral hazard effects.

The basic specification is:

$$Screen_{it} = HI_{it}^{cure} * \alpha + HI_{it}^{cure} * HI_{it}^{screen} * \beta + \epsilon_{it}, \tag{2.1}$$

where $Screen_{it}$ measure whether individual i uses preventive screening in year t, HI_{it}^{cure} and HI_{it}^{screen} are binary variables indicating whether health insurance covers curative treatment and preventive screening respectively. Typical Difference-in-Differences framework requires inclusion of a third term, HI_{it}^{screen}, on the right hand side of equation (2.1). But few health insurance covers only screenings but not cover treatment. Thus, HI_{it}^{screen} is dropped in the model specification.

The key coefficients in the model are α and β, which measure *ex ante* and *ex post* moral hazard effects respectively. If insurance coverage of curative treatment reduces incentives to use cancer screenings (*i.e.*, *ex ante* moral hazard exists), then α is negative. If insurance coverage of cancer screening increases incentives to use those screenings (*i.e.*, *ex post* moral hazard exists), then β is positive.

However, there are two problems associated with the estimation of equation (2.1). The first problem is the endogeneity of insurance coverage. The age 65 boundary for Medicare eligibility provides a plausibly exogenous variation in insurance status and this variation has been exploited by several papers (Card et al., 2007; Decker and Rapaport, 2002; Lichtenberg, 2002; McWillams, 2003; Decker, 2005). Figure 2.4 shows the age profiles of Medicare coverage estimated with data from MEPS. The rate of Medicare coverage (female or male) shows a great discontinuity at age 65, jumping from 10% at age64 to 90% at age 65.

Another problem is the identification of *ex post* moral hazard from *ex ante* moral hazard. Medicare expansion which included coverage of preventive services offers a credible source of exogenous variation. By this expansion, Medicare covers screening mammogram for women since 1998 and covers prostate cancer screening tests for men since 2000 [1]. The different timing of Medicare eligibility and Medicare expansion allows me to separate *ex ante* and *ex post* moral hazard.

Combining above information on Medicare eligibility and Medicare expansion with equation (2.1) and adding some control variables, the reduced form model for prevention becomes:

$$\begin{aligned} Screen_{it} &= Post65_{it} * \alpha + Post65_{it} * PostExpansion_t * \beta \\ &\quad + f(age_{it};\theta) + control_{it} * \gamma + \mu_t + \epsilon_{it}, \end{aligned} \tag{2.2}$$

where $Post65_{it}$ denotes an indicator for being age 65 or older for individual i in year

[1] Detailed discussion on validity of this variation is in Section 2.1.3

t, and $PostExpansion_t$ denotes an indicator for being after Medicare expansion in year t. That is,

$$Post65_{it} = 1 \text{ if } age \geq 65,$$

and

$$PostExpansion_t = \begin{cases} Post1998_t = 1 \text{ if } t \geq 1998 & \text{for female (mammogram)} \\ Post2000_t = 1 \text{ if } t \geq 2000 & \text{for male (PSA test).} \end{cases}$$

The function of $f(age_{it};\theta)$ represents a smooth age profile. The reason for adding a age profile function is that the decision on Medicare enrollment fits a fuzzy regression discontinuity. In general, individuals are eligible for Medicare when they are 65 years or older. Meanwhile, people who are under 65 are also eligible if they are disabled and have been receiving either Social Security or the Railroad Retirement Board disability benefits for at least 24 months, or they get continuing dialysis for permanent kidney failure or need a kidney transplant, or they have Amyotrophic Lateral Sclerosis. I follow DiNardo and Lee (2004), Cart et al. (2007), and Lee and Card (2008) assuming that the age profile function, $f(age_{it};\theta)$, is a continuous polynomial with potential discontinuities in the derivatives at age 65.

The coefficient on $Post65_{it}$ measures the effect of Medicare enrollment on preventive behaviors and it should be negative if *ex ante* moral hazard exists; the coefficient on $Post65_{it} * PostExpansion_t$ measures the effect of Medicare expansion on the use of preventive screenings and it should be positive if *ex post* moral hazard exists. Combining them yields the overall effect of Medicare on the use of preventive screenings. Section 2.1.2 and 2.1.3 discuss the key assumption on the design. Section 2.1.4 describes the data and summary statistics, and Section 2.1.5 presents the estimation issues.

2.1.2 Changes in Insurance Coverage and Employment at Age 65

Medicare provides health insurance coverage for the elderly in the U.S., and its coverage begins on the first day of the month in which they turn 65. Younger people might also qualify for coverage if they receive Social Security Disability Insurance (DI) or have an End-Stage Renal disease. Eligible individuals can obtain Medicare Part A (hospital insurance) free of charge, and Part B (medical insurance) for a modest monthly premium.

Figure 2.1 shows the effects of reaching age 65 on Medicare and other coverage for males and females respectively. Figure 2.2 to 2.3 show the male Medicare enrollment pattern by education and by race/ethnicity. The data for analysis on males in Section 2.1.2 and 2.1.3 are drawn from the 1996-2005 MEPS.

Medicare coverage for male sample jumps from 17% at age 64 to 92% at age 65 (Figure 2.1). There are two reasons why the fraction of Medicare coverage does not sharply jump from 0 to 1. First, younger people with DI or End-Stage Renal disease are qualified for Medicare and thus Medicare enrollment prior to 65 is not zero. Autor and Duggan (2003) find that high school dropouts are more likely to receive DI benefits than those who have completed high school. Consistent with their finding, Figure 2.2 shows that Medicare enrollment prior to 65 is higher for high school dropouts than for high school graduates and people with above-college schooling. A 55-64 year old high school dropout is five times more likely to enroll in

Medicare than an individual of the same age who has completed at least some years of college. Figure 2.3 depicts that pattern of Medicare enrollment by race/ethnicity. Medicare enrollment rate prior to 65 is higher for blacks and Hispanics while the post-65 rate is slightly higher for whites.

The validity of the regression discontinuity approach relies on the assumption that other factors trend smoothly at age 65. The first concern is that there could be an abrupt change in insurance coverage other than Medicare at age 65, and that change would lead to differences in the uptake of cancer screenings. Figure 2.4 depicts the fraction of Medicare coverage, the fraction of private coverage, and the fraction of other public coverage except Medicare among males, using data from the 1996-2005 MEPS. Private coverage and other public coverage (except Medicare) are hardly affected by the onset of Medicare eligibility.

The stability of private coverage and other public coverage comes from the fact that most people who have private coverage and/or other public coverage (except Medicare) before age 65 carry over the coverage, or purchase Medigap policy and hold a combination of Medicare and supplemental coverage because neither Part A nor Part B pays for all the medical costs [2].

Another concern is that changes in the fraction of people working at 65 could lead to changes in the uptake of cancer screenings. Compared with working people, retired people's opportunity costs of visiting doctors are lower and they have flexible time schedule. Changes in employment trend at 65 may invalid the regression

[2] Medicare program contains premiums, deductibles and coinsurance and the covered individual must pay out-of-pocket cost.

discontinuity approach. Figure 2.4 also displays the age profiles of employment for the MEPS male sample. As people age, the employment rate declines smoothly, and there is no abrupt change at age 65.

Female sample shows similar patterns on Medicare enrollment, other insurance coverage and employment. Curves on females in Figure 2.1, Figure 2.5 to 2.7 are drawn using data from the 1996-2005 MEPS. Medicare coverage jumps from 15% at age 64 to 95% at age 65 (Figure 2.1), and Medicare enrollment prior to 65 is higher for the less-educated and minorities (Figure 2.5 and 2.6). In comparison with males, the disparity in pre-65 Medicare enrollment among females with different education levels is smaller. Private coverage and public coverage other than Medicare remain pre-65 trends. Employment rate steadily declines over the 55-75 age range and there is no discontinuity at age 65.

Above all, age 65 provides a credible source of exogenous variation in insurance status. First, there is a sharp rise in insurance coverage at age 65, mainly due to Medicare enrollment. Many of those who were not covered prior to 65 obtain Medicare coverage at 65. The better-educated and whites experience relatively larger gains at age 65 because of relatively lower level of DI enrollment. Second, private coverage (either employer-provided plan or an individually purchase policy) and public coverage other than Medicare are hardly affected by the onset of Medicare eligibility, mostly because multiple coverages are prevalent after age 65. Third, employment trends smoothly at age 65, and thus it is unlikely to affect cancer screening utilization in an abrupt way at age 65. I also checked family structure and family income. Neither show significant discontinuities at age 65 for males and females.

2.1.3 Changes in Medicare Preventive Coverage

According to the Balanced Budget Act of 1997, Medicare covers an annual screening mammogram for all women over age 39 since January 1, 1998, and an annual prostate cancer screening for men over age 50 since January 1, 2000. Eligible women are only responsible for the Part B 20% coinsurance to get the screening mammogram, as Part B deductible is waived. Eligible men can get the PSA test free of charge, with no coinsurance and no Part B deductible.

I use the two policy changes to identify the *ex post* moral hazard effect. The key assumption is that factors other than the policy changes, which may affect individuals' incentives to use cancer screenings, trend smoothly. As discussed in Section 2.1.2, insurance coverage and employment are important factors. Figure 2.8 and 2.9 depict the trend of the insurance coverage and employment among males and females respectively. The sample is drawn from individuals aged 55-75 years in 1996-2005 MEPS. For each characteristic, I show the incidence rate at age 55-64 and at age 65-75.

Curves for insurance coverage and employment show no discontinuities in 2000 among males. Medicare coverage remains stable at 8% among 55-64 year olds, and at 98% among 65-75 years olds from 1996 to 2005. The great difference between pre-65 and post-65 rate of Medicare coverage is consistent with Medicare eligibility rule (Section 2.1.2). Pre-65 private coverage trends down slightly and there is a small increase from 1998 to 1999. Most people get private coverage through their employers, and thus private coverage is correlated with employment status. The increase in pre-65 private coverage is probably because of a jump in pre-65 employment rate in 1999 as depicted in Figure 2.8. Post-65 private coverage and employment rate do not change much over the years.

In public coverage other than Medicare, the pre-65 and post-65 rates are similar before 2001, and there is some disparity in 2002 and after, about 7 percentage point. Public coverage other than Medicare is defined by TRICARE, Medicaid, and some other public coverage asked in the MEPS. The disparity in public coverage is caused by the onset of TRICARE for Life program. TRICARE provides civilian health benefits for military personnel, military retirees, and their dependents. TRICARE for Life (TFL) originated in October of 2001 to fulfill a promise of life-long health care many of which were given when they first joined the military. Prior to 2001, TRICARE coverage expired at age 65. As of October 1, 2001, TFL provides TRICARE as supplemental health insurance for all Medicare-eligible military retirees age 65 or older who are enrolled in Medicare Part B, and thus they do not experience a break in TRICARE coverage. TFL largely explains the disparity in other public coverage since 2002.

In all, there are no major changes in insurance coverage and employment in 2000 among males. Figure 2.9 shows similar patterns on females. Although there is a 3% increase in pre-65 private coverage in 1999 and a 7% increase in other public coverage in 2002, there are no discontinuities from 1997 to 1998. Therefore, I conclude that insurance coverage and employment are unlikely to confound the analysis of the impact of Medicare expansion of preventive services.

One more concern is that campaigns for cancer awareness and technology advances in cancer screening may affect the usage of cancer screening procedures. For example, (1) the National Breast Cancer Awareness Month program started as a week-long campaign in 1985 and is dedicated to increasing the nationwide awareness about the importance of the early detection of breast cancer, and (2) in 1997, the National Cancer Advisory Board recommends that National Cancer Institute should advise all women age 40 years and older to receive screening mammograms every one to two years. Those campaigns increase people's awareness of cancer, update their information on cancer screenings, and thus change people's behaviors.

However, I found no cancer campaigns or technology advances which specially target the elderly (aged 65 or older), or Medicare beneficiaries. Thus, campaigns for cancer awareness and technology advances in cancer screening influence non-elderly and elderly at the same time. While I do not have specific data on cancer screening campaigns, their impact on the general population is absorbed in the year fixed effect.

2.1.4 Data

The National Health Interview Survey (NHIS) is the principal source of information on the health of the civilian non-institutionalized population of the United States. The survey was initiated in 1957 and has been conducted annually since then. Data are collected through a personal household interview. The NHIS questionnaire that was used from 1993 to 1994 consisted of two parts: (1) a set of basic health and demographic items (known as the Core questionnaire), and (2) one or more sets of questions on current health topics (known as the Supplement). The 1993 and 1994 NHIS Supplements cover topics on preventive services. Specifically, it asks questions on the history of mammogram use in the past 3 years.

The Medical Expenditure Panel Survey (MEPS), which began in 1996, is a nationally representative survey of the U.S. civilian non-institutionalized population. The sampling frame is drawn from a nationally representative subsample of households that participated in the prior year's NHIS. MEPS collects detailed information for each person in the household on demographic characteristics, health conditions, health status, use of medical services, access to care, health insurance coverage, employment and income. It asks history of PSA use and mammogram use in the past 5 years.

The data used for male prostate cancer screening is from the pooled 1998-2005 MEPS, and the data for female breast cancer screening is from pooled 1993-1994 NHIS and 1998-2005 MEPS. The 1993-1994 NHIS is necessary in the female data because the MEPS only contains post-expansion data on mammogram (*i.e.*, the MEPS only covers period after 1998 when Medicare covers mammogram screening) and there is no pre-expansion data. In this sense, the NHIS complements the MEPS's limitation.

The key variables - use of PSA test and mammogram - come from the following type of question:

"About how long has it been since (PERSON) has a prostate exam?"

"About how long has it been since (PERSON) has a mammogram?"

1) within past year

2) within past 2 years

3) within past 3 years

4) within past 5 years

5) more than 5 years

6) never

From above question, I can recover part of the history on cancer screening use. Consider MEPS 2004 as an example. Questions on cancer screening use were asked in the second half of year 2004 with reference period start date concentrating from August to October. Thus the date when questions on prevention were asked is presumably toward end of year 2004. Combining the inferred date of being asked questions and the type of questions and answers, I make the following assumptions (taking PSA test by respondent i in MEPS 2004 for example):

(1) If answer is "*1) within past year*", individual i is assumed to have taken the PSA test in 2004;

(2) if answer is "*2) within past 2 years*", he is assumed to have taken the PSA test in 2003 and have not taken the test in 2004;

(3) if answer is "*3) within past 3 years*", he is assumed to have taken the PSA test in 2002 and have not taken the test in 2003 and 2004;

(4) if answer is "*4) within past 5 years*", he is assumed to have taken the PSA test in 2000 and 2001 with 50% chances each year, and have not taken the test since 2002;

(5) if answer is "*5) more than 5 years*" or "*6) never*", he is assumed to have never taken the PSA test since 2000.

Based on above assumptions, I impute individual i's PSA test use from 2000 to 2004, and the data are shown as follows:

Answer	$PSA_{i,2000}$	$PSA_{i,2001}$	$PSA_{i,2002}$	$PSA_{i,2003}$	$PSA_{i,2004}$
1)	.	.	.	.	1
2)	.	.	.	1	0
3)	.	.	1	0	0
4)	0.5	0.5	0	0	0
5)	0	0	0	0	0
6)	0	0	0	0	0

$Mammogram_{it}$, which indicates female mammogram use, is constructed in a similar way. I recover the past 5 year history of PSA use and mammogram use for the MEPS respondents and the past 3 year history of mammogram use for the NHIS respondents because of different length of history being asked. Sample is restricted to respondents aged from 55 to 75. The final male sample includes 13760 respondents, and the imputed sample includes 68800 observations and 47% is uncensored. The female sample includes 22892 respondents, and the imputed sample size is 97687 (44% uncensored).

Table 2.1 gives the summary statistics on demographics, insurance status, and cancer screening use. Rates of screening tests are normalized by percentage. Age is distributed around 65, and pre-65 sample slightly overweights post-65. The NHIS provides a nationally representative sample of the U.S. civilian non-institutionalized population, with an over-sampling of Hispanics and blacks. The MEPS sample is selected from the NHIS and thus that over-sampling carries over to the MEPS sample. The MEPS also over-samples low-income people, which are considered a policy-relevant population subgroup. The table reports the simple average instead of the weight-adjusted average because of the pooling of the MEPS and the NHIS.

Gender difference is consistent with the Census Bureau's Population Estimates. More males are married than females. More females graduated from high school and more males have at least some college education. The male employment rate is higher than female by 15 percentage point. Insurance coverage rates are similar.

Table 2.2 does a raw difference-in-differences analysis. For PSA test, the raw difference-in-differences estimate of *ex post* moral hazard is 4.97. That is, male Medicare beneficiaries increased the use of PSA test after 2000 by 4.97 percentage point as compared to the rate before 2000. The difference in PSA use around age 65 is positive no matter it is before or after 2000. It seems to contradict the hypothesis of *ex ante* moral hazard. The reason is that age trend is not taken out. As will be seen in Section 2.2 when age trend is controlled, *ex ante* moral hazard shows up. The raw difference-in-differences analysis on mammogram is similar. Figure 2.10 displays a raw difference-in-differences analysis similar to Table 2.2.

2.1.5 Estimation Issues

Estimation issues arise from data imputation. First, a linear probability model, instead of a probit model, will be estimated because the screening variables, PSA_{it} and $Mammogram_{it}$, are not binary. Second, I cannot recover the full history of every respondent's cancer screening use within five years up to the survey time. Since part of the information on some people's cancer screening use is missing, OLS estimator may be biased.

Let D_{it} be an indicator for data availability, which is 1 if data is not missing and is 0 if data is missing. Then

$$
\begin{aligned}
&E[Screen_{it}|Screen_{it} \text{ is observed}] = E[Screen_{it}|D_{it} = 1] \\
=&Post65_{it} * \alpha + Post65_{it} * PostExpansion_t * \beta + f(age_{it}; \theta) + control_{it} * \gamma \\
&+ \mu_t + E[\epsilon_{it}|D_{it} = 1]. \qquad (2.3)
\end{aligned}
$$

The existence of $E[\epsilon_{it}|D_{it} = 1]$ may lead to bias in OLS estimation.

In this chapter, to estimate the impact of Medicare on cancer screening use, I apply a sample selection model, where selection is based on taking cancer screening in recent years or not. The selection problem arises from the design of the survey question on cancer screening use. It does not trace the history of PSA test or mammogram use, and it only asks the time of the most recent PSA test or mammogram use. Therefore, in the imputed data, history before most recent screening is missing and information on cancer screening use is selected. As will seen in Section 2.2.1, selection is not random with respect to the dependent variable.

One potential instrument/exclusion restriction for use in a selection equation is identified in Table 2.3. From the design of the survey question on cancer screenings, I know that the non-missing rate in the imputed data for year $t = Survey\ Year$ is 100%, and that non-missing rates for year $t < Survey\ Year$ are less than 100%. Table 2.3 proves this. Non-missing rates in use of PSA test and mammogram, for year $t = Survey\ Year$ are significantly higher than those for all other years by more than 50 percentage points (100% versus 29% to 46% for PSA test use; 100% versus 18% to 45% for mammogram use). Let $D_{survey\ year=t}$ be an indicator, which turns on if survey year equals t and turns off if survey year is later than t. The correlation between year $t = Survey\ Year$ and being non-missing suggests that $D_{survey\ year=t}$ is a strong candidate to be used as an instrument to account for this selection.

A valid instrument requires that it has little effect on cancer screening use and $D_{survey\ year=t}$ satisfies this. $D_{survey\ year=t}$ is defined to be 1 if survey year $= t$ and 0 otherwise. Taking cancer screenings or not happened before the MEPS or NHIS survey was given, and taking MEPS or NHIS survey does not change the decision to use cancer screening. Thus the timing of survey is not related with cancer screening use, and $D_{survey\ year=t}$ is a valid instrument.

The third issue is that standard errors need to be clustered on two dimensions. The reasons are as follows. First, Lee and Card (2008) point out that conventional standard errors ignore the group structure induced by specification errors in the regression discontinuity research design. In their proposed procedure, standard errors should be computed clustering on age in this study. Second, errors can be expected to be correlated from one period to the next for each individual and therefore individuals should serve as a second dimension for clustering. I use a new variance estimator suggested by Cameron et al. (2006), which provides cluster-robust inference when there is a two-way or multi-way clustering that is non-nested.

There are two typical methods to eliminate the selection bias using a Heckman sample selection model: the traditional two-step method, and full information maximum likelihood (FIML). This chapter will focus on the maximum likelihood (ML) estimator for two reasons. First, ML estimator is more efficient than the two-step estimator as the two-step estimator is a limited information maximum likelihood (LIML) estimator. In asymptotic theory and in finite samples as demonstrated by Monte Carlo simulations, FIML estimator exhibits better statistical properties (Puhani, 2000). Second, the robust variance estimator with two-way clustering provided by Cameron et al. (2006) cannot be implemented with the two-step estimation. For comparison, I report the two-step estimates along with the ML estimates. Because the covariance matrix generated by OLS estimation of the second stage is inconsistent, standard errors of two-step estimates are generated through bootstrapping.

2.2 Results and Discussion

2.2.1 *Ex Ante* & *Ex Post* Moral Hazards

Table 2.4 presents estimates of equation (2.2) by maximum likelihood with two-way clustered standard errors and by two-step with bootstrapping standard errors respectively. Estimates on PSA test are listed in columns (1) to (5) and those on mammogram are in columns (6) to (10). In panels A1 and A2 (*i.e.*, rows 1 through 4), *ex ante* and *ex post* moral hazard effects are separated while the two are not separated in panels B1 and B2 (*i.e.*, rows 5 and 6). Panels A1 and B1 report ML estimates with two-way clustered standard errors. For comparison, panels A2 and B2 show the two-step estimates with bootstrapping standard errors. Coefficients on *ex ante* and *ex post* moral hazards are normalized by percentage.

It is clear from Table 2.4 that males exhibit strong *ex post* moral hazard in taking PSA test, with about 2.65 percentage point increase by the Medicare expansion of PSA test coverage. Medicare enrollment at age 65 decreases PSA use by about 1.75 percentage points. Tests of selection reject the null, i.e., selection is not random and OLS estimator is biased. Estimates on selection equation by maximum likelihood are presented in Appendix B.

In Table 2.4, column (1) shows estimates of the simplest model (without any controls), column (2) controls demographics (including marital status, race/ethnicity, education, and income), column (3) and column (4) add in employment and insurance coverage status (including private coverage, other public coverage, and no coverage), and column (5) controls potential error from imputed employment and insurance coverage. It is plausible to assume that demographics do not change over a short period time, but the same assumption may not be carried over to employment and insurance status. An indicator D_{impute} is constructed, which turns on for imputed observations, and $\{$Employ, Ins$\} * D_{impute}$ tries to control errors arising from the imputed data.

The reasons for including insurance coverage status as control variables are as follows. Firstly, according to Kaiser Family Foundation (2005), on average, basic

Medicare benefits cover about 45 percent of the personal health care expenditures of Medicare beneficiaries. Given the financial burden from medical expenditures, people with other insurance coverage may behave differently from those without coverage. Secondly, it has been shown that the rates of private insurance coverage and public coverage other than Medicare are hardly affected by the onset of Medicare eligibility, which has also been proved by Card *et al.* (2008). Thirdly, although including private purchased insurance may pose an endogeneity problem, having employer provided plan and other public coverage has less to do with Medicare coverage. They are more related to employment status and eligibility for relevant public plans. In the Health and Retirement Study (HRS) sample in Chapter 3, less than a third of Medicare beneficiaries who are covered by private or other public plans have other health insurance which includes private purchased plans. However, the inclusion of insurance status remains arguable.

The rate of PSA test use among pre-65 males is 27%. The 2.65 percentage point gain at age 65, the estimated *ex post* moral hazard, represents 2.65/27%=9.8 percent increase in PSA testing. And the 1.75 percentage point drop at 65, the estimated *ex ante* moral hazard, represents 1.75/27%=6.5 percent decrease in testing. It is expected that the uninsured response to Medicare enrollment and Medicare policy change more than the insured group, and they may account for most of the changes at 65. Fourteen percent of the pre-65 male sample is uninsured. In the extreme case where the changes are solely driven by the uninsured, the estimates imply that *ex ante* moral hazard decreases PSA testing by 1.75/14%=12.5 percentage point and *ex post* moral hazard increases it by 2.65/24%=18.9 percentage points among this group.

Panels B1 and B2 show the combined effect at age 65. Models with only $Post65$, but not $Post65 * PostExpansion$, are estimated. Using maximum likelihood and two-step methods, I find no significant discontinuity at age 65. The two countervailing effects, *ex ante* and *ex post* moral hazards, are of similar magnitudes, and cancel off each other if combined. This finding helps explain why previous literature did not find evidence on *ex ante* moral hazard at Medicare enrollment.

Similar results are found in mammogram use. Columns (6) through (10) of Table 2.4 show that evidence on *ex post* moral hazard is strong, which is about 3.12 percentage point increase by Medicare mammogram coverage. *Ex ante* moral hazard decreases mammogram use by 2.56 percentage points, and it is significant when insurance coverage is controlled. Given the rate of pre-65 mammogram use (43.8%), *ex ante* and *ex post* moral hazards change the rate by 5.8% and 7.1% respectively. If the uninsured (15% of the sample) account for all the changes, *ex ante* and *ex post* moral hazards affect mammogram screening among the uninsured group by 17.1 percentage points and 20.8 percentage points respectively. Again, *ex ante* and *ex post* moral hazards cancel off each other if combined. Tests of selection indicate that selection error needs to be corrected as well.

2.2.2 Do People Delay Screenings?

One concern that may undermine the research design is that people may delay screenings due to anticipation. In fact, the delay may appear in two ways. First, people may delay taking screenings before the policy because they expect future policy change. Specifically, the BBA of 1997 was signed into law on August 5, 1997, and therefore Medicare beneficiaries and those who became eligible in 2000 might have known about Medicare expansion of PSA test coverage before it became effective. This expectation effect may induce a plunge of PSA test use before 2000 and a jump after 2000. If this kind of delay effect is significant, it may invalidate the estimates on *ex ante* and *ex post* moral hazards.

Panel A of Table 2.5 studies this delay effect. Rows 3 and 4 present the changes in two years before Medicare expansion and two years after for affected age groups respectively. Specifically, I look at males aged 63 or over in 1998 and 1999 ($Post63 * Yr_{98,99}$) versus those aged 65 or over in 2000 and 2001 ($Post65 * Yr_{00,01}$), and females aged 63 or over in 1996 and 1997 ($Post63 * Yr_{96,97}$) versus those aged 65 or over in 1998 and 1999($Post65 * Yr_{98,99}$).

People aged 63 or over ($Post63$) are chosen to study the change in two years before the expansion because they become eligible to enroll in Medicare when the policy is in effect and may potentially be affected by the policy change. If they delay, we should observe a negative coefficient on $Post63 * Yr_{98,99}$ for males and on $Post63 * Yr_{96,97}$ for females, and a positive coefficient on $Post65 * Yr_{00,01}$ for males and on $Post65 * Yr_{98,99}$ for females.

Columns (1) through (5) show that this delay effect is not found for male PSA test. Male post-65 group did not increase PSA test use in two years after the policy was enacted as much as the average post-2000 increase. One explanation is that Medicare beneficiaries were not aware of this new coverage when it was effective.

Mammogram use is tested for this delay effect and nothing is found as well, which is shown in columns (6) - (10).

The second delay effect can happen after policy is in effect. People may stop using screenings before age 65 and delay testing until 65. This kind of delay effect may bias *ex post* moral hazard upwards. Rows 7 and 8 of Panel B list two age groups within two-year boundary of Medicare eligibility rule. That is, people aged 63-64 ($Age_{63,64}$) versus people aged 65-66 ($Age_{65,66}$). If the delay effect exists, we should observe a negative coefficient on $Age_{63,64} * PostExpansion$, and a positive coefficient on $Age_{65,66} * PostExpansion$.

Again, this delay effect is not found for neither screenings. For males aged 63-64 years, there is no significant decrease in PSA test use, and for those aged 65-66, there is a significant decrease, contrary to the delay effect hypothesis. One reason might be that people are not well aware of the detailed Medicare coverage (similar to the case of expectation in previous paragraph). As they interact more with doctors, they know this benefit and use more tests.

2.2.3 Falsification Test

Table 2.6 conducts a falsification test using post-expansion data. Pre-expansion data is not used for the falsification test due to small sample size. This test uses $Post2004$ instead of $Post2000$ to construct a proxy for the false *ex post* moral hazard (shown in row 2). If the false *ex post* moral hazard shows up, previous estimates and the model would be invalid. The sample contains MEPS 2002-2005, *i.e.*, post

Medicare expansion years, to guarantee the results are not affected changes around 2000 for male and around 1998 for female.

Row 2 shows that $Post65*Post2004$ is not significant, and this further confirms significant results on *ex post* moral hazard. Row 1 is not significant because it actually captures the sum of two countervailing moral hazards, which is about zero as shown in Panel B1 and B2 of Table 2.4. The results do not change when the false test is run at 2003 as shown in row 4 of Panel B.

2.2.4 Different Effects by Demographic Groups

Table 2.7 and Table 2.8 show the detailed estimates on control covariates. Table 2.7 is on PSA test, showing details of columns (3) - (5) of Table 2.4 Panel A1, and Table 2.8 is on mammogram, showing details of columns (8) - (10) of Table 2.4 Panel A1. The average PSA and mammogram use varies by marital status and race/ethnicity. Individuals with at least some college education use more tests than high school dropouts, and high income individuals seem to use more than the low income ones. Employment is related to value of time since the working people value time more than the retired. The negative sign on employment indicates that working people use less PSA test or mammogram. Private coverage may provide coverage for PSA test or mammogram, or function as a Medigap plan, and thus people with private coverage take more tests. Row (17) captures those without any coverage before age 65, and it shows that they take much less tests.

While different demographic groups vary in the rate of PSA test and mammogram use, they respond differently to Medicare enrollment and coverage expansion of PSA test and mammogram. Table 2.9 estimates equation (2.2) on different demographic groups. Regressions are run on different samples by demographics. The white respond more to the Medicare enrollment and expansion of preventive cares than the sample average. *Ex ante* moral hazard effects on PSA test and mammogram use are respectively about 65% and 43% larger than the sample average, and the *ex post* moral hazard effects are respectively 24% and 13% larger than the sample average.

Greater *ex ante* and *ex post* moral hazards among the white may be explained by financial burden of health care spending borne by them. Neuman, Cubanski and Damico (2009) find that among Medicare beneficiaries the white spent a greater share of income on health care than other race/ethnicity groups. They show that medium out-of-pocket health care spending as percent of income among the white in 1997 is 12.5%, higher than the black (9.6%), Hispanic (9.9%), and other non-Hispanic (6.5%), and in 2005 the financial burden of health care grows and the medium among the white still leads other groups by 3 - 4 percentage point.

There are big differences among education groups as well. Higher education is related to larger *ex ante* and *ex post* moral hazards.This finding seems puzzling. The better-educated are typically less liquidity-constrained and should be less sensitive to price change. There are a few studies on education and health.

On the theoretical side, Grossman (1972) modeled schooling and prevention. He hypothesizes that schooling increases the efficiency of the household production of health. In his model prevention choices are viewed as inputs into the household production of health. He finds ambiguous predictions about the relationship between schooling and prevention. Schooling reduces the shadow price of health capital which increases the demand for health capital, but the derived demand for health inputs such as prevention only increases if the price elasticity of the demand for health capital exceeds one. Thus, the relationship between education and use of prevention is not definitive.

On the empirical side, Kenkel (1990, 1991) finds empirical evidence on the relationship between education and information. He also shows that information increases the probability that a consumer uses medical care. Leigh (1990) finds that people with more schooling are more likely to use seatbelts. These findings may help to explain the big difference in screening use by education level.

There are other views on the relationship between schooling and health behaviors. Fuchs (1982) and Farrell and Fuchs (1982) suggest that the estimated relationships between schooling and the health behaviors might be due to unobservable differences across individuals. They suggest the individual rate of time preference as a candidate for the "hidden third variable" behind the link between schooling and health, if people with low rates of time preference are more likely to invest in both schooling and prevention.

Results by income level suggest that income decreases *ex ante* moral hazard. Among males, low income (defined by income lower than 25 quantile) decreases PSA test use at age 65 by 4.81 percentage point (significant at 10% level), and high income (defined by income higher than 75 quantile) by 2.55 percentage point. Among females, low income decreases mammogram use at 65 by 3.19 percentage point, and medium high income by 1.77 percentage point. One exception is the high income females. *Ex ante* moral hazard effect among high income females is surprisingly high, 3.19 percentage point, and significant at 5% level.

The relationship between *ex post* moral hazard and income is unclear. Medicare reduces cost of taking PSA test from up to \$400 (without insurance) to free of charge, and reduces cost of taking mammogram from average \$100 (up to \$400 without insurance) to the Part B 20% coinsurance amount. The financial incentive among the low income people should be higher than the high income people, and larger *ex post* moral hazard effect is expected among low income people. However, estimated *ex post* moral hazard shows no big variation by income level. The role of income in taking screenings will be discussed in Chapter 3.

2.2.5 The Uninsured

People who are uninsured before age 65 is expected to respond more to Medicare enrollment and Medicare expansion of preventive coverage than those who are insured, and they may account for most of the changes at 65. According the back-of-envelop calculation earlier in this section, in the extreme case where the changes are solely driven by the uninsured, *ex ante* moral hazard may decrease PSA testing by up to 12.5 percentage point and *ex post* moral hazard may increase it by up to 18.9 percentage points among this group; and *ex ante* and *ex post* moral hazards may affect mammogram screening by 17.1 percentage points and 20.8 percentage points respectively.

Since the MEPS and NHIS are cross-sectional, one cannot follow the pre-65 uninsured and observe their behavioral change upon Medicare enrollment. In order to assess the *ex ante* and *ex post* moral hazards among the uninsured, the pre-65 sample who is uninsured and post-65 sample who has only Medicare are pool to estimate equation (2.2).

Table 2.10 compares the results. The first row is estimated using the entire sample and the second row is on the pre-65 uninsured and post-65 Medicare only. The estimated *ex ante* and *ex post* moral hazards among females in uptake of mammogram are about twice the size of the entire sample. This is consistent with the expectation that the uninsured is more responsive to Medicare enrollment and Medicare expansion of preventive service than the insured. The size is much smaller than the back-of-envelop calculation.

The result on male uptake of PSA test is not significant. There are two possible causes. First, the size of the pooled male sample is small, which has less than 3,000 individuals. Second, due to data imputation, the information on insurance is imprecise and the pooled sample may not be well defined.

2.3 Conclusion

Moral hazard theory predicts that health insurance may reduce preventive care due to *ex ante* moral hazard. Meanwhile, *ex post* moral hazard may encourage use of preventive care if it is covered by health insurance. This chapter empirically examines the issue of *ex ante* and *ex post* moral hazards among the elderly. Using discrete changes generated by Medicare eligibility rule and Medicare expansion of preventive care, this chapter identifies *ex ante* and *ex post* moral hazard effects of Medicare on cancer prevention.

I focus on the utilization of two cancer screenings, female uptake of breast cancer screening and male uptake of prostate cancer screening. For both of them, I find evidence in support of *ex ante* and *ex post* moral hazards. No evidence shows that people try to delay taking screenings until it has been covered by Medicare or they reach age 65. Falsification tests further support the research design. Moreover, the level of prevention and responsiveness to insurance changes varies with demographics, with larger effects among the whites and more educated people.

Understanding the effect of health insurance on uptake of preventive care has important policy implications. Chronic diseases bring patients inconvenience and discomfort, and cause huge medical cost. Even more costs are incurred from the disability and the diminished quality of life resulting from chronic diseases, especially among the elderly. According to estimates by CDC (2003), chronic diseases account for roughly 75% of the $1 trillion spend on health care costs each year, and more than 125 million Americans live with chronic conditions.

However, the focus of our health care system over the past century has not been on prevention of chronic diseases, but on treatment. Take cancer research for example. The huge majority of funding has gone into the search for a cure rather than to prevent normal cells from becoming malignant in the first place.

A public policy that encourages individuals to utilize more preventive care could improve the welfare of individuals and the society. Cutler (2008) studies the reduction in cancer mortality between 1990 and 2004 and highlights three factors that lead to improved survival. He finds that cancer screening is the most important one and that it has had the largest impact on survival, at relatively moderate cost.

This chapter studies breast cancer and prostate cancer which are leading cause of death from cancer, and finds that Medicare coverage of cancer screenings increases female uptake of breast cancer screening and male uptake of prostate cancer screening among the elderly. It suggests that policies that reduce the cost of preventive care can boost its use and countervail the negative effect of health insurance caused by *ex ante* moral hazard. And such policies are expected to increase survival rate, and prevent huge medical cost at late stage.

With the enactment of PPACA, all new group health plans and plans in the individual market must provide full coverage for preventive services without co-pay and deductibles in 2010. According to the Census 2009 estimate, 26.8 million men and 50.7 million women fall into the recommended age group for prostate cancer screening and breast cancer screening and are not eligible for Medicare yet in 2008. The estimates from the MEPS and NHIS predict that each year 710 thousand more men and 1,582 thousand more women would use regular prostate cancer screening and breast cancer screening respectively.

Table 2.1: **Summary Statistics**

	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Original Sample:				
Age	63.47	6.02	64.10	6.10
Demographics				
White non-Hispanic	0.70	0.46	0.70	0.46
Black non-Hispanic	0.11	0.32	0.14	0.34
Hispanic	0.14	0.34	0.13	0.33
Married	0.76	0.42	0.53	0.50
High School Dropout	0.25	0.43	0.24	0.43
High School Graduate	0.45	0.50	0.52	0.50
At Least Some College	0.31	0.46	0.24	0.43
Above Poverty Line	0.89	0.31	0.86	0.35
Employment, Insurance				
Employed	0.51	0.50	0.36	0.48
Private Coverage	0.69	0.46	0.67	0.47
Other Public Coverage	0.15	0.36	0.17	0.38
# individuals	13760		22892	
Imputed Sample:				
	PSA Test		Mammogram	
Screening Test(%)	31.54	45.80	42.72	48.72
# observations	68800		97687	
Data Source	1998-2005 MEPS		1993-1994 NHIS & 1998-2005 MEPS	

Table 2.2: **Raw Difference-in-Differences Analysis**

PSA Test (%)

	Before age 65 (Medicare ineligible)	After age 65 (Medicare eligible)	Difference
Before 2000 (PSA not covered)	13.51	25.97	12.46
After 2000 (PSA covered)	31.95	49.38	17.43
DD			4.97

Mammogram (%)

	Before age 65 (Medicare ineligible)	After age 65 (Medicare eligible)	Difference
Before 1998 (Mammogram not covered)	33.31	35.48	2.17
After 1998 (Mammogram covered)	44.75	47.64	2.89
DD			0.72

Table 2.3: **Sample Sizes and Percent Non-missing**

	PSA Test		Mammogram	
Year t	N	% Non-missing	N	% Non-missing
$t = Survey\ Year$	13760	100	21587	100
$t = Survey\ Year - 1$	13760	45.5	22892	44.6
$t = Survey\ Year - 2$	13760	32.7	18606	25.4
$t = Survey\ Year - 3$	13760	28.5	17301	18.1
$t = Survey\ Year - 4$	13760	28.5	17301	18.1
Total	68800	47.1	97687	43.8

Table 2.4: **Estimated *Ex Ante* and *Ex Post* Moral Hazards**

	PSA Test					Mammogram				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Separate *Ex Ante* and *Ex Post* Moral Hazards										
A1: Maximum Likelihood (two-way clustering)										
1. *Post65*	-0.76	-1.08	-1.55	-1.79	-1.75	-0.69	-0.94	-0.92	-2.63*	-2.56*
Ex Ante	(1.29)	(1.26)	(1.25)	(1.27)	(1.24)	(1.53)	(1.42)	(1.40)	(1.45)	(1.46)
2. $Post65 * PostExpansion$	3.22**	2.72**	2.71**	2.65**	2.65**	2.29*	2.55**	2.56**	3.18***	3.12***
Ex Post	(1.47)	(1.35)	(1.32)	(1.33)	(1.33)	(1.32)	(1.21)	(1.22)	(1.20)	(1.18)
A2: Two Step (bootstrap)										
3. *Post65*	-0.13	-0.56	-0.97	-1.25	-0.93	-0.40	-0.74	-0.73	-2.48**	-2.46**
Ex Ante	(1.33)	(1.34)	(1.55)	(1.39)	(1.49)	(1.07)	(1.48)	(1.18)	(1.15)	(1.11)
4. $Post65 * PostExpansion$	2.87***	2.46**	2.39*	2.31**	1.76	2.35**	2.61**	2.63**	3.27***	3.15***
Ex Post	(1.06)	(1.07)	(1.35)	(1.10)	(1.41)	(0.93)	(1.11)	(1.22)	(1.03)	(1.06)
Do Not Separate *Ex Ante* and *Ex Post* Moral Hazards										
B1: Maximum Likelihood (two-way clustering)										
5. *Post65* only	1.47	0.81	0.34	0.06	0.09	0.92	0.90	0.93	-0.36	-0.34
Ex Ante + *Ex Post*	(1.11)	(1.08)	(1.06)	(1.04)	(1.04)	(0.98)	(0.90)	(0.88)	(1.00)	(1.04)
B2: Two Step (bootstrap)										
6. *Post65* only	1.92	1.20	0.74	0.41	0.33	1.26	1.15	1.18	-0.14	-0.22
Ex Ante + *Ex Post*	(1.18)	(1.02)	(1.14)	(1.02)	(1.13)	(0.87)	(0.76)	(0.90)	(0.88)	(0.92)
Controls:										
Demographics		X	X	X	X		X	X	X	X
Employment			X	X	X			X	X	X
Insurance				X	X				X	X
{Employ, Ins}*D_{impute}					X					X

Note: 1. Standard errors (in parentheses) in panel A1 and B1 are clustered by age and individual. Standard errors in panel A2 and B2 are estimated by bootstrap. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2. Demographics include marital status, race/ethnicity (white non-Hispanic, black non-Hispanic, and Hispanic), education (high school dropout and at least some college), and income. Insurance status includes private coverage, public coverage (other than Medicare), and no coverage. D_{impute} *is an indicator which turns on if the observation is imputed.*

Table 2.5: **Delay Taking Screenings?**

	PSA Test					Mammogram				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A: Delay before policy is in effect										
1. $Post65$	-0.31	-0.76	-1.06	-1.17	-1.16	-0.76	-1.15	-1.13	-2.73*	-2.75*
Ex Ante	(1.38)	(1.43)	(1.44)	(1.49)	(1.46)	(1.55)	(1.48)	(1.46)	(1.52)	(1.55)
2. $Post65 * PostExpansion$	3.72*	3.31*	3.05	2.76	2.81	2.50*	2.88**	2.90**	3.45***	3.43***
Ex Post	(1.98)	(1.93)	(1.91)	(1.90)	(1.88)	(1.35)	(1.29)	(1.30)	(1.25)	(1.24)
3. M:$Post63 * Yr_{98,99}$	-0.91	-0.65	-0.99	-1.29	-1.25	0.81	1.56	1.58	1.01	1.54
F: $Post63 * Yr_{96,97}$	(1.37)	(1.51)	(1.52)	(1.57)	(1.55)	(1.90)	(1.87)	(1.87)	(1.96)	(1.99)
4. M:$Post65 * Yr_{00,01}$	-2.44*	-2.31*	-2.19*	-2.05*	-2.07*	-0.60	-0.47	-0.47	-0.67	-0.40
F: $Post65 * Yr_{98,99}$	(1.34)	(1.22)	(1.20)	(1.16)	(1.16)	(1.48)	(1.43)	(1.42)	(1.54)	(1.52)
B: Delay after policy is in effect										
5. $Post65$	1.01	0.69	0.02	-0.30	-0.22	-0.53	-0.68	-0.67	-2.59	-2.51
Ex Ante	(1.50)	(1.43)	(1.45)	(1.51)	(1.46)	(1.69)	(1.58)	(1.56)	(1.59)	(1.59)
6. $Post65 * PostExpansion$	4.52***	3.90***	3.79***	3.72***	3.75***	2.39*	2.71**	2.72**	3.24**	3.19**
Ex Post	(1.32)	(1.21)	(1.21)	(1.22)	(1.20)	(1.44)	(1.33)	(1.34)	(1.34)	(1.34)
7. M:$Age_{63,64} * Post_{2000}$	1.48	2.08*	1.61	1.24	1.32	-0.35	-0.29	-0.27	-1.04	-1.13
F: $Age_{63,64} * Post_{1998}$	(1.34)	(1.23)	(1.26)	(1.20)	(1.16)	(0.71)	(0.64)	(0.62)	(0.82)	(0.84)
8. M:$Age_{65,66} * Post_{2000}$	-3.83***	-3.24***	-3.08***	-3.18***	-3.23***	-0.70	-0.93	-0.89	-1.00	-1.12
F: $Age_{65,66} * Post_{1998}$	(1.13)	(1.03)	(1.06)	(1.05)	(1.02)	(0.82)	(0.79)	(0.78)	(0.82)	(0.83)
Controls:										
Demographics		X	X	X	X		X	X	X	X
Employment			X	X	X			X	X	X
Insurance				X	X				X	X
{Employ, Ins}*D_{impute}					X					X

Note: 1. Coefficients are estimated by maximum likelihood. Standard errors (in parentheses) are clustered by age and individual. $^{***}\,p < 0.01$, $^{**}\,p < 0.05$, $^{*}\,p < 0.1$.

2. Demographics include marital status, race/ethnicity (white non-Hispanic, black non-Hispanic, and Hispanic), education (high school dropout and at least some college), and income. Insurance status includes private coverage, public coverage (other than Medicare), and no coverage. D_{impute} *is an indicator which turns on if the observation is imputed.*

3. $Post63 = 1$ *if* $age \geq 63$. $Post65 = 1$ *if* $age \geq 65$.

4. Subscript of $Yr_{96,97}$, $Yr_{98,99}$, *and* $Yr_{00,01}$ *stands for the condition when this indicator for year turns on.*

5. $Age_{63,64} = 1$ *if* $age = 63, 64$. $Age_{65,66} = 1$ *if* $age = 65, 66$.

Table 2.6: **Falsification Test**

	PSA Test					Mammogram				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A: Discontinuity at 2004										
1. $Post65$	1.78	0.92	0.43	0.18	0.12	0.99	0.89	0.96	-0.47	-0.36
false *Ex Ante*	(1.72)	(1.63)	(1.61)	(1.58)	(1.58)	(1.12)	(1.10)	(1.10)	(1.14)	(1.13)
2. $Post65 * Post2004$	0.36	0.17	0.07	0.05	0.33	1.12	0.72	0.79	1.31	1.17
false *Ex Post*	(1.74)	(1.39)	(1.36)	(1.37)	(1.41)	(1.65)	(1.54)	(1.56)	(1.58)	(1.62)
B: Discontinuity at 2003										
3. $Post65$	2.11	1.24	0.73	0.43	0.37	1.13	1.20	1.26	-0.26	-0.13
false *Ex Ante*	(1.87)	(1.70)	(1.67)	(1.67)	(1.67)	(1.26)	(1.29)	(1.30)	(1.39)	(1.38)
4. $Post65 * Post2003$	-0.39	-0.47	-0.51	-0.42	-0.26	0.40	-0.13	-0.07	0.40	0.26
false *Ex Post*	(1.63)	(1.26)	(1.23)	(1.29)	(1.32)	(1.47)	(1.42)	(1.44)	(1.58)	(1.58)
Controls:										
Demographics		X	X	X	X		X	X	X	X
Employment			X	X	X			X	X	X
Insurance				X	X				X	X
{Employ, Ins}*D_{impute}					X					X

Note: 1. Coefficients are estimated by maximum likelihood. Standard errors (in parentheses) are clustered by age and individual. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
2. Demographics include marital status, race/ethnicity (white non-Hispanic, black non-Hispanic, and Hispanic), education (high school dropout and at least some college), and income. Insurance status includes private coverage, public coverage (other than Medicare), and no coverage. D_{impute} *is an indicator which turns on if the observation is imputed.*
3. Sample is from MEPS 2002-2005.

Table 2.7: **Detailed Screening Equation: Male**

	PSA Test		
	(1)	(2)	(3)
1. $Post65$	-1.55	-1.79	-1.75
	(1.25)	(1.27)	(1.24)
2. $Post65 * PostExpansion$	2.71**	2.65**	2.65**
	(1.32)	(1.33)	(1.33)
3. $(Age - 65)$	1.04***	0.98***	0.96***
	(0.10)	(0.10)	(0.10)
4. $(Age - 65)^2$	-0.03***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)
<u>Control Variables:</u>			
5. Married	9.02***	7.57***	7.43***
	(0.86)	(0.89)	(0.88)
6. White non-Hispanic	13.94***	12.78***	12.49***
	(1.67)	(1.54)	(1.51)
7. Black non-Hispanic	18.20***	17.57***	17.20***
	(1.93)	(1.85)	(1.81)
8. Hispanic	10.77***	11.71***	11.41***
	(1.75)	(1.68)	(1.65)
9. At Least Some College	8.83***	8.37***	8.22***
	(1.17)	(1.17)	(1.16)
10. High School Dropout	-13.37***	-11.62***	-11.43***
	(1.02)	(1.04)	(1.03)
11. Poor	-6.64***	-4.46***	-4.39***
	(1.12)	(1.13)	(1.11)
12. High Income	8.08***	6.04***	5.91***
	(0.97)	(0.96)	(0.93)
13. Employment	-6.03***	-6.41***	-5.57***
	(0.93)	(0.85)	(0.73)
14. Private Coverage		6.91***	7.72***
		(1.16)	(1.12)
15. Other Public Coverage		-0.70	1.62
		(1.22)	(1.30)
16. No Coverage		-10.28***	-12.11***
		(1.31)	(1.82)
17. {Employ,Ins}$*D_{impute}$			X
Observations	68410	68410	68410

Note: Coefficients are estimated by maximum likelihood. Standard errors (in parentheses) are clustered by age and individual. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.8: **Detailed Screening Equation: Female**

	Mammogram		
	(1)	(2)	(3)
1. $Post65$	-0.92	-2.63*	-2.56*
	(1.40)	(1.45)	(1.46)
2. $Post65 * PostExpansion$	2.56**	3.18***	3.12***
	(1.22)	(1.20)	(1.18)
3. $(Age - 65)$	-0.06	-0.16*	-0.17*
	(0.09)	(0.09)	(0.09)
4. $(Age - 65)^2$	-0.03***	-0.03***	-0.03***
	(0.01)	(0.01)	(0.01)
<u>Control Variables:</u>			
5. Married	6.44***	4.81***	4.77***
	(0.78)	(0.74)	(0.73)
6. White non-Hispanic	8.24***	6.00***	5.89***
	(1.95)	(1.91)	(1.90)
7. Black non-Hispanic	15.50***	14.55***	14.36***
	(2.18)	(2.10)	(2.09)
8. Hispanic	8.78***	10.79***	10.64***
	(2.06)	(2.15)	(2.14)
9. At Least Some College	8.26***	6.88***	6.80***
	(0.89)	(0.83)	(0.82)
10. High School Dropout	-12.17***	-9.66***	-9.52***
	(0.73)	(0.79)	(0.77)
11. Above Poverty Line	6.78***	3.54***	3.48***
	(0.91)	(0.89)	(0.88)
12. Employment	0.36	-0.78	-2.30*
	(0.94)	(0.97)	(1.17)
13. Private Coverage		9.45***	10.99***
		(1.18)	(1.24)
14. Other Public Coverage		0.77	2.03**
		(0.96)	(0.97)
15. No Coverage		-16.53***	-16.70***
		(1.48)	(1.56)
16. {Employ,Ins}$*D_{impute}$			X
Observations	96044	95984	95984

Note: Coefficients are estimated by maximum likelihood. Standard errors (in parentheses) are clustered by age and individual. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.9: ***Ex Ante*** **and** ***Ex Post*** **Moral Hazards by Demographics**

	PSA Test		Mammogram	
	$Post65$ *ex ante* (1)	$Post65 * Post2000$ *ex post* (2)	$Post65$ *ex ante* (3)	$Post65 * Post1998$ *ex post* (4)
Overall Sample	-1.75	2.65**	-2.56*	3.12***
	(1.24)	(1.33)	(1.46)	(1.18)
Classified by Race/Ethnicity				
White non-Hispanic	-2.89	3.29*	-3.67**	3.54***
	(1.84)	(1.80)	(1.70)	(1.37)
Black non-Hispanic	2.52	-0.83	0.51	-0.60
	(3.87)	(3.72)	(3.54)	(3.00)
Hispanic	1.55	2.43	-1.29	3.66
	(2.74)	(2.69)	(3.71)	(3.82)
Classified by Education				
At Least Some College	-4.71*	5.25**	-2.66	2.79
	(2.79)	(2.50)	(3.35)	(2.71)
High School Graduate	-0.76	2.91	-3.50**	4.55***
	(2.25)	(2.20)	(1.62)	(1.53)
High School Dropout	-0.41	0.65	-1.41	1.54
	(2.16)	(2.06)	(2.42)	(2.02)
Classified by Income				
0 to 0.25 quantile	-4.81*	1.31	-3.19	2.42
(low income)	(2.49)	(2.45)	(3.30)	(3.07)
0.25 to 0.5 quantile	-3.47	7.10**	-2.16	-0.93
(medium low income)	(2.67)	(2.79)	(2.17)	(2.06)
0.5 to 0.75 quantile	4.30^+	0.89^+	-1.77	2.41
(medium high income)	(2.86)	(2.69)	(2.99)	(2.87)
0.75 to 1 quantile	-2.55	1.83	-3.19**	3.64***
(high income)	(4.09)	(3.43)	(1.46)	(1.22)

Note: 1. Each row represents a separate regression.
2. Coefficients are estimated by maximum likelihood. Standard errors (in parentheses) are clustered by age and individual. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
3. Control variables include demographics, employment and insurance status.
4. $^+$ *Those two coefficients are estimated by two step method with bootstrap standard errors because of computational difficulty in ML estimation.*

Table 2.10: ***Ex Ante* and *Ex Post* Moral Hazards among the Uninsured and Medicare only**

	PSA Test		Mammogram	
	$Post65$ *ex ante* (1)	$Post65 * Post2000$ *ex post* (2)	$Post65$ *ex ante* (3)	$Post65 * Post1998$ *ex post* (4)
Overall Sample	-1.75	2.65**	-2.56*	3.12***
	(1.24)	(1.33)	(1.46)	(1.18)
Uninsured & Medicare only	-1.92	1.92	-5.88**	5.15**
	(2.78)	(2.60)	(2.63)	(2.36)

Note: 1. The sample used to estimate the second row is composed of the pre-65 sample who does not have private or public plans and the post-65 sample who does not have private coverage and does not have public coverage except Medicare.
Note: 2. Each row represents a separate regression.
3. Coefficients are estimated by maximum likelihood. Standard errors (in parentheses) are clustered by age and individual. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
4. Control variables include demographics, and employment.

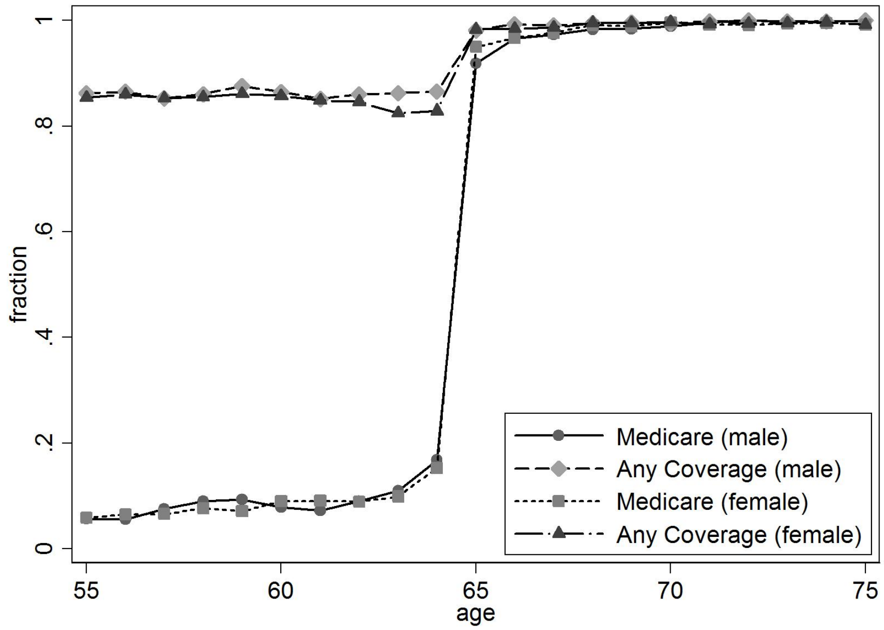


Figure 2.1: Age Profile of Coverage by Medicare and by Any Insurance
Data Source: 1996-2005 MEPS.

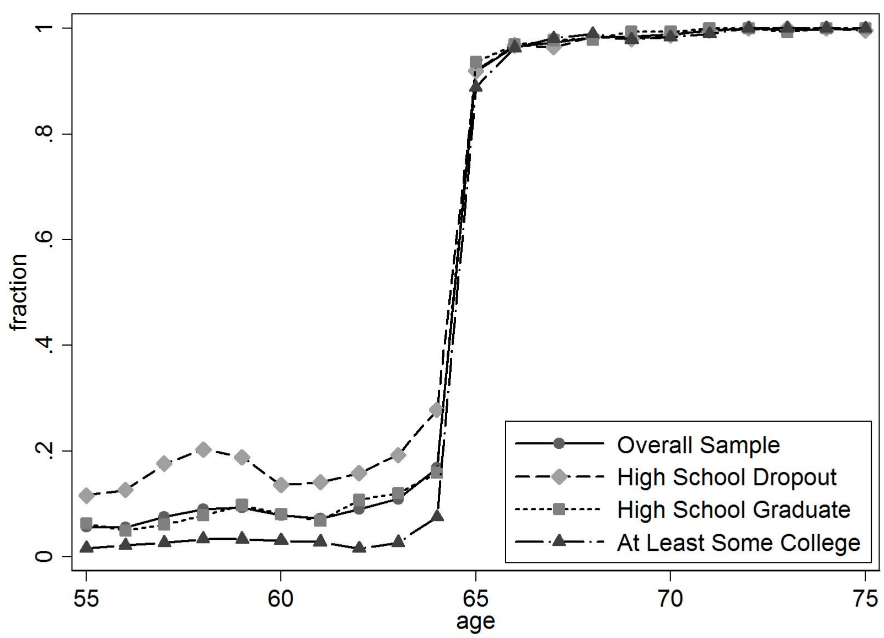


Figure 2.2: Age Profile of Medicare Coverage by Education: Male
Data Source: 1996-2005 MEPS.

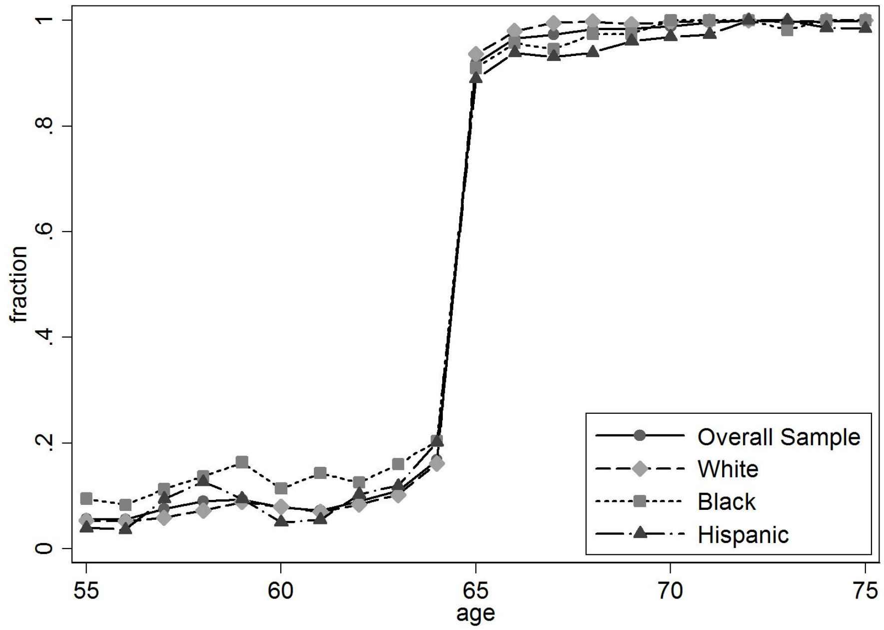


Figure 2.3: Age Profile of Medicare Coverage by Race/Ethnicity: Male
Data Source: 1996-2005 MEPS.

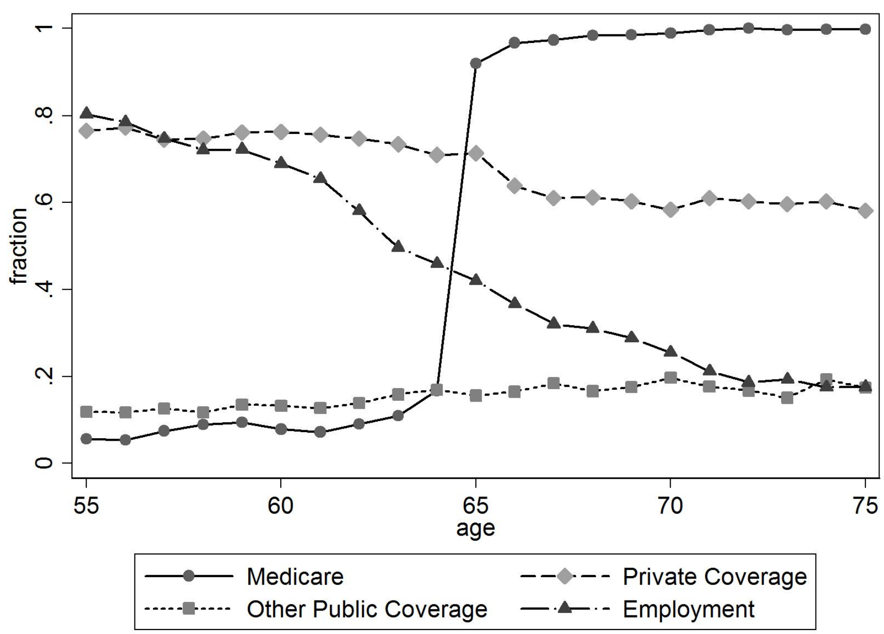


Figure 2.4: Age Profile of Employment Status and Insurance Coverage: Male
Data Source: 1996-2005 MEPS.

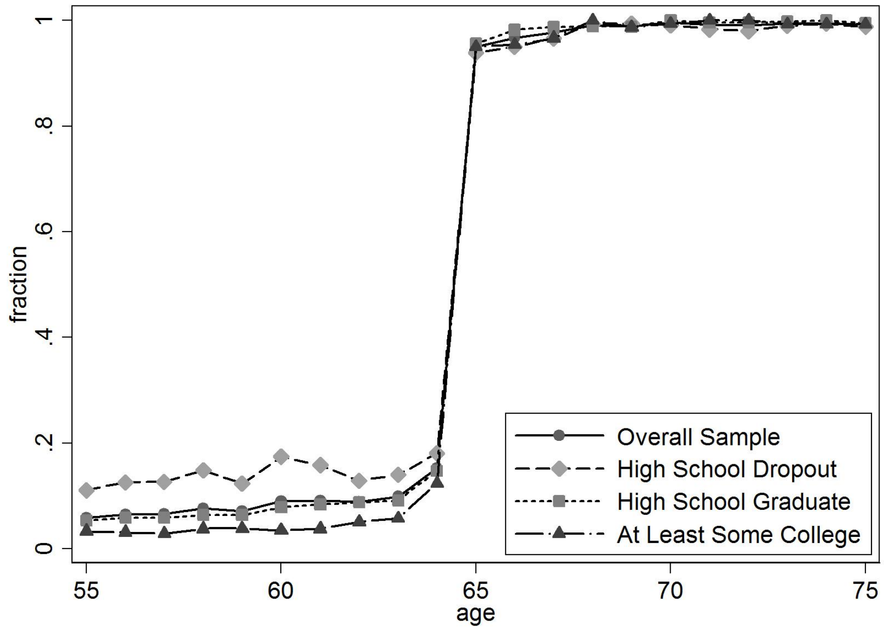


Figure 2.5: Age Profile of Medicare Coverage by Education: Female
Data Source: 1996-2005 MEPS.

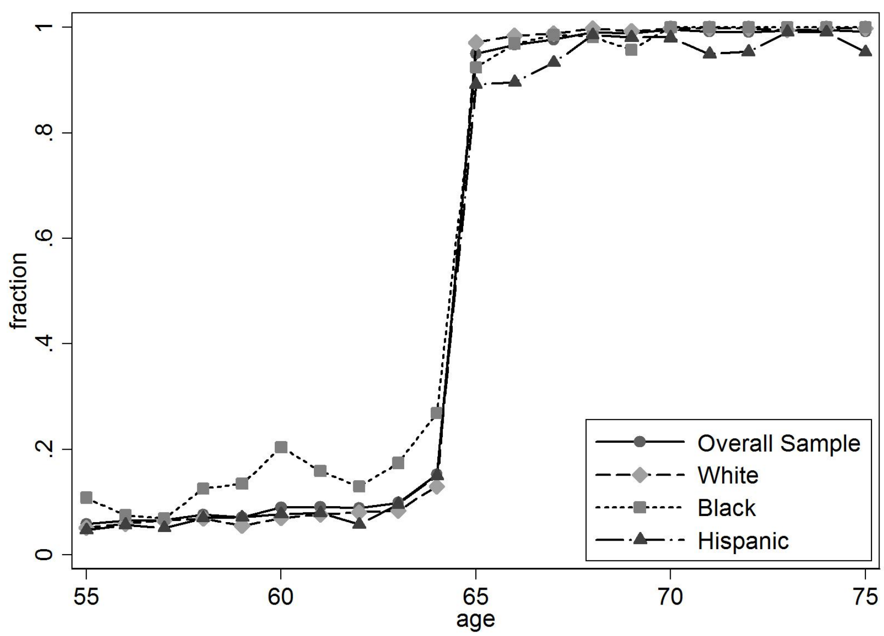


Figure 2.6: Age Profile of Medicare Coverage by Race/Ethnicity: Female
Data Source: 1996-2005 MEPS.

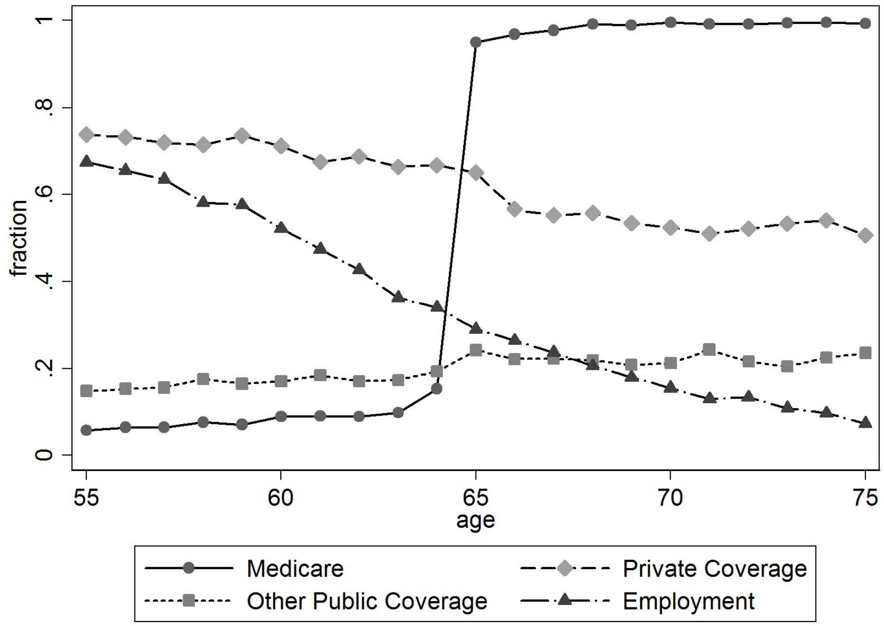


Figure 2.7: Age Profile of Employment Status and Insurance Coverage: Female

Data Source: 1996-2005 MEPS.

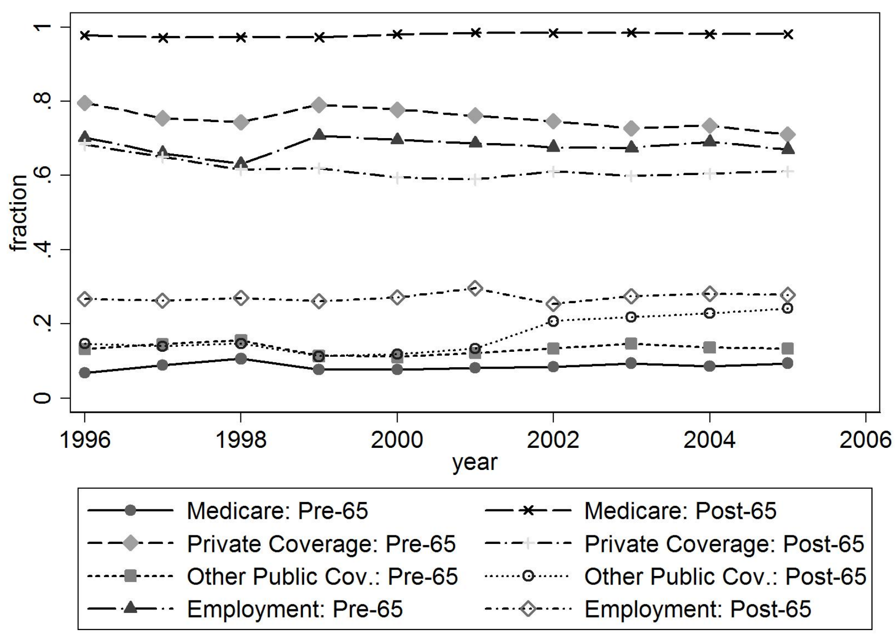


Figure 2.8: Pre-65 and Post-65 Insurance Coverage and Employment: Male

Data Source: 1996-2005 MEPS.

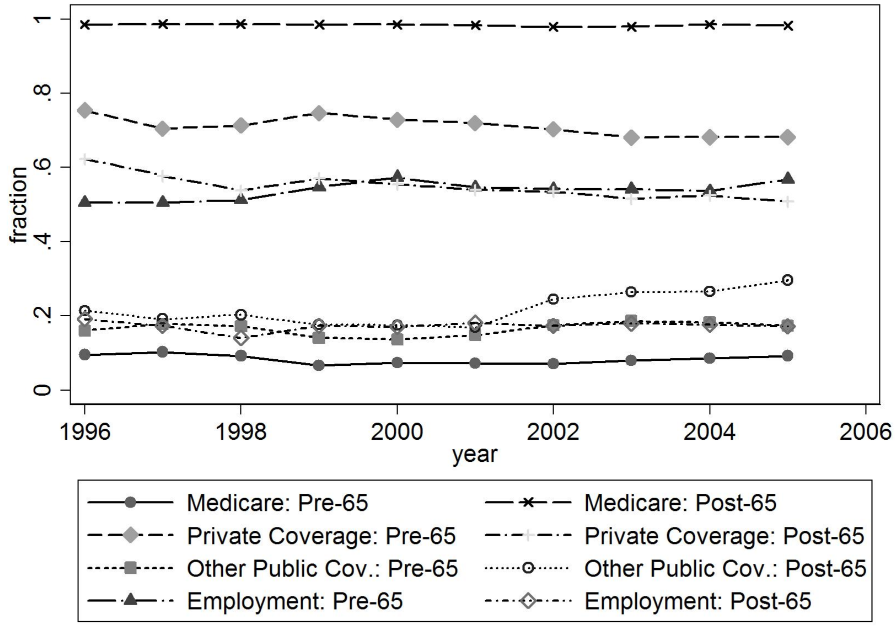


Figure 2.9: Pre-65 and Post-65 Insurance Coverage and Employment: Female

Data Source: 1996-2005 MEPS.

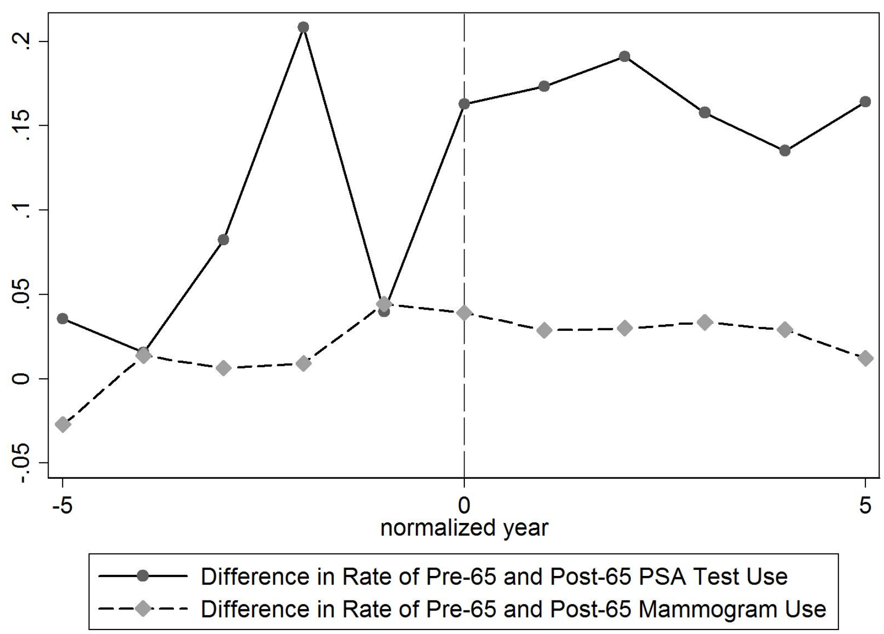


Figure 2.10: Difference in Rate of Pre-65 and Post-65 Cancer Screening Use

Data Source: 1998-2005 MEPS and 1993-1994 NHIS.

Chapter 3

Evidence from HRS

3.1 MEPS, NHIS vs HRS

The combine Medical Expenditure Panel Survey (MEPS) and National Health Interview Survey (NHIS) allow me to do a cross-sectional analysis with a large sample. The advantages of a cross-sectional analysis are efficiency and large numbers of subjects. MEPS and NHIS are carried out annually and the combined sample size is large. Table 2.1 shows that there are 13760 males and 22892 females in the sample. The imputed numbers of observations on the use of PSA test and mammogram are 68800 and 97687 respectively.

But there are shortcomings associated with MEPS and NHIS data. One cannot follow the same individuals over time. With cross-sectional data, the observed preventive behavior is representative of the population at a single period in time and the temporal aspects of a specific individual's preventive behavior is not necessarily available. In the case of MEPS, one may follow for a couple of years, but not for a long time. Another disadvantage arises from data censoring and data selection.

This research is concerned with change that occurs over age and year. This fact brings forward another research choice: longitudinal study using panel data. Longitudinal studies involve studying the same group of participants over a particular time period, while cross-sectional studies involved studying groups of participants in different age groups at the same point in time.

Longitudinal studies collect panel data, which follows a cohort of individuals with the purpose of monitoring changes over a period of time. The Health and Retirement Study (HRS) is a longitudinal household survey data set for the study of retirement and health among the elderly. The survey time period is referred to as a "wave", and a total of seven waves of data have been collected at approximately two-year intervals.

There are three reasons why the HRS longitudinal data is valuable. Firstly, the HRS follows the same group of individuals, thus making possible the observation of any one individual's preventive behavior over time. It provides the best information about the continuity or discontinuity of preventive behavior over time and allows for the individual tracking of patterns of behavior, as well as trends of development, within the elderly group.

With individual effects being extracted, I can better track the change in individual's preventive behavior that happens over age and year. And policy changes are not expected to be correlated with individual effects. Therefore, the research design can be better fulfilled and the HRS avoids a disadvantage that the cross-sectional study suffers. That is, age differences do not show age change and cohort effects.

Secondly, HRS does not have the similar data censoring and data selection issues like the MEPS and NHIS. Due to the type of questions being asked in the MEPS and NHIS, the data on the use of preventive screenings are imputed, thus making data censoring and selection a potential problem. Chapter 2 uses the Heckman selection model to solve the problem arising from data imputation while the

HRS data is free of that problem.

Thirdly, as will seen in this chapter, the HRS does not only circumvent the shortcomings of the MEPS and NHIS, but also strengthens the results from the MEPS and NHIS. As will seen later in this chapter, Chapter 2 and 3 come to the same conclusion though different data and estimation methods are used.

However, there is a limitation of using HRS, which has a small number of panels. In contrast to MEPS which is an annual survey, HRS is carried out every other year. And the panels available for this study is even fewer. In total, there are three panels available for female, which are wave 3 (pre-1998), wave 5 and 7 (post-1998) and there are two panels available for male, which are wave 3 (pre-2000) and wave 7 (post-2000).

Wave 5 is not included in analysis on male because Medicare expanded coverage of prostate cancer screening tests in 2000, the same year wave 5 interview was carried out. The survey asks male uptake of prostate screening test in the last two years before the survey and thus it is impossible to tell whether individuals took tests before or after the date when Medicare began to cover the tests. For that reason, wave 5 is dropped and there are only two panels of data available for estimation on male uptake of PSA tests, one before 2000 and one after.

In all, the HRS and the MEPS/NHIS each have pros and cons. No one data set is perfect for this study. As is known, the benefits of a longitudinal analysis over a repeated cross-sectional study include the ability to control individual effects. And the HRS does not have data censoring and data selection issues. This chapter tries to utilize these benefits to redo our exercise and to compare the results obtained from the MEPS and NHIS.

3.2 Empirical Framework & Data

3.2.1 Empirical Framework

In this chapter, I still work with the same reduced form model as in Chapter 2, equation (2.2). Individual effects will be controlled because of the nature of longitudinal data. A linear probability model, instead of probit model, will be estimated because of the large number of individual fixed effect.

$$\begin{aligned} Screen_{it} &= Post65_{it} * \alpha + Post65_{it} * PostExpansion_t * \beta \\ &\quad + f(age_{it};\theta) + control_{it} * \gamma + \mu_t + \epsilon_{it} \end{aligned} \tag{3.1}$$

where $Post65_{it}$ denotes an indicator for being age 65 or older for individual i in year t, and $PostExpansion_t$ denotes an indicator for being after Medicare expansion in year t. That is,

$$Post65_{it} = 1 \text{ if } age \geq 65,$$

and

$$PostExpansion_t = \begin{cases} Post1998_t = 1 \text{ if } t \geq 1998 & \text{for female (mammogram)} \\ Post2000_t = 1 \text{ if } t \geq 2000 & \text{for male (PSA test).} \end{cases}$$

$f(age_{it};\theta)$, is a continuous polynomial with potential discontinuities in the derivatives at age 65.

The coefficient on $Post65_{it}$ measures the effect of Medicare enrollment on preventive behaviors and it should be negative if *ex ante* moral hazard exists; the coefficient on $Post65_{it} * PostExpansion_t$ measures the effect of Medicare expansion on the use of preventive screenings and it should be positive if *ex post* moral hazard exists. Combining them yields the overall effect of Medicare on the use of preventive screenings. Section 3.2.2 describes the data in use, and Section 3.2.3 discusses the variables and summary statistics.

3.2.2 Data

The Health and Retirement Study (HRS) is a longitudinal household survey data set for the study of retirement and health among the elderly in the United States. It began as a panel survey of a nationally representative sample of people aged 51 to 61 in 1992, including their spouses. The original cohort (wave 1) has been re-interviewed every other year since then. In 1998 the sample was supplemented with both older and younger cohorts. A total of 7 waves are available now. Thus HRS is particularly well-suited to a study of the elderly.

The HRS is rich and complex. It contains detailed information on preventive services that the respondents had, along with rich data on their other health insurance coverage, economic and demographic variables (including age, race/ethnicity, marital status, education, wealth), own assessment of health status, and subjective life expectancy.

The RAND Center for the Study of Aging created a RAND HRS data file, which is a subset of the HRS. RAND HRS is derived from the HRS and more accessible than the raw data. It contains all the information I need for this study. Therefore I use data from RAND HRS in this chapter.

I focus on a panel of respondents who were continuously interviewed in wave 3, wave 5 and 7, and aged 56 to 75 during my sample period (wave 3 to wave 7). Wave 3 interview was carried out in 1995 and 1996 for two cohorts, and wave 5 and 7 were carried out in 2000 and 2004 for both cohorts. Data in wave 4 and wave 6 is not included in the study because no question was asked on preventive behaviors in those two waves. In addition, Wave 5 is not used for men group because it was carried out in 2000, the first year PSA tests were covered by Medicare. There is no way to tell if the test was taken before or after the expansion of the Medicare preventive services.

The original sample includes 2712 males and 3178 females. Two types of individuals are excluded from the sample. First, individuals who are/were on Social Security Disability Insurance (DI) or possibly are/were on DI are excluded from the sample due to DI enrollment patterns (Autor and Duggan 2003). Because of this, 266 males and 298 females are excluded.

Second, individuals who report to have cancer or do not answer cancer questions in any waves are excluded from the sample. Because mammograms and PSA tests help detect breast cancer and prostate cancer in the early stage, cancer patients may not need to take the screening tests after the cancer has been detected or may have to take more tests for diagnostic purpose. Therefore, cancer patients are excluded from the sample as well. 243 males (191 reporting cancer) and 148 females (122 reporting cancer) are excluded. In all, the final sample includes 2203 males and 2732 females.

3.2.3 Variables

Dependent variables, *i.e.*, uptake of mammogram and PSA test are derived from the following yes-no questions:

"Did you have a mammogram/examination of prostate to screen for cancer in the last two years?"

Dependent variables on use of mammogram and PSA test do not indicate actual use in survey year, but two years before that. One should be careful when interpreting the rates because they mean the rates two years before corresponding ages. In general, rates fluctuate over ages.

$Post65$ turns on when the individual's age at the survey is equal to or over 65. $Post1998$ indicates female coverage of mammograms, and $Post2000$ shows male coverage of PSA tests. In this specific data set, $Post1998$ is coded 0 for wave 3 (carried out in 1995 and 1996), and 1 for wave 5 (carried out in 2000) and wave 7 (carried out in 2004); $Post2000$ is coded 0 for wave 3, and 1 for wave 7.

Control variables are demographic characteristics, employment status, other insurance coverage, and life expectancy. Demographics include age, race/ethnicity, marital status, education and wealth. Information on other health insurance includes coverage by Medicaid, Champs/VA, employer provided plan, spouse's employer provided plan, and other insurance plans.

Table 3.1 gives the summary statistics on cancer screening use, demographics, employment status, insurance coverage and life expectancy. Rates of screening tests are normalized by percentage. The statistics from the HRS sample are consistent with those from the MEPS and NHIS. One seemingly discrepancy is the rate of taking cancer screening test. For male PSA testing rate, Table 3.1 reports 71.83% while Table 2.1 reports 31.54%; for female mammogram uptake rate, Table 3.1 reports 75.54% while Table 2.1 reports 42.72%.

The reason for this seemingly discrepancy is that the HRS surveys biennial screening test utilization instead of the annual one in MEPS and NHIS. Thus the means calculated from the HRS sample for screening test utilization (Table 3.1) is about double the size of the ones from the MEPS and NHIS sample (Table 2.1). In both tables, females use the screening test more frequently than males.

All other statistics are similar and consistent with the MEPS and NHIS, which include age, race/ethnicity, education, employment, and insurance coverage. Besides the common variables, the HRS asks questions on probability of living to a given age. The self-reported probability of living to age 75 or older is included in some estimations. The problem with the subjective probability is that it may be affected by health conditions and test results on cancer screenings. Details will be discussed in the next section.

Table 3.2 does a raw difference-in-differences analysis. For mammogram, the raw difference-in-differences estimate of *ex post* moral hazard is 3.05. That is, female Medicare beneficiaries increased the use of mammogram after 1998 by 3.05 percentage point as compared to the rate before 1998. The difference in mammogram around age 65 is -2.96 before 1998. It conforms to the hypothesis of *ex ante* and *ex post* moral hazards. But the results on PSA test contradict the hypothesis. As will be discussed in the next section, the data on male uptake of PSA test is limited. Figure 3.1 and 3.2 present the graph results.

3.3 Results and Comparison

3.3.1 *Ex Ante* & *Ex Post* Moral Hazards

Summarized estimation results on the linear probability model (equation 2.2) are presented in Table 3.3 and Table 3.4. Table 3.3 is on female uptake of mammogram and Table 3.4 is on male uptake of PSA test. In panels A1 and A2 (*i.e.*, rows 1 through 4), *ex ante* and *ex post* moral hazards are separated while they are not in panels B1 and B2 (*i.e.*, rows 5 and 6). Panels A1 and B1 report fixed effect estimates, and Panels A2 and B2 use random effect estimation. As suggested by Lee and Card (2008), standard errors are clustered by age in some fixed effect regressions, which are shown in even-numbered columns. Coefficients on *ex ante* and *ex post* moral hazards are normalized by percentage.

In Table 3.3, columns (1) and (2) show estimates of the basic model (without control variables) on female uptake of mammogram, columns (3) and (4) control demographics (including marital status, race/ethnicity, education, and wealth), columns (5) and (6) add employment, columns (7) and (8) control insurance status other than Medicare coverage, and finally columns (9) and (10) add self-assessed life expectancy. One problem with the subjective measure of life expectancy is that it may be affected by the mammogram test result. For that reason, columns (7) and (8) are preferred to columns (9) and (10) though there is no big difference among them.

Panels A1 and A2 in Table 3.3 indicate that females exhibit strong *ex ante* and *ex post* moral hazards in taking mammogram, with about 5 to 6 percentage point decrease after Medicare enrollment and about 7 percentage point increase after Medicare expansion of mammogram coverage. Coefficients on $Post65$ and $Post65 * PostExpansion$ are significant in all specifications. The result is based on the full sample, *i.e.*, 2732 females who were interviewed in wave 3 (carried out in 1995 and 1996), wave 5 (in 2000) and wave 7 (in 2004).

Column (7) and (8) indicate that there is a 5.54 percentage point drop at age 65 and 7.30 percentage point gain among age 65 and older after year 1998. The biennial rate of mammogram use among pre-65 HRS female sample is 74.67%. The 5.54 percentage point drop at age 65, which is shown in row 1 and column (7) or (8), represents $5.54/74.67 = 7.4$ percent decrease in mammogram utilization, and the 7.30 percentage point gain at age 65 and year 1998, which is shown in row 2 and column (7) or (8), means $7.30/74.67 = 9.8$ percent increase. Therefore, *ex ante* and *ex post* moral hazards change the rate of mammogram utilization by 7.4% and 9.8% respectively.

Panels B1 and B2 show the combined effect at age 65. That is the summation of *ex ante* and *ex post* moral hazards. In both fixed effect and random effect estimations, I find no significant discontinuity at age 65. This is consistent with results shown in Panels A1 and A2, which indicate that *ex ante* and *ex post* moral hazards are of similar magnitudes, and have opposite signs. When combined, they cancel off each other. When combined, they cancel off each other. Therefore, it might be a reason why previous literature did not find evidence on *ex ante* moral hazard at Medicare enrollment and helps explain the puzzling question.

Results on male uptake of PSA test are not showing any *ex ante* moral hazard, nor *ex post* moral hazard. In Table 3.4 Panels A1 and A2, the estimated coefficients are insignificant, and their signs are opposite to the theoretical prediction. One possible cause is poor quality of data. The reasons are as follows.

First, there is a short panel problem. The sample consists of 2203 males who were interviewed in wave 3 (carried out in 1995 and 1996), and wave 7 (in 2004). Wave 5 (in 2000) is not used because it was carried out the same year as Medicare coverage of PSA test. There is no way to tell if the test was taken before or after the expansion. Second, there are large gaps between the time the surveys were taken and the policy change. One panel is four to five years before the policy change and one is four years after. It makes the fuzzy regression discontinuity estimation imprecise and may even invalid the design. Third, the selected surveys were taken eight to nine years apart, and the 2004 sample is aged. The average age of wave 3 sample is 60.7 while that of wave 7 sample is 68.6. It makes the data poor in terms of comparability.

3.3.2 Control Variables

Table 3.5 and Table 3.6 show the detailed random effect estimation of the full model. Fixed effect estimation is not presented because several control variables are dropped due to no variation. Each column from left to right corresponds to column (1), (3), (7) and (9) of Table 3.3 and Table 3.4 respectively.

The utilization of mammogram and PSA test varies by the control variables. The average rate is different for the white, the black and the Hispanic. Married or partnered people tend to use more frequently. The screening rates decrease significantly as education level drops. Non-housing assets also play a role here. More non-housing assets are related to a higher level of screening use.

3.3.3 Different Effects by Demographic Groups

Different demographic groups vary not only in the level of screening test use, but also in the responsiveness to Medicare enrollment and coverage expansion. That is, people show different *ex ante* and *ex post* moral hazards. Table 3.7 estimates *ex ante* and *ex post* moral hazards by demographics. Since the estimates on PSA test are poor and not informative due to data limitation, I will focus the discussion on mammogram utilization in this section. The results are listed in columns (3) and (4), and the model specification corresponds to column (8) in Table 3.3.

There are a few observations. Firstly, *Ex ante* and *ex post* moral hazards are found to vary by race/ethnicity. The sample is divided into two subsamples, and the white show different responsiveness from the Black and the Hispanic combined.

Secondly, better education is related to larger *ex ante* and *ex post* moral hazards. Females with some college education or having a college degree or above modify their behavior greatly at age 65 and at year 1998. Their estimated *ex ante* moral hazard is more than doubled of the sample average, and their estimated *ex post* moral hazard is thirty percent more than the sample average. Thirdly, wealth affects the two effects as well.

3.3.4 HRS versus MEPS/NHIS

As discussed earlier in this chapter, both the HRS and the MEPS/NHIS have pros and cons. The HRS is valuable because the longitudinal data allows the observation of development and the control of individual effects. And the strength of the MEPS/NHIS is large sample size which increases efficiency of estimation. Results obtained from those two sources are discussed here.

The estimated *ex ante* and *ex post* moral hazards do not differ statistically across the two data sets. Columns (7) and (8) in Table 3.3 corresponds to column (9) in Table 2.4. The estimates do not seem to be consistent in that the magnitude of estimates using the HRS is larger than those using the MEPS and NHIS. This is because the HRS is biennial and the MEPS and NHIS is annual. Estimates from the HRS is slightly more than doubled of those from the MEPS/NHIS. As calculated earlier in this section, *ex ante* moral hazard reduce the rate of mammogram utilization by 7.4%, and *ex post* moral hazard increase the rate by 9.8%. Those numbers are slight higher than what have been calculated in previous chapter, which are 5.9%

and 7.1%, but they are not statistically different.

The finding that *ex ante* and *ex post* moral hazards cancel off each other when combined is consistent from both studies. Panels B1 and B2 in Table 3.3 show the summation of *ex ante* and *ex post* moral hazards at age 65. In both fixed effect and random effect estimations, there is no significant discontinuity at age 65. This is consistent with the finding with the MEPS/NHIS data.

In regard to demographic differences, the findings on demographic control variables are consistent between the two data sources. The only exception is employment. With the MEPS/NHIS, employment significantly decreases the use of PSA test in all model specification, and it is significant at 10% level for the use of mammogram in full specification. However, it is not significant for neither mammogram nor PSA test in any of the specifications with the HRS data.

Table 2.9 and Table 3.7 present the estimated *ex ante* and *ex post* moral hazards by demographics. The sample classifications in Table 3.7 are a bit different from Table 2.9 due to sample size constraint.

Major results are similar. Firstly, *ex ante* and *ex post* moral hazards vary by race/ethnicity. Secondly, better education is related to larger *ex ante* and *ex post* moral hazards. Thirdly, income/wealth affects the two moral hazard effects as well.

However, the HRS produces some results different than the MEPS and NHIS do. Table 3.7 indicates that the white are less responsive to Medicare enrollment and screening test coverage while Table 2.9 shows the opposite. In Table 2.9, the relationship between income, and *ex ante* and *ex post* moral hazards is unclear. But Table 3.7 clear shows that people with above average non-housing assets have larger *ex ante* and *ex post* moral hazards.

One possible reason for the different results on income/wealth is that Table 2.9 uses income while Table 3.7 uses non-housing assets as an indicator for wealth. Another possible reason is that HRS uses variations within an individual but MEPS uses variations across individual. If no individual fixed effect is controlled, the estimated *ex ante* and *ex post* moral hazards among people with above average non-housing assets are -3.77 and 6.93 percentage point respectively, and are statistically significant. Since they are less than the overall sample in absolute value, the second reason is plausible in explaining the difference.

Since the HRS is longitudinal, one can follow the pre-65 uninsured individuals and observe their behavioral change at age 65 and in year 1998 and 2000. It seems that the HRS offers an opportunity to study the uninsured and provides better data than the MEPS and NHIS. However, similar study on the uninsured cannot be carried out due to data limitation. One cannot identify the comparison group composed of individuals who got on Medicare before 1998 and did not have insurance before Medicare enrollment. Therefore, *ex ante* and *ex post* moral hazards cannot be separated.

3.4 Conclusion

The Health and Retirement Study (HRS) is a longitudinal household survey of the elderly and it allows for controlling the individual effects. It overcomes the disadvantage of data from the Medical Expenditure Panel Survey (MEPS) and National Health Interview Survey (NHIS). However, the HRS does not have a large sample as compared to the MEPS and NHIS and has only a few panels for use. The HRS, MEPS and NHIS each have pros and cons. No single data set is perfect for the study of two moral hazards. Therefore, results obtained from the HRS, MEPS and NHIS complement each other, and have equal importance.

The results on female uptake of mammogram are largely consistent with the findings in Chapter 2. Evidence supports the existence of *ex ante* and *ex post* moral hazards. The HRS suggests larger effects than the MEPS and NHIS. The level of screening utilization and the size of the two moral hazards vary with demographics. Higher education is associated with more frequent use and more responsiveness to insurance change. Wealthy people show similar pattern. Estimation on male uptake of PSA test is not as good as Chapter 2 due to data limitation. The results are insignificant, and the signs of the estimated coefficients are opposite to the theoretical prediction and empirical findings from the MEPS.

In all, *ex ante* moral hazard is found at Medicare enrollment and *ex post* moral hazard is found at Medicare expansion of cancer screening procedures. Medicare enrollment reduces breast cancer screening due to *ex ante* moral hazard. This study also shows that *ex post* moral hazard can offset the negative effect caused *ex ante* moral hazard. Therefore, one way to encourage people to use preventive screening procedures is to reduce the cost. This study supports insurance coverage of preventive care.

All new group health plans and plans in the individual market must provide full coverage for preventive services without co-pay and deductibles in 2010 under

PPACA. About 50.7 million women fall into the recommended age group for annual mammogram and are not eligible for Medicare in 2008, according to the Census 2009 estimate. A simple back-of-envelope calculation shows that each year 1,901 thousand more women would use regular breast cancer screening.

Table 3.1: **Summary Statistics**

	Male		Female	
	Mean	Std. Dev.	Mean	Std. Dev.
Dependent Variable	PSA Test		Mammogram	
Screening Test(%)	71.83	44.99	75.54	42.99
Key Independent Variable				
$Post65$	0.52	0.50	0.48	0.50
$Post1998$	-	-	0.67	0.47
$Post2000$	0.50	0.50	-	-
Controls				
Age	64.67	5.08	64.30	4.40
White non-Hispanic	0.78	0.41	0.74	0.40
Black non-Hispanic	0.11	0.32	0.16	0.36
Hispanic	0.08	0.28	0.08	0.27
Married or Partnered	0.86	0.35	0.65	0.48
College and Above	0.24	0.43	0.15	0.36
Some College	0.19	0.39	0.21	0.40
High School Graduate	0.29	0.45	0.37	0.48
GED	0.05	0.23	0.04	0.20
Non-housing Assets (in million)	0.32	1.38	0.25	0.69
Employed	0.53	0.50	0.38	0.49
Employer provided plan	0.48	0.50	0.30	0.46
Spouse's employer provided plan	0.11	0.32	0.23	0.42
Medicaid	0.03	0.18	0.06	0.23
Champs/VA	0.08	0.27	0.04	0.19
Other health insurance	0.16	0.37	0.19	0.40
Prob. of Living 75+	74.69	9.49	82.53	5.05
# observations	4406		8196	
# individuals	2203		2732	

Note: Number of observations varies across variables due to missing values. Means, standard deviations and the number of observations are unweighted.

Table 3.2: **Raw Difference-in-Differences Analysis**

Mammogram (%)

	Before age 65 (Medicare ineligible)	After age 65 (Medicare eligible)	Difference
Before 1998 (Mammogram not covered)	73.07	70.11	-2.96
After 1998 (Mammogram covered)	76.86	76.95	0.09
DD			3.05

PSA Test (%)

	Before age 65 (Medicare ineligible)	After age 65 (Medicare eligible)	Difference
Before 2000 (PSA not covered)	64.38	78.79	14.41
After 2000 (PSA covered)	75.21	77.38	2.17
DD			-12.24

Table 3.3: **Estimated *Ex Ante* and *Ex Post* Moral Hazards: Female**

	Mammogram									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Separate *Ex Ante* and *Ex Post* Moral Hazards										
A1: Fixed Effect										
1. $Post65$	-5.77*	-5.77*	-5.86*	-5.86*	-5.70*	-5.70**	-5.54*	-5.54*	-5.08*	-5.08**
Ex Ante	(3.00)	(2.83)	(3.00)	(2.80)	(3.00)	(2.70)	(3.01)	(2.79)	(3.01)	(2.12)
2. $Post65 * PostExpansion$	7.10**	7.10***	7.19**	7.19***	7.11**	7.11***	7.30**	7.30***	7.44**	7.44***
Ex Post	(2.91)	(1.80)	(2.91)	(1.77)	(2.91)	(1.74)	(2.92)	(1.75)	(2.92)	(1.53)
A2: Random Effect										
3. $Post65$	-6.28**		-6.33**		-6.20**		-5.12*		-5.38**	
Ex Ante	(2.67)		(2.66)		(2.66)		(2.67)		(2.73)	
4. $Post65 * PostExpansion$	7.22***		7.36***		7.23***		7.18***		7.56***	
Ex Post	(2.53)		(2.52)		(2.52)		(2.53)		(2.65)	
Do Not Separate *Ex Ante* and *Ex Post* Moral Hazards										
B1: Fixed Effect										
5. $Post65$ only	0.03	0.03	0.01	0.01	0.11	0.11	0.41	0.41	0.99	0.99
Ex Ante + Ex Post	(1.83)	(2.66)	(1.83)	(2.66)	(1.83)	(2.60)	(1.84)	(2.73)	(1.84)	(2.28)
B2: Random Effect										
6. $Post65$ only	-0.49		-0.43		-0.41		0.63		0.60	
Ex Ante + Ex Post	(1.74)		(1.73)		(1.73)		(1.74)		(1.74)	
VCE Clustered by Age		X		X		X		X		X
Controls:										
Demographics			X	X	X	X	X	X	X	X
Employment					X	X	X	X	X	X
Insurance							X	X	X	X
Prob. of Living 75+									X	X

Note: 1. Panels A1 and B1 are estimated by fixed effect, and Panels A2 and B2 are estimated by random effect. Standard errors in even-numbered columns are clustered by age. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2. Demographics include marital status, race/ethnicity (white non-Hispanic, black non-Hispanic, and Hispanic), education (GED, high school graduate, some college and above college), and non-housing assets. Insurance status includes several indicators for private coverage, and public coverage (other than Medicare).

Table 3.4: **Estimated *Ex Ante* and *Ex Post* Moral Hazards: Male**

	PSA Test									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Separate *Ex Ante* and *Ex Post* Moral Hazards										
A1: Fixed Effect										
1. $Post65$	1.14	1.14	1.13	1.13	1.01	1.01	1.43	1.43	1.48	1.48
Ex Ante	(6.14)	(5.60)	(6.13)	(5.56)	(6.13)	(5.55)	(6.15)	(5.56)	(6.28)	(5.72)
2. $Post65 * PostExpansion$	-10.00	-10.00*	-9.87	-9.87*	-10.00	-10.00*	-9.92	-9.92*	-10.02	-10.02*
Ex Post	(6.98)	(5.55)	(6.98)	(5.47)	(6.98)	(5.49)	(7.01)	(5.47)	(7.51)	(5.23)
A2: Random Effect										
3. $Post65$	3.64		3.43		3.34		4.24		5.95*	
Ex Ante	(3.42)		(3.35)		(3.35)		(3.35)		(3.49)	
4. $Post65 * PostExpansion$	-3.67		-3.57		-3.50		-2.97		-7.57*	
Ex Post	(2.92)		(2.85)		(2.86)		(2.85)		(3.92)	
Do Not Separate *Ex Ante* and *Ex Post* Moral Hazards										
B1: Fixed Effect										
5. $Post65$ only	-4.54	-4.54	-4.47	-4.47	-4.66	-4.66	-4.17	-4.17	-4.06	-4.06
Ex Ante + *Ex Post*	(4.69)	(3.44)	(4.69)	(3.43)	(4.69)	(3.41)	(4.70)	(3.53)	(4.71)	(3.63)
B2: Random Effect										
6. $Post65$ only	1.69		1.53		1.49		2.66		2.50	
Ex Ante + *Ex Post*	(3.05)		(2.99)		(2.99)		(2.99)		(3.00)	
VCE Clustered by Age		X		X		X		X		X
Controls:										
Demographics			X	X	X	X	X	X	X	X
Employment					X	X	X	X	X	X
Insurance							X	X	X	X
Prob. of Living 75+									X	X

Note: Please refer to the note after Table 3.3

Table 3.5: **Detailed Screening Equation: Female**

	Mammogram			
	(1)	(2)	(3)	(4)
1. $Post65$	-6.28**	-6.33**	-5.12*	-5.38**
Ex Ante	(2.67)	(2.66)	(2.67)	(2.73)
2. $Post65 * PostExpansion$	7.22***	7.36***	7.18***	7.56***
Ex Post	(2.53)	(2.52)	(2.53)	(2.65)
3. $(Age - 65)$	0.59*	0.65*	0.85**	1.59
	(0.35)	(0.35)	(0.35)	(1.56)
4. $(Age - 65)^2$	-0.05**	-0.04**	-0.04**	-0.01
	(0.02)	(0.02)	(0.02)	(0.07)
5. $(Age - 65)^3$	-0.010**	-0.009**	-0.011**	-0.010**
	(0.004)	(0.004)	(0.004)	(0.004)
Controls:				
6. White non-Hispanic		-2.64	-3.08	-3.10
		(4.76)	(4.70)	(4.71)
7. Black non-Hispanic		3.42	3.71	3.70
		(4.98)	(4.91)	(4.92)
8. Hispanic		-2.16	-0.68	-0.64
		(5.25)	(5.18)	(5.19)
9. Married		8.75***	8.18***	8.17***
		(1.20)	(1.23)	(1.23)
10. College or Above		17.98***	15.26***	15.30***
		(2.21)	(2.23)	(2.23)
11. Some College		10.93***	9.37***	9.41***
		(2.01)	(2.00)	(2.01)
12. High School Graduate		8.72***	7.22***	7.24***
		(1.78)	(1.78)	(1.78)
13. GED		5.43	4.14	4.14
		(3.38)	(3.34)	(3.34)
14. Non-housing Assets		2.78***	2.81***	2.82***
		(0.74)	(0.74)	(0.74)
15. Employment			0.71	0.74
			(1.08)	(1.08)
16.Prob. of Living 75+				-0.67
				(1.37)
17.Other Insurance Coverage			X	X
# observations	8180	8180	8180	8180
# individuals	2732	2732	2732	2732

Note: Coefficients are estimated by random effect. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.6: **Detailed Screening Equation: Male**

	PSA Test			
	(1)	(2)	(3)	(4)
1. $Post65$	3.64	3.43	4.24	5.95*
Ex Ante	(3.42)	(3.35)	(3.35)	(3.49)
2. $Post65 * PostExpansion$	-3.67	-3.57	-2.97	-7.57*
Ex Post	(2.92)	(2.85)	(2.85)	(3.92)
3. $(Age - 65)$	1.54***	1.56***	1.50***	-0.88
	(0.58)	(0.56)	(0.57)	(1.50)
4. $(Age - 65)^2$	-0.07***	-0.07***	-0.07***	-0.16***
	(0.02)	(0.02)	(0.02)	(0.06)
5. $(Age - 65)^3$	-0.01	-0.01	-0.004	-0.01
	(0.01)	(0.01)	(0.006)	(0.01)
Controls:				
6. White non-Hispanic		9.82*	9.40*	9.40*
		(5.42)	(5.38)	(5.38)
7. Black non-Hispanic		10.08*	10.08*	10.03*
		(5.81)	(5.77)	(5.76)
8. Hispanic		3.30	5.09	4.84
		(5.98)	(5.95)	(5.95)
9. Married		11.11***	10.03***	10.14***
		(2.03)	(2.05)	(2.05)
10. College or Above		23.95***	22.40***	22.33***
		(2.29)	(2.31)	(2.31)
11. Some College		17.01***	15.83***	15.66***
		(2.36)	(2.37)	(2.37)
12. High School Graduate		14.58***	13.42***	13.38***
		(2.16)	(2.16)	(2.16)
13. GED		10.64***	9.34***	9.53***
		(3.56)	(3.55)	(3.55)
14. Non-housing Assets		0.78	0.79*	0.79*
		(0.48)	(0.48)	(0.48)
15. Employment			-2.01	-2.03
			(1.48)	(1.48)
16. Prob. of Living 75+				1.49*
				(0.87)
17.Other Insurance Coverage			X	X
# observations	4377	4377	4377	4377
# individuals	2203	2203	2203	2203

Note: Coefficients are estimated by random effect. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3.7: ***Ex Ante*** **and** ***Ex Post*** **Moral Hazards by Demographics**

	PSA Test		Mammogram	
	$Post65$	$Post65 * Post2000$	$Post65$	$Post65 * Post1998$
	ex ante	*ex post*	*ex ante*	*ex post*
	(1)	(2)	(3)	(4)
Overall Sample	1.43	-9.92*	-5.54*	7.30***
	(5.56)	(5.47)	(2.79)	(1.75)
Classified by Race/Ethnicity				
White Non-Hispanic	1.49	-15.05**	-3.49	5.19*
	(6.26)	(7.11)	(3.66)	(2.79)
Black Non-Hispanic	-1.81	14.44	-13.93***	15.71**
& Hispanic	(12.96)	(11.99)	(4.72)	(6.91)
Classified by Education				
At Least Some College	-3.62	1.08	-12.36**	9.63**
	(4.57)	(4.88)	(4.66)	(4.54)
High School Graduate	3.86	-17.88*	-1.00	4.76
& GED	(7.56)	(8.80)	(3.66)	(3.40)
Classified by Non-housing Assets				
Below average	4.15	-22.33**	-1.93	5.71**
	(7.70)	(8.28)	(3.22)	(2.38)
Above average	2.85	-0.53	-9.40**	9.71***
	(10.96)	(11.61)	(3.44)	(2.46)

Note: 1. Each row represents a separate regression.
2. Coefficients are estimated by fixed effect. Standard errors (in parentheses) are clustered by age. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
3. Control variables include demographics, employment, and insurance status.

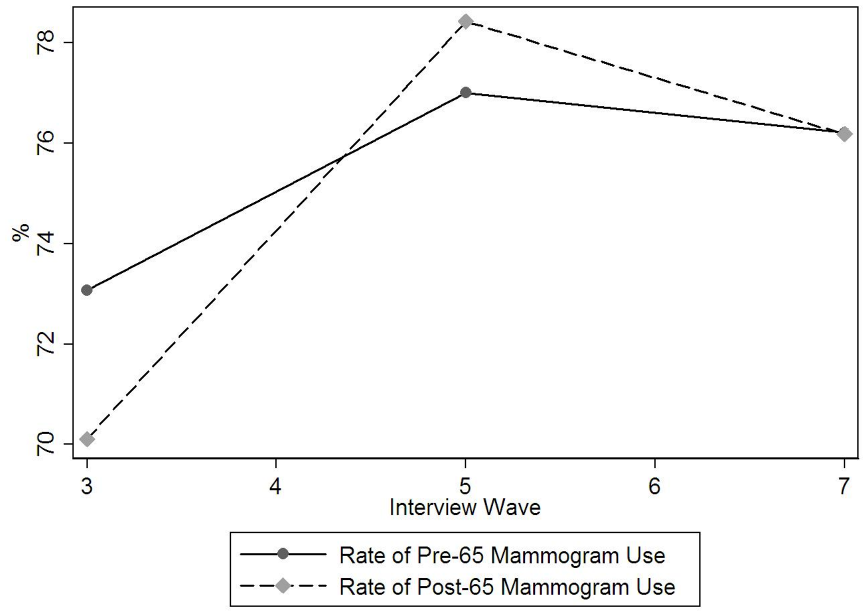


Figure 3.1: Raw Difference-in-Differences Graph: Female
Data Source: HRS wave 3, 5, and 7.

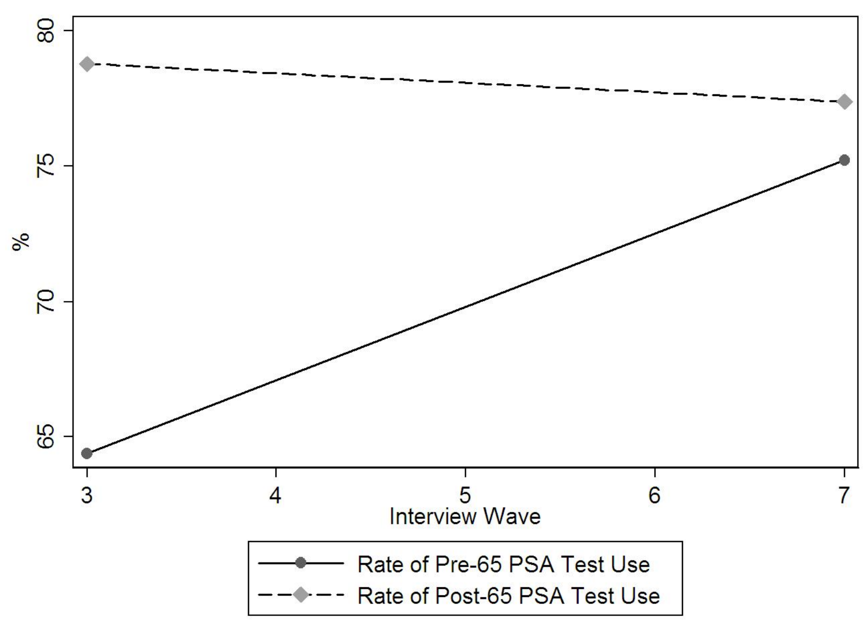


Figure 3.2: Raw Difference-in-Differences Graph: Male
Data Source: HRS wave 3 and 7.

Appendix A

Selected Prevention Provisions

Table A.1: **Selected Prevention Provisions**

TITLE I	QUALITY, AFFORDABLE HEALTH CARE FOR ALL AMERICANS
Subtitle A	*Immediate Improvements in Health Care Coverage for All Americans*
Sec. 2713	Coverage of preventive health services
Subtitle D	*Available Coverage Choices for All Americans*
Sec. 1302	Essential health benefits requirements
TITLE IV	PREVENTION OF CHRONIC DISEASE AND IMPROVING PUBLIC HEALTH
Subtitle A	*Modernizing Disease Prevention and Public Health Systems*
Sec. 4001	National Prevention, Health Promotion and Public Health Council
Sec. 4002	Prevention and Public Health Fund
Sec. 4003	Clinical and community preventive services
Sec. 4004	Education and outreach campaign regarding preventive benefits
Subtitle B	*Increasing Access to Clinical Preventive Services*
Sec. 4101	School-based health centers
Sec. 4102	Oral healthcare prevention activities
Sec. 4103	Medicare coverage of annual wellness visit providing a personalized prevention plan
Sec. 4104	Removal of barriers to preventive services in Medicare
Sec. 4105	Evidence-based coverage of preventive services in Medicare
Sec. 4106	Improving access to preventive services for eligible adults in Medicaid
Sec. 4107	Coverage of comprehensive tobacco cessation services for pregnant women in Medicaid
Sec. 4108	Incentives for prevention of chronic diseases in Medicaid

(Continue)

Subtitle C	*Creating Healthier Communities*
Sec. 4201	Community transformation grants
Sec. 4202	Healthy aging, living well; evaluation of community-based prevention and wellness programs for Medicare beneficiaries
Sec. 4203	Removing barriers and improving access to wellness for individuals with disabilities
Sec. 4204	Immunizations
Sec. 4205	Nutrition labeling of standard menu items at chain restaurants
Sec. 4206	Demonstration project concerning individualized wellness plan
Sec. 4207	Reasonable break time for nursing mothers
Subtitle D	*Support for Prevention and Public Health Innovation*
Sec. 4301	Research on optimizing the delivery of public health services
Sec. 4302	Understanding health disparities: data collection and analysis
Sec. 4303	CDC and employer-based wellness programs
Sec. 4304	Epidemiology-Laboratory Capacity Grants
Sec. 4305	Advancing research and treatment for pain care management
Sec. 4306	Funding for Childhood Obesity Demonstration Project

Note: This table lists some selected sections in Patient Protection and Affordable Care Act (HR 3590) that reforms prevention provisions.Details on the provisions can be found in the Patient Protection and Affordable Care Act, which is available online at http://democrats.senate.gov/reform/patient-protection-affordable-care-act-as-passed.pdf

Appendix B

Selection Equation

Table B.1: **Selection Equation: Male**

	PSA Test		
	(1)	(2)	(3)
1. $D_{surveyyear=t}$	8.21***	8.23***	8.78***
	(0.07)	(0.07)	(0.08)
2. *Ex Ante*	-0.05	-0.05	-0.05
	(0.05)	(0.04)	(0.04)
3. *Ex Post*	-0.07**	-0.07*	-0.07*
	(0.04)	(0.04)	(0.04)
4. $(Age - 65)$	-0.014**	-0.011**	-0.011**
	(0.006)	(0.005)	(0.005)
5. $(Age - 65)^2$	0.0009**	0.0009**	0.0009**
	(0.0004)	(0.0004)	(0.0004)
6. Married	-0.26***	-0.22***	-0.22***
	(0.02)	(0.03)	(0.03)
7. White non-Hispanic	-0.36***	-0.33***	-0.34***
	(0.05)	(0.05)	(0.05)
8. Black non-Hispanic	-0.48***	-0.47***	-0.47***
	(0.06)	(0.06)	(0.06)
9. Hispanic	-0.25***	-0.29***	-0.29***
	(0.06)	(0.05)	(0.06)
10. At Least Some College	-0.23***	-0.22***	-0.22***
	(0.03)	(0.03)	(0.03)
11. High School Dropout	0.39***	0.36***	0.36***
	(0.03)	(0.03)	(0.03)
12. Poor	0.18***	0.13***	0.13***
	(0.03)	(0.04)	(0.04)
13. High Income	-0.21***	-0.16***	-0.16***
	(0.03)	(0.03)	(0.03)

(Continue)

	PSA Test		
	(1)	(2)	(3)
14. Employment	0.20***	0.20***	0.21***
	(0.03)	(0.03)	(0.02)
15. Private Coverage		-0.12***	-0.12***
		(0.03)	(0.03)
16. Other Public Coverage		0.02	0.03
		(0.03)	(0.03)
17. No Coverage		0.46***	0.46***
		(0.04)	(0.04)
18. Employ,Ins$*D_{impute}$			X

*Note: 1. Coefficients are estimated by maximum likelihood. Standard errors (in parentheses) are clustered by age and individual. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*
2. $D_{survey\ year=t} = 1$ if survey year $= t$.

Table B.2: **Selection Equation: Female**

	Mammogram		
	(1)	(2)	(3)
1. $D_{surveyyear=t}$	7.85***	7.92***	8.17***
	(0.06)	(0.07)	(0.07)
2. *Ex Ante*	-0.05	-0.03	-0.03
	(0.05)	(0.04)	(0.04)
3. *Ex Post*	-0.06**	-0.06**	-0.06**
	(0.03)	(0.03)	(0.03)
4. $(Age - 65)$	0.015***	0.018***	0.018***
	(0.005)	(0.005)	(0.005)
5. $(Age - 65)^2$	0.0007**	0.0007**	0.0007**
	(0.0003)	(0.0003)	(0.0003)
6. Married	-0.16***	-0.13***	-0.13***
	(0.02)	(0.02)	(0.02)
7. White non-Hispanic	-0.21***	-0.16***	-0.16***
	(0.05)	(0.05)	(0.05)
8. Black non-Hispanic	-0.37***	-0.36***	-0.36***
	(0.06)	(0.06)	(0.06)
9. Hispanic	-0.22***	-0.29***	-0.29***
	(0.05)	(0.06)	(0.06)
10. At Least Some College	-0.22***	-0.19***	-0.19***
	(0.02)	(0.02)	(0.02)
11. High School Dropout	0.31***	0.26***	0.26***
	(0.02)	(0.02)	(0.02)
12. Above Poverty Line	-0.16***	-0.08***	-0.08***
	(0.02)	(0.02)	(0.02)
13. Employment	0.05*	0.08***	0.07**
	(0.03)	(0.03)	(0.03)
14. Private Coverage		-0.21***	-0.20***
		(0.03)	(0.03)
15. Other Public Coverage		0.004	0.01
		(0.026)	(0.03)
16. No Coverage		0.55***	0.55***
		(0.04)	(0.04)
17. Employ,Ins$*D_{impute}$			X

Note: Please refer to the note after Table B.1

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