1-1-2020

Essays on the effects of public health insurance policies on health care utilization, expenditure, and well-being

Tu Thi Cam Nguyen
University at Albany, State University of New York, nguyencamtukt07@gmail.com

ESSAYS ON THE EFFECT OF PUBLIC HEALTH INSURANCE POLICIES ON HEALTH CARE UTILIZATION, SPENDING, AND WELL-BEING

by

Tu Nguyen

A Dissertation

submitted to the University at Albany, State University of New York

in Partially Fulfillment of

the Requirement for the Degree of

Doctor of Philosophy

College of Arts and Sciences

Department of Economics

May 2020

ABSTRACT

This dissertation consists of essays on the causal impact of public health insurance policies in the United States. Three chapters investigate how Medicare program, Medicare Prescription coverage program, and the Affordable Care Act Medicaid expansion impact on health-related outcomes, health care expenditure, and food wellbeing.

The first chapter in this dissertation examines the causal treatment effects of Medicare on health care utilization and cost among the elderly. We provide new estimates of the impact of Medicare on healthcare utilization, including office-based and outpatient, hospital inpatient, and emergency department visits. We exploit the discontinuity in health insurance coverage rates at the Medicare eligibility age of 65 to investigate the impact of Medicare on health care utilization and spending among the elderly. We find that the discrete change in insurance coverage rates at age 65 leads to a significant increase in office-based physician and outpatient visits, which is mainly driven by those who were not insured before age 65. We also document that the Medicare eligibility at age 65 is associated with up to 40 percent decrease in out-of-pocket spending for physician and outpatient visits. On the other hand, we find that Medicare eligibility does not have a significant impact on the utilization of inpatient or emergency department services.

The second chapter studies the impact of Medicare prescription drug coverage on out of pocket spending and food access among the elderly in the US. Prescription drugs were first included in Medicare in 2006, under the Medicare Modernization Act. We use data from the Health and Retirement Study(HRS) wave 2000-2014 with a difference-in-difference-in-difference approach by comparing the variation in the outcome of seniors aged 66-70 and younger seniors aged 60-64, before and after Medicare Part D, and across health status. The estimation indicated that Medicare Part D is associated with an increase in the probability of

having enough money for food, an increase in the weekly spending for food, and a reduction in the SNAP participation among lone seniors with multiple chronic conditions. We also find evidence of an increase in the probability of report having enough money for food among couple seniors families aged over 65 but in smaller magnitude.

The third chapter explores the impact of 2014 Medicaid expansions under the Affordable Care Act (ACA) on the utilization for diabetes among low-income childless adults. The Medicaid expansion aims to provide Medicaid coverage to the low-income population regardless of parent or age. We use difference-in-difference design to compare the outcomes in expansion states with non-expansion states before and after 2014. Our estimation suggested evidence that Medicaid expansions lead to more appropriate in particular care for diabetes but not all; and improvement in self-accessed health outcomes among people with diabetes.

ACKNOWLEDGEMENT

First and foremost, I would like to express my deepest gratitude to my advisors, Professor Pinka Chatterji, and Professor Yoruk, for their guidance, encouragement, and support. Their immense knowledge and patience guided me through this Ph.D. journey and encouraged me to overcome all the difficulties. Professor Pinka Chatterji is a passionate scholar and dedicated mentor who inspired me to the field of health economics. I am also incredibly grateful to Professor Lahiri as a committee member. His support and insightful comments are crucial to help me improve this dissertation.

My appreciation goes to every faculty member of the Economics Department. I am grateful to Professor Kwan Koo Yun, Professor John Jones, Professor Michael Jerrison, Professor Adrian Masters, Professor Rui Zhao, Professor Zhongwen Liang, and Professor Michael Satttinger for their useful courses and their support during my Ph.D. journey.

I want to thank my fellows and my friends Ngoc Tran, Siyang Li, Oleg Ivashchenko, Nayoung Kim, Fang Cheng, Holden Diethorn, Erting Sa, Liang Fu, Xiaoqi Zhu, Duong Ngo, Huy Dang, Gusang Kang for their encouragement, support, and fun during more than six years in Albany.

Last but not least, I wanted to thank my parents and my husband, for their love, support, and prayer. They always give me strength during any hard time. And this dissertation is dedicated to them.

Table of Contents

List of Tables

List of Figures

Chapter 1 The effect of Medicare on health care utilization and spending among the elderly

1.1. Introduction

Medicare, the federal health insurance program for more than 60 million people ages 65 and over and people with long-term disabilities, is one of the largest social programs. In 2018, Medicare benefit payments were 15 percent of total federal spending and totaled $731 billion, up from $462 billion in 2008 (Cubanski, Neuman, and Meredith, 2019). Yet the evidence on the effects of Medicare on health and health care consumption is mixed and relatively limited. On the one hand, the existing literature shows that Medicare coverage does not lead to significant changes in self-reported health status and mortality rates in the population (Finkelstein and McKnight, 2008; Card, Dobkin, and Maestas, 2008). Similarly, Barcellos and Jacobson (2015) find that the likelihood of a physician visit, an outpatient hospital visit, or an inpatient stay remains unchanged at Medicare eligibility age of 65. On the other hand, Decker and Rapaport (2002), Card, Dobkin, and Maestas (2008), and McWilliams et al. (2003, 2007) find that the utilization of health care services increases once people become eligible for Medicare. Card, Dobkin, and Maestas (2009) document the positive effects of Medicare eligibility on mortality rates for severely ill patients who are admitted to hospitals through emergency departments.

In this paper, we contribute to the literature on the effects of Medicare coverage on health care utilization and spending and provide new evidence-based on differences in monthly health care utilization and expenditures for people just before and just after their 65th birthday. Our research design is a regression discontinuity (RD) design that exploits the age-based eligibility for Medicare. Even though few earlier studies use a RD design to estimate the impact of Medicare eligibility on certain health care utilization and spending outcomes (Card, Dobkin, and

Maestas, 2008 and 2009; Barcellos and Jacobson, 2015), our paper is the first to use a person-month level data to explore this issue for a wider selection of outcomes including the intensity of utilization and length of hospital stays for inpatient visits. In contrast to majority of the existing papers in the literature, we also provide a detailed analysis of the di§erential effects of Medicare eligibility at age 65 on different socioeconomic groups and changes in health care utilization for speciÖc conditions and diagnoses.

Our RD analysis is based on the event-level records of the household component of the Medical Expenditure Panel Survey (MEPS). In contrast to the previous studies, these data allow us to track the respondents's health insurance coverage status, health care utilization, and spending for each month rather than for each quarter or the entire year. Furthermore, compared to previous studies, we use data from a longer time period.[1] This, combined with our use of month-person level data, enables us to use a shorter age bandwidth without sacrificing from the sample size, which are both desirable for our empirical methodology.[2]

We find that Medicare eligibility at age 65 is associated with significant increases in health insurance coverage rates among the elderly. In particular, we find that at age 65, the probability of being covered under Medicare goes up by 61 to 76 percentage points. This leads to sharp increases in both the probability and the intensity of office-based physician or outpatient visits, while decreasing the out-of-pocket costs for these services. These e§ects are almost entirely coming from those who were not insured before age 65. On the other hand, we find that

[1] For instance, Card, Dobkin, and Maestas (2008) use data for 1992-2003, while Barcellos and Jacobson (2015) use data for 1996-2010. We use 20 waves of the MEPS from 1996 to 2015

[2] Although we consider alternative age bandwidths, the largest bandwidth choice in our empirical analysis is three years, which restricts the sample to those who are 62 to 68 years old. In comparison, Card, Dobkin, and Maestas (2008) use an age bandwidth of 10 years, while Barcellos and Jacobson (2015) use an age bandwidth of 15 years. Our sample size is also considerably larger compared to the previous studies.

Medicare eligibility does not have a significant impact on the utilization of inpatient or emergency department services and related costs. Our results for alternative diagnosis types also indicate that Medicare eligibility at age 65 is mainly associated with non-urgent health care. In general, these results are robust to selection of alternative age bandwidths, models, and sub-samples.

This chapter proceeds as follows. The next section provides the background of the Medicare program and previous research on health insurance coverage and health care utilization. Section 1.3 describes the data, while section 1.4 outlines the econometric framework. Section 1.5 presents the empirical results. Section 1.6 provides a discussion of policy implications and concluded

1.2. Background and review of the literature

1.2.1. Medicare Program

Medicare is a social health insurance program that provides insurance coverage for people aged over 65 regardless of income or health status. Starting in 1972, the Medicare program was extended to cover younger people who received Social Security Disability Insurance [3]. Currently, Medicare provides health insurance coverage, approximately 60 million seniors over 65 years old, and younger people with disabilities. Medicare spending in 2017 is $705.9 billion, accounted for 20 percent of total national health spending (Center for Medicare and Medicaid Service, 2019). Medicare Part A covers inpatient hospital stays and hospice care, and the benefit is subjected to a deductible. Medicare Part B includes physician visits, outpatient services, preventive services, and some durable medical equipment. Although Medicare Part A is

[3] 1People with End Stage Renal Disease (permanent kidney failure requiring dialysis or transplant) are also eligible for Medicare

free, beneficiaries have to enroll and pay a monthly premium for Medicare Part B. The average premium for Medicare Part B was $105 for seniors with annual income up to $85,000 the year 2015 (Kaiser Family Foundation, 2015). While many services are subject to deductible and coinsurance, preventive services that are rated ‘A’ or ‘B’ by the U.S. Preventive Services Task Force does not incur any out of pocket cost under the Affordable Care Act. Since 2006, everyone with Medicare, regardless of income, health status, or prescription drug usage, has had access to prescription drug coverage (Medicare Part D). People with Medicare are also eligible to buy Medigap as Medicare Supplement Insurance from private companies to fill the gap in the Original Medicare. Medigap can cover some of the remaining spendings in the original Medicare. However, Medicare and Medigap do not cover dental and vision services if they are not related to the diagnosis or treatment of other illnesses.

1.2.2. Previous Literature

Our paper contributes to the relatively small literature on the impact of Medicare eligibility on health care utilization and spending. Using a difference-in-differences (DID) approach and by exploiting the variation of health insurance coverage across geographic regions prior to and after Medicare implementation in 1966, Finkelstein (2007) finds that Medicare increased the utilization of the inpatient services as well as the total medical expenditures. Using a similar empirical strategy, Finkelstein and McKnight (2008) find that within five years of its introduction, Medicare decreased out-of-pocket medical spending by 40 percent among those in the top quartile of spending. Engelhardt and Gruber (2011) find substantial reductions in out-of-pocket drug spending due to the introduction of Medicare Part D, which is mostly concentrated among a small group of beneficiaries. McWilliams et al. (2007) use propensity matching method to compare changes in a variety of health outcomes before and after age 65 among previously insured and uninsured beneficiaries. They find a significant increase in the number of doctor visits and hospital admissions and a significant differential decrease in the odds of incurring high out-of-pocket medical spending due to Medicare eligibility.

Although these earlier papers provide important evidence, the role of Medicare in healthcare utilization and medical spending remains an important policy issue. Rather than relying on temporal variation as the DID does, our empirical strategy based on an RD design focuses on the short-run effects and compares the outcomes of those just eligible versus just ineligible for Medicare based on the age 65 cutoff. Few recent papers used a similar approach to estimate the effects of Medicare on health care utilization and health outcomes. Using an RD design, Card, Dobkin, and Maestas (2008) investigate the impact of Medicare on health care utilization. Their analysis is based on data from the National Health Interview Survey (NHIS), and hospital discharge records from three states (California, Florida, and New York). They find that the onset of Medicare eligibility at age 65 is associated with a sharp increase in health insurance coverage status. This change also leads to increases in the use of medical services, with a pattern of gains across different socioeconomic groups that varies by type of service. Their analysis based on the hospital discharge data indicates that Medicare increased hospital admission rates among the entire Medicare population as well as among each racial group.[4] The main limitation of this paper is that the NHIS only reports respondents' medical service utilization in the entire past year, while the respondents' age was calculated at the time of the interview. As a result, the estimation using an RD design can potentially be attenuated.[5]

[4] Later, Card, Dobkin, and Maestas (2009) focus on patients who are admitted to hospitals through emergency departments and find a significant drop in 7-day mortality rates for patients at age 65

[5] Card, Dobkin, and Maestas (2008) acknowledges this problem and argue that people who recently 65 could have had health problems in the past year but before their birthday. They suggest that such attenuation may be reduced if people tend to recall only their most recent experiences

Furthermore, in the NHIS, healthcare utilization is reported as binary indicators with no detail regarding the care category. Using nationally representative data from the MEPS, which contains information on health insurance coverage and utilization and spending at the person-month level, we formally address these potential problems.[6] Although it mainly focuses on the impact of Medicare on medical expenditure risk and financial strain, a recent paper by Barcellos and Jacobson (2015) is the most similar in spirit to ours. They use full-year aggregated data from 1996-2010 waves of the MEPS and RD design to show that although healthcare utilization exhibits a smooth pattern across age 65, Medicare offers substantial protection against large out-of-pocket health expenses. In particular, they find that at age 65, out-of-pocket healthcare expenditures drop by 33% at the mean and by 53% at the ninety-fifth percentile. Our paper is different than Barcellos and Jacobson (2015) in several ways. First, rather using entire year aggregated data, we make use of the person-month level information available in the MEPS to precisely identify respondents' coverage, healthcare utilization, and spending for each month before and after their 65th birthday. Second, our use of month-person level and five additional waves of the MEPS generates a sample size that is considerably larger with a much shorter age bandwidth, which is quite desirable for the RD design.[7] Finally, we provide a much more detailed analysis of healthcare utilization by estimating the impact of Medicare on the intensity

[6] Person-month level information of the MEPS was used for a RD analysis in different contexts. For instance, Dillender (2015), Yoruk (2018), and Xu and Yoruk (2019) use the MEPS and a RD analysis to estimate the impact of the dependent care provision of the Affordable Care Act on various outcomes.

[7] Although Barcellos and Jacobson (2015) use the 2007-2010 waves of the MEPS in their main analysis with slightly more than 30,000 observations, they also report results from the 1996-2010 waves as a robustness check with a maximum sample size of slightly more than 109,000. In both cases, they use an age bandwidth of 15 years, which includes respondents that are 50-80 years old. In comparison, our use of 1996-2015 waves with person-month level information and three year age bandwidth (62-68 year olds) generates a sample size of more than 345,000 observations. A large sample size and a short age bandwidth are quite desirable for the RD design.

of healthcare utilization at different settings, alternative diagnoses for visits, and length of hospital stays for inpatient visits.

As we describe in the Medicare background sections, Medicare Part B requires beneficiaries to enroll and pay premium monthly. In addition, seniors can also buy Medigap voluntarily to supplement their original Medicare. Therefore, the estimation of the causal impact of having Medicare having insurance on health insurance and health care utilization can be subjected to the self-selection issue. Previous literature also provided evidence of the self-selection issue when buying supplement health insurance among Medicare beneficiaries such as Lahiri and Xing (2004) and Ettner (1997). In this chapter, we do not focus on addressing the self-selection problem to Medicare Part B and Medigap. However, since the premium of Medicare Part B is much lower than the private health insurance premium for the elderly[8], the age 65 threshold still creates a discrete change for the access of more affordable health insurance. Thus it can provide us the exogenous sources to estimate the intent-to-treat impact of Medicare eligibility on health care utilization and health spending.

1.3. Data

The MEPS is a nationally representative survey of families and individuals, their medical providers (doctors, hospitals, pharmacies, etc.), and employers across the United States. In addition to very detailed information on health insurance coverage status, the MEPS also contains information on the specific health services that Americans use, how frequently they use them, the cost of these services, and how they are paid for. The MEPS has three components: the

[8] The premium for private health insurance among the senior aged 55-64 is about $790 per month (Ehealth, 2019 retrieved at: https://www.ehealthinsurance.com/resources/affordable-care-act/much-health-insurance-cost-without-subsidy) while the premium for Medicare Part B is $105 for the year 2015 (Kaiser Family Foundation, 2015)

household component (HC), insurance component (IC), and the medical provider component (MPC). In this paper, we use data 3 from the HC from 1996 to 2015, which provides data from individual households and their members. The HC component contains comprehensive information on respondents' demographic and socioeconomic characteristics, employment, income, health conditions, health insurance coverage, health care utilization, and medical costs. Each respondent is interviewed five rounds over two consecutive calendar years. Individuals who leave their original family unit are followed and remain in the survey. Every year, a new panel of approximately 15, 000 individuals is added to the survey. Therefore, two panels overlap at any given point in time (except the survey beginning year of 1996), resulting in roughly 30, 000 − 40, 000 individuals being interviewed each year.

We restrict our sample to those who are at most 3 years younger or older than the age 65 cutoff. As a robustness check, we also consider alternative age bandwidths such as 1 or 2 years.[9] In the HC, each respondent is asked about her insurance coverage status, the type (public, private, Medicare, etc.) of insurance that she held, and her health care use and spending in each calendar month during the two-year period that she remained in the survey. In our person-month level data, there are 19,998 respondents and for each respondent, there are up to 24 observations for each outcome; resulting in more than 345,000 observations for the full sample.

In order to investigate the potential change in insurance coverage status of individuals upon turning 65, we focus on four binary variables representing coverage in a given month. These are whether the respondent is covered under any type of medical insurance plan (private or public); whether the respondent is covered under a private insurance plan; whether the

[9] Since information on the exact birth date is not available, it is not possible to determine the exact date of turning 65 for each respondent. Therefore, it is impossible to determine the treatment status of a respondent for the month that she turns 65. In order to address this problem, we exclude the month that each respondent turns 65 from the sample

respondent is covered under a public insurance plan; and whether the respondent is covered under Medicare. In Table 1, we provide the summary statistics for these variables. Approximately 92% of the sample have health insurance, with those older than 65 being more likely (99%) compared with relatively younger respondents (85%). Compared to those who are older than 65, relatively younger respondents are also more likely to have private insurance (71% vs. 57%) but less likely to be covered under a publicly provided insurance plan (23% vs. 97%). Approximately 49% of the sample is covered by Medicare, with those older than 65 are much more likely (94%) compared with the rest of the sample (11%).

For our analysis of the impact of Medicare on medical service utilization and spending, we used HC's medical event data that consist of event-level records. The event file contains characteristics (time, care type, diagnosis code, etc.) associated with each event and imputed expenditure data. The MEPS reports detailed information on different types of health care utilization events, including based visits, outpatient visits, hospital inpatient stays, and emergency department visits. Emergency department visits are services related to emergency care, regardless of the ability to pay. Office-based visits include non-emergency medical care that occurs in a variety of settings such as doctors' offices, medical centers, and laboratories or x-ray facilities. Outpatient visits refer to all visits at a hospital, clinic, or associated facility for diagnosis or treatment. Outpatient and office-based visit events data both contain information of care category for each visit, such as a routine checkup, diagnosis/treatment, mental health counseling, etc. Using these variables, we analyze these services by treatment category to understand how Medicare impacts the use of preventive or acute care. Due to the similarity between office-based visits and outpatient visits, we group these two into one category. Inpatient care comprises of medical treatment that being provided in a hospital or other facility and requires at least one overnight stay. Although Medicare does not provide any dental benefits, we use HC's dental visit event files in our robustness checks. [10]

With the availability of the event files, the MEPS is well-suited for our analysis that utilizes a regression discontinuity design. We can track the respondents' coverage, health care utilization, and expenditure for each month rather than the aggregated number for the entire year. We reconstruct data by grouping the utilization and cost of each event into the person-month level. Specifically, for each person-month observation, we created a set of variables that include a binary indicator of health care utilization at a given month, the number of medical visits per month, length of hospital stays (for inpatient visits), total expenditures for each type of care, and out-of-pocket cost for each service.

Inpatient stays are slightly different from other medical events to the extent that one event record can last multiple days or months. Furthermore, we have a smaller sample size for inpatient stays. Until 2012, the MEPS reported the beginning and ending date of each hospital stay (including day, month, and year). Based on this information, we were able to compute the exact number of days in each month that an individual had stayed in a hospital. If the individual reports multiple inpatients stay at a given month or if the stay spans to multiple months, we calculate the total amount of expenditures and out of pocket costs based on the total number of stays at a given month.[11] Starting from 2013, the MEPS only reports the month and year of inpatient stays' beginning date and ending date. Without information on the exact day, we do not have enough information to calculate the length of stay and. Alternatively, if the stay spans

[10] The MEPS also contains information on prescribed medicines, and other medical expenses. However, date of utilization at the month level is not available for these services. Therefore, we cannot use them in our analysis
[11] For instance, if a patient reports two separate stays within the same month, we add up the spending from each stay in order to find the total spending in that particular month. Alternatively, if the stay spans multiple months, we calculate the spending for each month based on the number of days of stay for each particular month.

multiple months, we calculate the spending for each month based on the number of days of stay for each particular month and expenditure associated with it. Thus, our analysis of inpatient stays uses data from 1996 to 2012.

Table1. 2 reports the summary statistics for the health care utilization and expenditure variables. On average, approximately 36% of those younger than 65 have either an office-based physician visit or outpatient visits in a given month, 1.3% have an inpatient stay, and 1.4% have an emergency visit. On the other hand, those who are older than 65 are slightly more likely to use medical services. The average total payment and out-of-pocket costs for both groups are relatively similar. For the full sample, the average out-of-pocket cost is $22.6 for office visits ($68.3 for those with at least one visit), $6 for inpatient stays ($505.2 for those with at least one visit), and $1.2 for emergency room visits ($93 for those with at least one visit).

1.4. Methodology

Our identification strategy relies on the assumption that those who are slightly younger or older than 65 have very similar observable and unobservable characteristics. However, we expect that due to the eligibility criteria for Medicare, compared to those who are slightly older than 65, those who are slightly younger than 65 are less likely to be covered under a health insurance plan. Since individuals have no control over their age, the age-based cutoff for Medicare creates an exogenous variation in health insurance coverage status at age 65. We exploit this variation and use a RD design to estimate the relationship between access to Medicare and health care utilization and expenses. [12] In particular, we estimate the following RD model, which shows the effect of turning 65 on health insurance coverage status:

[12] Imbens and Lemieux (2008), Porter (2003), and Lee and Lemieux (2009) present a detailed discussion of the RD design and related issues.

$$Y_i = \beta_1' X_i + \alpha_1 Age65_i + f(age_i) + \epsilon_i \quad (1)$$

In this equation, Y_i is one of the outcome variables such as health insurance coverage status, health care utilization, or health care expenses. The individual-specific control variables are denoted by X_i and include family size, income as a percentage of the poverty line, and dummy variables for gender, race, educational attainment, and marital and employment status. The binary treatment variable is denoted by $Age65_i$ and is equal to 1 if the respondent is at least 65 years old in a given month and 0 otherwise. The coefficient of interest, α_i, is the estimated effect of turning 65 and becoming eligible for Medicare on the outcome variables. A smooth function of age profile is the forcing variable in the context of the RD design. Since information on the birth month and year of each respondent is available in the MEPS, it is possible to calculate the difference between the date of the actual outcome and the respondent's 65th birthday in months. Therefore, for each respondent, the variable age_i represents the number of months before or after the 65th birthday. Modeling the smooth function of the forcing variable correctly is one of the main problems in implementing the RD design. To test the robustness of our results under alternative parametric model specifications, we estimate several different models that contain the first, second, or third-order polynomial of age_i which is also fully interacted with the treatment variable. The age profile for alternative parametric models with different degrees of polynomials can be expressed as:

$$f(age_i) = \sum_{j=1}^{k} \delta_j age_i^j + \sum_{j=1}^{k} \lambda_j \left(Age65_i \times age_i^j\right) \; for \; k = \{1,2,3\} \quad (2)$$

For the empirical analysis, we restrict the data from the MEPS to all observations in which the respondent is up to 36 months (3 years) younger or older than the cutoff age of 65. Since the RD estimates may be sensitive to the selection of this bandwidth, we report results for alternative choices of bandwidths, i.e.,$|age_i| \leq 24\ (2\ years)$ and $|age_i| \leq 12\ (1 years)$. In all models, we exclude the month that each respondent turns 65 from the sample ($age_i = 0$). [13] We use the sample weights as reported in the MEPS and cluster standard errors by the forcing variable, which is age in months. We also estimate separate models for different demographic groups, and medical visits due to different clinical conditions.

It is also possible to estimate equation (1) using non-parametric estimators. For these models, following Hahn, Todd, and van der Klaauw (2001) and Porter (2003), we use local linear regressions to estimate the left and right limits of discontinuity at age 65. In all non-parametric models, we use mean squared error (MSE) optimal bandwidth selection procedure to determine the optimal bandwidth as discussed in Calonico, et al. (2017).

The identifying assumption in our RD models is that at age 65, the change in the insurance coverage status should be solely due to the age based cutoff and other observable and unobservable characteristics of respondents that may affect insurance coverage should not exhibit a discrete change around the 65th birthday. A potential problem with this assumption is that 65 is the traditional age for retirement and it is possible that employment status exhibits a discrete change at this age cutoff. Card, Dobkin, and Maestas (2008) and Barcellos and Jacobson (2015) demonstrate that changes in employment status at age 65 are small in magnitude and statistically insignificant in the MEPS, NHIS, and March Current Population Survey (CPS). The smoothness of employment status and other individual-level covariates around the cutoff age can also be partially tested with our data. Estimating an RD model that controls for the second or third order polynomial of age that is fully interacted with the treatment variable, we find that

[13] Since the MEPS does not report the exact birth date of the respondents, it is not possible to determine to treatment status for these individuals.

employment status does not exhibit a discrete change at age 65. [14] In appendix Figure 1.1, we also plot the 30-day averages of all control variables around the 65th birthday. The figures show that control variables vary smoothly around the 65th birthday. Therefore, we expect that they have minimal effect on the estimates of the discontinuity and serve mainly to increase the precision of our estimates. The main results that we present in the next section also show that the inclusion of control variables to our models have virtually no effect on our estimates.

Another possible concern to identification comes from the possibility of non-random sorting of respondents to either side of the cutoff. Appendix Figure 1.2 shows the distribution of observations around the age-65 cutoff. Overall, the distribution of the frequency of observations is smooth across the cutoff age, and hence, there is no evidence of nonrandom sorting around age 65 in our sample.

1.5. Results

1.5.1. Health insurance coverage

In Table 1.3, we report the RD estimates of the change in health insurance coverage status at age 65 under alternative parametric and non-parametric models and bandwidth choices. The estimates suggest that the probability of being covered under any health insurance plan goes up by 7.1 to 13.1 percentage point at the 65th birthday. This effect is highly significant, slightly smaller but comparable to that estimated by Barcellos and Jacobson (2015), and mainly driven by those who become eligible for Medicare at age 65. In particular, under alternative specifications, we find that at age 65, the probability of being covered under Medicare goes up

[14] The results are robust to the selection of alternative age bandwidths of such as 1, 2, or 3 years. These results are available from authors upon request

by 61 to 76 percentage points. [15] Not surprisingly, the probability of being covered under a private insurance plan goes down significantly at age 65. Furthermore, consistent with earlier findings, our results indicate a sharp increase (41 to 49 percentage points) in having multiple forms of insurance coverage at age 65. Figure 1.1 illustrates these findings. In each figure, we plot the mean of the outcome variables (the probability of being covered under alternative insurance plans) for one-month intervals three years before and after the 65th birthday. The solid lines are the first and second-order polynomials fitted on individual observations on both sides of the age-65 cutoff, as reported in the first two specifications of Table 1.3 for an age bandwidth of 36 months. Panels A, B, D, and E of Figure 1.1 clearly show the discrete jump in health insurance coverage rates at age 65 for those who are covered under any insurance plan, publicly provided plan, or Medicare.

Card, Dobkin, and Maestas (2008) document significant differences for health insurance coverage and the effect of access to Medicare on different demographic groups. There is also extensive literature that documents that individuals that belong to different demographic groups differ in their attitudes towards risk.[16] These differences may also affect health care decisions. To investigate the impact of the access to Medicare at age 65 on alternative demographic groups, we estimate parametric RD models for different types of insurance coverage status using a quadratic polynomial of the forcing variable that is also fully interacted with the treatment variable. The results reported in Table 4 shows that the discrete jump in Medicare coverage rates at age 65 remains highly significant for all demographic groups. Medicare takes up at age 65 is more

[15] Barcellos and Jacobson (2015) do not report the change in Medicare coverage rate at age 65. However, our estimates are comparable with Card, Dobkin, and Maestas (2008) who find that Medicare coverage rises by 60 percentage points at age 65.
[16] 1See, for example, Booth and Nolen (2012) and Powell and Ansic (1997)

pronounced for females. Similarly, compared with blacks and Hispanics, the increase in the Medicare coverage rate among whites is considerably larger. This pattern reflects the fact that Medicare enrollment before 65 due to the DI is higher for minorities and people with below-average schooling (Autor and Duggan, 2003). These groups experience relatively smaller gains at age 65. One would also expect that Medicare eligibility is less likely to affect insurance coverage rates of those who are employed since they are more likely to be covered under their employer-provided health insurance plan and may be less likely to immediately claim Medicare as a supplemental insurance. Our results show that compared with retired respondents, an increase in Medicare coverage rates among those who are employed are in fact 15.4 percentage points lower. The MEPS has detailed information on income and categorizes individuals into one of the five income groups: the poor (100% or less of the federal poverty level, i.e., FPL), the near-poor (100 124% of the FPL), low income (125 199% of the FPL), middle income (200 399% of FPL), and high income (400% or more of FPL). Table 1.4 shows that compared to the poor and near-poor, the increase in Medicare coverage rate at age 65 among the middle and high-income groups is larger. This is not surprising since lower-income individuals may already be eligible for other types of publicly provided insurance such as Medicaid or Medicare, due to DI and, therefore, experience relatively smaller gains at age 65. Overall, our estimates for the effects of the Medicare eligibility on health insurance coverage rates are consistent with Card, Dobkin, and Maestas (2008). Many of those who lacked health insurance prior to 65 obtain coverage, equalizing coverage rates across different demographic groups. We also document a significant increase in multiple coverages, particularly among whites, retired, and married respondents.

1.5.2. Health care utilization and expenditure

1.5.2.1. Office and outpatient visits

We first investigate the impact of the eligibility for Medicare at age 65 on office and outpatient visits and related costs and report our results in Table 1.5 and Figure 1.2. The probability of an office or outpatient visit goes up by 1.2 to 2.7 percentage points at age 65. This effect remains statistically significant under alternative model specifications and robust to bandwidth selection. This effect also corresponds to a 3.3 to 7.5 percent increase from the average utilization before age 65.[17] We find a similar effect on the number of visits at a given month. Our estimates suggest that Medicare eligibility at age 65 is associated with a 0.03 to 0.09 times more office or outpatient visits per month (3.3 to 11.5 percent increase compared to pre-age-65 mean). Our estimates for the effect of the Medicare eligibility on total payments for office visits are small in magnitude, mixed in sign, and in general, not statistically significant. Although one may expect an increase in total payments due to an increase in health care consumption at age 65, our results may be explained by Medicare's significant market power and ability to pay significantly lower prices (Clemens and Gottlieb, 2017). A significant decrease in total payments for Medicare beneficiaries due to Medicare's bargaining power may be balancing out the increase in total payments due to the increased health care consumption. On the other hand, our results show that the eligibility for Medicare at age 65 is associated with $7.5 to $12.4 per month

[17] Using the estimates of the discontinuity in health insurance coverage rates at age 65, it is also possible to estimate the direct impact of the Medicare coverage status on health care utilization. This is essentially an instrumental variables (IV) method that relies on using the discrete change in the probability of having Medicare at age 65 as an instrument for the Medicare coverage status in the first stage. In this context, the IV estimate is actually the ratio of the discontinuity in a particular outcome at age 65 to the discontinuity in the probability of having Medicare at the same age cutoff. Using our estimates from the model that uses a two year age bandwidth and contains a quadratic polynomial of age, we find that those who were covered under Medicare are 3.5 percentage point higher probability of having an office or outpatient visit than those who are not covered by a health insurance. However, since the sample sizes for Medicare coverage and office and outpatient visit outcomes are slightly different, this estimate is quite similar but not precisely the same as the IV estimate.

decrease in out-of-pocket spending (25 to 40 percent decrease compared to pre-age-65 mean). This effect is consistent with Barcellos and Jacobson (2015), who find a 33 percent drop in out-of-pocket medical spending for all types of health care consumption at age 65.

In Table 1.6, we report the effect of the Medicare eligibility on office and outpatient visits and related costs for different demographic groups. The discrete jump in both the probability and the number of visits remains significant for all groups, except for males, blacks, and retired. Compared to other groups, Hispanics are more likely to have a routine physician or outpatient visit when they turn 65. These results are in line with our earlier findings reported in Table 1.4, which show that Hispanics are less likely to have insurance before they turn 65, and compared with females and whites, an increase in Medicare coverage rates at 65 among males and blacks are relatively small. Although Medicare enrollment rates at age 65 among those who are retired are higher than those who are not retired, those who are not retired are more likely to visit a physician when they turn 65. This is consistent with our previous results, which show that compared to those who are not retired, retired people are more likely to be covered under an insurance plan before they turn 65. For the majority of the retired people, Medicare becomes a supplemental insurance at age 65, which significantly decreases the out-of-pocket costs but does not have a significant impact on the number of visits. The MEPS also contains information on different categories of care types for each office or outpatient visit.[18] Among others, the most popular reasons for an office or outpatient visit are checkup, diagnosis and treatment, and mental health counseling. We estimate separate RD models for these care types and report results in

[18] For each particular visit, the MEPS reports the information on "the best category for care patient received on visit". The possible answers are: general checkup, diagnosis and treatment, emergency, psychotherapy/mental health counseling, follow-up or post-operative visit, immunizations or shots, vision exam, pregnancy-related, and well child exam, laser eye surgery.

Appendix Table 1.1. Our results indicate that the increase in the probability and number of office and outpatient visits at age 65 is mainly due to the visits for diagnosis and treatment.

1.5.2.3. Emergency Department visits

Table 1.7 and Figure 1.3 show that emergency department visits and associated medical spending do not exhibit discrete change at age 65. In particular, our results imply a null and statistically insignificant effect of turning 65 on the probability and total number of emergency department visits. The effects for total and out-of-pocket spending for emergency department visits are mostly negative and statistically significant under certain specifications. However, this effect is not consistent and sensitive to bandwidth selection and model specification.

1.5.2.3. Inpatient visits

Table 1.9 and Figure 1.4 show that the discrete change in health insurance coverage at the 65^{th} birthday does not have a statistically significant impact on inpatient visits. Similarly, the results for the number of visits, length of stay, total payments, and out-of-pocket costs are mostly insignificant and the sign and the magnitude of the estimates for these outcomes are not robust under alternative specifications.

It is possible that those who are about to turn 65 delay medical care and related spending until they reach the cutoff age and become eligible for Medicare. This can generate a discrete jump in reported levels of health care utilization at age 65 even there is no true change in actual behavior. In order to investigate this possibility, we compare health care utilization of those who are about to turn 65 with those who are about to turn 64 or 66. One could expect that compared with those who are slightly younger than 64 or 66, those who are slightly younger than 65 would be less likely to use medical care since the Medicare eligibility should not affect the insurance coverage rates around these alternative age cutoffs. However, Appendix Figure 1.3 shows that the probability of using alternative medical care services up to six months before the 64th, 65th, and 66th birthdays exhibit similar trends. Therefore, there is no evidence that individuals anticipate the effects of the Medicare and significantly alter their health care consumption just before their 65th birthday. We also consider an additional falsification exercise to test the plausibility of our results. Medicare does not include any provisions for dental care. Therefore, we expect that gaining access to Medicare at age 65 should not have any meaningful impact on dental care use or associated costs. The results reported in Appendix Table 1.5 show that this is indeed the case and Medicare eligibility at age 65 does not lead to a discrete change in dental visits and related costs.

1.5.3. Additional results and sensitivity tests.

1.5.3.1. Sample of non-insured under 65 versus always insured under 65

We document a sharp increase in the probability of having multiple insurances at age 65 by 13 percent. This result implies that many people had already been covered under an insurance plan before they were eligible for Medicare. Appendix Table 1.1 shows the summary statistics of the characteristic of the two samples. We can see that the group of uninsured are less likely to be white, more likely to be Hispanic. They are also less educated, less likely to be married, and low income than the insured group.

How does Medicare eligibility affect the health care consumption of these people compared to those who did not have any type of health insurance before age 65? To investigate the question, we restrict our sample to those who are at most one year younger and older than 65 and estimate separate models for those who were not covered under any type of insurance plan before they turn 65 and became eligible for Medicare and those who were continuously covered under at least one insurance plan before they became eligible for Medicare[19]. The results reported in Table 1.11 shows an interesting pattern and indicate that the discrete jump in routine physician and outpatient visits at age 65 is almost entirely due to those who were not insured before age 65. For this group, the probability of an office or outpatient visit goes up by 5.6 to 12 percentage point at the cut-off age (26 to 55 percent increase compared to pre age-65 mean). Similarly, we find significant and relatively large effects on the number of office visits for this group. In contrast to our findings for the full sample, the considerable increase in office and outpatient visits for this group leads to a significant increase in total payments that jump up to 274 percent at age 65 compared to pre age-65 mean. However, we should be cautious when interpreting the estimation of it as the causal impact of having health insurance among users with no insurance before turning age 65. That is because of the self-selection problem we discussed in section 2.2. Seniors aged over 65 can self-select to the Medigap and Medicare Part B program, thus lead to an overestimation in the causal impact of health insurance on medical service used.

1.5.3.2. Utilization by conditions

The event files of the MEPS contain information on the clinical codes of each particular visit. These codes precisely identify the diagnosis for each patient. In this section, we investigate the effect of the change in Medicare take up at age 65 on health care utilization for selected chronic conditions that are highly prevalent among the elderly such as diabetes, hypertension, and heart disease. We estimate parametric RD models for different types of diagnosis types using a quadratic polynomial of the forcing variable that is also fully interacted with the treatment variable and report our results in Table 1.12. Our results for alternative diagnosis types are in line

[19] The Appendix Table 1.1 report the summary statistics for the demographic characteristics of sample of insured under 65 and sample of uninsured under 65. The former group is more likely to be white, higher educated, high income, and married then the later group.

with the main results and indicate that Medicare eligibility at age 65 is mainly associated with non-urgent health care. We find significant increases in office or outpatient visits due to diabetes or hypertension at age 65. Under certain model specifications, inpatient visits due to diabetes also exhibit a small but statistically significant increase at age 65. However, we find no discrete change in health care utilization due to heart disease at the cutoff age. We already showed that our results are robust under parametric and non-parametric specifications and the selection of alternative age bandwidths.

1.5.3.3. Sensitivity check for the possibility of delay in care before Medicare eligibility

Another possible concern for the validity of our results is that those who are about to turn 65 may delay medical care and related spending until they reach the cut off age and become eligible for Medicare. That can generate a discrete jump in reported levels of health care utilization at age 6, although there is no true change in actual behavior. Since we have documented significant impacts of Medicare eligibility on office and outpatient visits and associated out-of-pocket costs, we further investigate the possibility of delaying medical care until turning 65 for these outcomes using a donut RD design, in which we exclude observations for three months before and after the cutoff age of 65 from our sample. The results reported in Appendix Table 1.3 shows that the estimates from the donut RD analysis are slightly larger, but comparable to those reported in Table 1.5. We also consider an additional falsification exercise to test the plausibility of our results. Medicare does not include any provisions for dental care. Therefore, we expect that gaining access to Medicare at age 65 should not have any meaningful impact on dental care use or associated costs. The results reported in Appendix Table 1.5 indicates that this is indeed the case and Medicare eligibility at age 65 does not lead to a discrete change in dental visits and related costs

In order to investigate this possibility, we compare health care utilization of those who are about to turn 65 with those who are about to turn 64 or 66. If those are slightly younger than 65 were delaying medical care, one would expect that compared with those who are slightly younger than 64 or 66, those who are slightly younger than 65 should be less likely to use medical care since the Medicare eligibility should not affect the insurance coverage rates around these alternative age cut off. However, Appendix Figure 1.3 shows that the probability of using alternative medical care services up to six months before the 64th, 65th, and 66th birthdays exhibit similar trends. Therefore, there is no evidence that individuals anticipate the effects of Medicare and significantly alter their health care consumption just before their 65th birthday.

1.6. Conclusion

Understanding more about health care consumption and spending due to changes in health insurance coverage status is essential to evaluate public policies that are aimed at increasing access to health care. Using detailed person-month level data from the MEPS and a RD design, this paper evaluates the impact of the Medicare eligibility on health insurance coverage rates, health care utilization, and spending among the elderly. We show that the onset of Medicare eligibility at age 65 leads to sharp increases in the health insurance coverage rates of the U.S. population. That leads to significant and sizable increases in both the probability and intensity of routine physician and outpatient visits without having any significant impact on inpatient and emergency department visits. Furthermore, the increase in office and outpatient visits are driven by those who were not covered under any insurance plan before they become eligible for Medicare at age 65. Our analysis of the event files that contain information on clinical codes and diagnosis types for each visit shows that the increase in the probability and number of office and outpatient visits at age 65 is mainly due to the visits for diagnosis and treatment of diabetes or hypertension. In this paper, we provide the first estimates of the effect of Medicare eligibility on certain outcomes, such as the intensity of health care visits and length of inpatient stays. On the other hand, for the remaining outcomes, our estimates are not directly comparable to previous studies since we estimate the effects of the Medicare eligibility at the person-month level rather than the person-year level. Nevertheless, a brief comparison may prove to be useful. In contrast to Barcellos and Jacobson (2015), who find that the likelihood of a physician visit or an outpatient hospital visit is essentially unchanged at age 65, we find that the probability of an office or outpatient visit goes up by 1.2 to 2.7 percentage points at age 65. Our estimate for this outcome is comparable to Lichtenberg (2002) and Card, Dobkin, and Maestas (2008) who find that the probability of visiting a doctor's office last year goes up by 1.3 percentage points. Our result that the Medicare eligibility does not have a significant impact on inpatient stays at age 65 is in line with Barcellos and Jacobson (2015) but in contrast with Card, Dobkin, and Maestas (2008), who find that the probability of a hospital stay in the last year increases by 1.2 percentage points at age 65. Barcellos and Jacobson (2015) find a 33 to 35 percent drop in both total and out-of-pocket annual health care spending (relative to the pre-65 mean) at age 65. Although our results for total spending is mixed and often insignificant, we find that Medicare eligibility is associated with a 25 to 40 percent decrease in out-of-pocket spending for office and outpatient visits relative to the pre-65 mean. On the other hand, our estimates for the effect of the Medicare eligibility of total spending and out-of-pocket costs for inpatient stays and emergency department visits are small and insignificant. Our analysis of the effects of Medicare eligibility on different demographic groups is mostly in line with Card, Dobkin, and Maestas (2008). We document that many of those who lacked health insurance before 65 obtain coverage, equalizing coverage rates across different demographic groups. We also find a significant increase in multiple coverages at the Medicare eligibility age, particularly among whites, retired, and married respondents. On the other hand, relative to other demographic groups, routine doctor visits increase more for minorities who are more likely to lack insurance before age 65. Due to the nature of the RD design, the findings of this paper represent the short-run effects of Medicare eligibility among the elderly. The short-run effects may be different than the long-run effects since individuals may shift the timing of health care visits across the age 65 threshold. In particular, individuals may be more likely to delay health care consumption until they become eligible for Medicare at age 65. However, we find no evidence that people anticipate the effects of Medicare and significantly alter their health care consumption just before their 65th birthday. Furthermore, previous literature also documents that there is little evidence that individuals shift the timing of health care visits in anticipation of gaining or losing insurance coverage. Since all RD designs estimate local treatment effects, the results of this paper apply to individuals close to their 65th birthday and cannot be generalized to the whole population. However, our results are important for policymakers because several recent proposals involve increasing the Medicare eligibility age to address the increasing costs of the Medicare program. Our findings indicate that those who just turn 65 would face a substantial decline in insurance coverage and an increase in out-of-pocket.

Table 1.1. Sample statistics: Health insurance coverage

	Full sample	62-64 year olds	65-67 year olds
Any insurance	0.917	0.853	0.992
	(0.275)	(0.354)	(0.089)
Medicare	0.493	0.108	0.938
	(0.500)	(0.311)	(0.242)
Private insurance	0.643	0.711	0.565
	(0.479)	(0.453)	(0.496)
Public insurance	0.571	0.228	0.968
	(0.495)	(0.420)	(0.177)
Two or more health insurance	0.333	0.089	0.615
	(0.471)	(0.285)	(0.487)
No. of. obs.	341,060	180,733	160,327

Notes: Sample weighted means are reported. Standard deviations are reported. 62-64 years include those who are up to 36 months younger than the 65th birthday. 65-67 years include those who are up to 36 months older than the 65th birthday. The month that the respondent turns 65 is excluded from the sample.

Table 1.2. Sample statistics: Health care utilization

	Prob. of visit	No. of visits	LOS	Total payment	Out-of-pocket cost
Full sample					
Office and Outpatient	0.377	0.830		218.071	25.756
	(0.485)	(1.778)		1217.499	(201.912)
Inpatient	0.014	0.016	0.071	200.416	5.826
	(0.119)	(0.136)	(0.924)	(2801.091)	(324.312)
Emergency	0.015	0.017		17.572	1.378
	(0.121)	(0.144)		(403.634)	(48.271)
62-64 year olds					
Office and Outpatient	0.359	0.774		221.010	30.654
	(0.480)	(1.690)		(1,357.000)	(197.102)
Inpatient	0.013	0.015	0.065	206.980	8.279
	(0.115)	(0.129)	(0.877)	(3104.691)	(421.404)
Emergency	0.014	0.016		20.293	1.966
	(0.119)	(0.140)		(490.918)	(60.094)
65-67 year olds					
Office and Outpatient	0.398	0.895		214.678	20.100
	(0.489)	(1.873)		(1,033.275)	(207.183)
Inpatient	0.016	0.017	0.078	192.763	2.965
	(0.124)	(0.143)	(0.984)	(2399.075)	(144.037)
Emergency	0.015	0.017		14.431	0.700
	(0.123)	(0.147)		(269.737)	(29.155)

Notes: Sample weighted means are reported. Standard deviations are reported. 62-64 years include those who are up to 36 months younger than the 65^{th} birthday. 65-67 years include those who are up to 36 months older than the 65^{th} birthday. LOS denotes the length of inpatient stay in a given month in days. Number of observations for the full sample is 341,524. Number of observations for 62-64 years old is 180,947. Number of observations for 65-67 year olds is160,577.

Table 1.3. RD estimates of change in health insurance coverage at age 65

	Any insurance		Medicare		Private insurance		Public Insurance		Having two or more	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(7)	(8)
Bandwidth=36 months										
Parametric (Linear)	0.131***	0.131***	0.756***	0.758***	-0.105***	-0.108***	0.627***	0.630***	0.488***	0.490***
	(0.005)	(0.005)	(0.008)	(0.008)	(0.002)	(0.002)	(0.031)	(0.032)	(0.005)	(0.005)
Parametric (Quadratic)	0.117***	0.116***	0.709***	0.712***	-0.089***	-0.093***	0.521***	0.524***	0.461***	0.462***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.003)	(0.003)	(0.040)	(0.040)	(0.006)	(0.005)
Parametric (Cubic)	0.097***	0.098***	0.679***	0.685***	-0.093***	-0.092***	0.416***	0.419***	0.438***	0.441***
	(0.006)	(0.006)	(0.007)	(0.008)	(0.003)	(0.003)	(0.031)	(0.032)	(0.005)	(0.005)
Mean pre-65	0.851	0.853	0.108	0.108	0.710	0.711	0.229	0.228	0.089	0.090
No. of obs.	345,474	341,060	345,474	341,060	345,474	341,060	345,474	341,060	116,648	341,060
Bandwidth=24 months										
Parametric (Linear)	0.126***	0.125***	0.733***	0.736***	-0.096***	-0.099***	0.579***	0.583***	0.476***	0.477***
	(0.006)	(0.006)	(0.009)	(0.008)	(0.002)	(0.002)	(0.038)	(0.038)	(0.006)	(0.006)
Parametric (Quadratic)	0.101***	0.101***	0.687***	0.692***	-0.093***	-0.093***	0.446***	0.449***	0.442***	0.445***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.004)	(0.003)	(0.035)	(0.036)	(0.005)	(0.005)
Parametric (Cubic)	0.086***	0.087***	0.672***	0.676***	-0.089***	-0.087***	0.344***	0.346***	0.433***	0.437***
	(0.004)	(0.004)	(0.009)	(0.009)	(0.003)	(0.003)	(0.015)	(0.015)	(0.005)	(0.006)
Mean	0.852	0.853	0.116	0.116	0.704	0.706	0.247	0.246	0.094	0.094
No. of obs.	231,383	228,454	231,383	228,454	231,383	228,454	231,383	228,454	116,648	228,454
Bandwidth=12 months										
Parametric (Linear)	0.106***	0.106***	0.699***	0.703***	-0.092***	-0.092***	0.466***	0.469***	0.451***	0.454***
	(0.006)	(0.007)	(0.009)	(0.009)	(0.003)	(0.003)	(0.037)	(0.037)	(0.005)	(0.005)
Parametric (Quadratic)	0.083***	0.082***	0.671***	0.675***	-0.091***	-0.092***	0.334***	0.337***	0.435***	0.439***
	(0.003)	(0.003)	(0.010)	(0.010)	(0.004)	(0.004)	(0.010)	(0.011)	(0.006)	(0.007)
Parametric (Cubic)	0.072***	0.071***	0.643***	0.647***	-0.083***	-0.085***	0.290***	0.292***	0.422***	0.424***
	(0.001)	(0.001)	(0.008)	(0.008)	(0.004)	(0.004)	(0.006)	(0.005)	(0.007)	(0.007)

Mean	0.855	0.856	0.133	0.132	0.698	0.700	0.288	0.287	0.102	0.102
No. of obs.	116,648	115,174	116,648	115,174	116,648	115,174	116,648	115,174	116,648	115,174
Non-parametric	0.088***		0.609***		-0.062***		0.295***		0.411***	
	(0.001)		(0.011)		(0.011)		(0.005)		(0.007)	
	44,627		93,969		201,212		44,627		103,798	
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: In all models, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The means of the variables are reported for those who are younger than 65. The sign *** denotes the statistical significance at 1 percent level.

Table 1.4. RD estimates of change in health insurance coverage at age 65: Alternative samples

	Any insurance	Medicare	Private insurance	Public insurance	Two or more insurance
Female	0.115***	0.718***	-0.082***	0.392***	0.455***
	(0.008)	(0.007)	(0.003)	(0.041)	(0.004)
No. of obs.	123,939	123,939	123,939	123,939	123,939
Male	0.086***	0.663***	-0.106***	0.510***	0.434***
	(0.004)	(0.010)	(0.004)	(0.030)	(0.008)
No. of obs.	104,515	104,515	104,515	104,515	104,515
White	0.093***	0.733***	-0.110***	0.474***	0.477***
	(0.005)	(0.008)	(0.004)	(0.038)	(0.005)
No. of obs.	142,560	142,560	142,560	142,560	142,560
Hispanic	0.191***	0.563***	-0.062***	0.363***	0.284***
	(0.018)	(0.016)	(0.018)	(0.037)	(0.008)
No. of obs.	33,120	33,120	33,120	33,120	33,120
Black	0.095***	0.527***	-0.025***	0.354***	0.352***
	(0.006)	(0.005)	(0.006)	(0.023)	(0.006)
No. of obs.	37,746	37,746	37,746	37,746	37,746
Retired	0.093***	0.788***	-0.094***	0.461***	0.532***
	(0.006)	(0.008)	(0.005)	(0.035)	(0.006)
No. of obs.	80,086	80,086	80,086	80,086	80,086
Not retired	0.105***	0.634***	-0.096***	0.437***	0.389***
	(0.006)	(0.009)	(0.005)	(0.035)	(0.007)
No. of obs.	146,085	146,085	146,085	146,085	146,085
Married	0.064***	0.721***	-0.112***	0.421***	0.479***
	(0.007)	(0.008)	(0.004)	(0.045)	(0.006)
No. of obs.	145,369	145,369	145,369	145,369	145,369
Poor/near poor	0.157***	0.576***	-0.081***	0.350***	0.292***
	(0.006)	(0.007)	(0.008)	(0.023)	(0.004)
No. of obs.	75,863	75,863	75,863	75,863	75,863
Middle/high income	0.084***	0.729***	-0.098***	0.481***	0.494***
	(0.006)	(0.009)	(0.003)	(0.040)	(0.007)
No. of obs.	152,591	152,591	152,591	152,591	152,591

Notes: Estimates from parametric RD models with an age bandwidth of two years are reported. All models contain a quadratic polynomial of the forcing variable that is also fully interacted with the treatment variable. All models contain a set of control variables, as discussed in the text. In all regressions, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The sign *** denotes statistical significance at 1 percent level.

Table 1.5. RD estimates of change in office and outpatient visits at age 65

	Prob. of visit		No. of visits		Total payment		Out of pocket cost	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bandwidth=36 months								
Parametric (Linear)	0.013***	0.012***	0.028**	0.028**	-21.103**	-21.904**	-10.419***	-10.514***
	(0.003)	(0.003)	(0.012)	(0.012)	(9.673)	(9.926)	(2.206)	(2.223)
Parametric (Quadratic)	0.026***	0.024***	0.064***	0.055***	-14.292	-17.703	-7.523***	-7.699***
	(0.004)	(0.004)	(0.013)	(0.013)	(12.451)	(12.337)	(2.555)	(2.586)
Parametric (Cubic)	0.027***	0.027***	0.091***	0.093***	11.036	10.859	-12.431**	-12.392**
	(0.006)	(0.006)	(0.016)	(0.016)	(15.769)	(16.016)	(4.894)	(4.937)
Pre-65 Mean	0.358	0.359	0.772	0.774	220.240	221.010	30.552	30.654
No. of obs.	345,993	341,524	345,993	341,524	345,993	341,524	345,993	341,524
Bandwidth=24 months								
Parametric (Linear)	0.022***	0.020***	0.056***	0.050***	-16.371	-19.853*	-9.569***	-9.739***
	(0.004)	(0.004)	(0.012)	(0.012)	(11.418)	(11.171)	(2.087)	(2.109)
Parametric (Quadratic)	0.025***	0.024***	0.068***	0.067***	0.299	-1.667	-11.098**	-11.084**
	(0.006)	(0.006)	(0.013)	(0.013)	(15.164)	(15.200)	(4.338)	(4.399)
Parametric (Cubic)	0.014**	0.015**	0.074***	0.077***	10.828	11.007	-3.222	-3.138
	(0.006)	(0.007)	(0.018)	(0.020)	(16.568)	(16.433)	(4.566)	(4.656)
Pre-65 Mean	0.361	0.362	0.786	0.788	226.3955	227.126	30.372	30.479
No. of obs.	231,739	228,761	231,739	228,761	231,739	228,761	231,739	228,761
Bandwidth=12 months								
Parametric (Linear)	0.022***	0.021***	0.077***	0.076***	-0.591	-1.871	-7.609**	-7.618**
	(0.004)	(0.004)	(0.014)	(0.014)	(11.514)	(11.468)	(3.217)	(3.244)
Parametric (Quadratic)	0.022***	0.024***	0.066***	0.067***	19.546	19.746	-3.452	-3.403
	(0.007)	(0.007)	(0.022)	(0.022)	(17.343)	(17.252)	(4.204)	(4.296)
Parametric (Cubic)	0.014**	0.017**	0.019	0.017	-35.240	-36.270	-7.705	-7.875
	(0.006)	(0.006)	(0.031)	(0.031)	(27.435)	(27.460)	(6.111)	(6.323)

Pre-65 Mean	0.360	0.361	0.781	0.783	218.155	219.212	29.919	29.972
No. of obs.	116,842	115,337	116,842	115,337	116,842	115,337	116,842	115,337
Non-parametric	0.017***		0.047***		-4.0088		-7.219***	
	(0.003)		(0.008)		(6.492)		(1.848)	
	182,916		143,710		153,500		192,706	
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: In all models, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The means of the variables are reported for those who are younger than 65. The signs *, **, and *** denote the statistical significance at 10, 5, and 1 percent levels, respectively.

Table 1.6. RD estimates of change in office and outpatient visits at age 65: Alternative samples

	Prob. of Visit	No. of visit	Total payment	Out of pocket payment
Female	0.033***	0.086***	-10.432	-12.662***
	(0.009)	(0.018)	(21.480)	(4.466)
No. of obs.	124,087	124,087	124,087	124,087
Male	0.015	0.045*	6.199	-9.353
	(0.009)	(0.025)	(25.664)	(5.864)
No. of obs.	104,674	104,674	104,674	104,674
White	0.028***	0.074***	-9.896	-12.533**
	(0.008)	(0.021)	(17.740)	(5.161)
No. of obs.	142,708	142,708	142,708	142,708
Hispanic	0.043***	0.111***	45.007*	-11.496
	(0.011)	(0.035)	(24.617)	(7.540)
No. of obs.	33,178	33,178	33,178	33,178
Black	-0.013	0.055	40.403	-7.580**
	(0.022)	(0.068)	(28.486)	(3.537)
No. of obs.	37,814	37,814	37,814	37,814
Retired	0.012	0.025	-32.067	-21.982***
	(0.014)	(0.036)	(26.106)	(7.876)
No. of obs.	80,144	80,144	80,144	80,144
Not Retired	0.029***	0.085***	15.714	-4.192
	(0.006)	(0.025)	(18.971)	(3.055)
No. of obs.	146,334	146,334	146,334	146,334
Married	0.026***	0.034*	-17.947	-11.863**
	(0.007)	(0.020)	(14.825)	(4.761)
No. of obs.	145,453	145,453	145,453	145,453
Poor/near poor	0.024***	0.030	-36.438	-3.731
	(0.008)	(0.027)	(22.435)	(2.421)
No. of obs.	76,051	76,051	76,051	76,051
Middle/high income	0.025***	0.079***	9.773	-13.592**
	(0.008)	(0.020)	(19.208)	(5.880)
No. of obs.	152,710	152,710	152,710	152,710

Notes: Estimates from parametric RD models with an age bandwidth of two years are reported. All models contain a quadratic polynomial of the forcing variable that is also fully interacted with the treatment variable. All models contain a set of control variables as discussed in the text. In all regressions, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The signs *, **, and *** denote statistical significance at 10, 5, and 1 percent levels, respectively.

Table 1.7. RD estimates of change in emergency department visits at age 65

	Prob. of visit		No. of visits		Total payment		Out of pocket cost	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bandwidth=36 months								
Parametric (Linear)	-0.0001	0.0000	0.0004	0.0005	-10.5052***	-10.630***	-1.1012***	-1.1032***
	(0.0009)	(0.0009)	(0.0010)	(0.0010)	(3.5744)	(3.624)	(0.2671)	(0.2706)
Parametric (Quadratic)	0.0004	0.0003	0.0009	0.0008	-14.0268**	-14.468**	-0.6248	-0.6373
	(0.0012)	(0.0012)	(0.0013)	(0.0013)	(5.8790)	(5.973)	(0.3811)	(0.3868)
Parametric (Cubic)	0.0013	0.0011	0.0022*	0.0020	-15.3947*	-15.960**	-0.4254	-0.4499
	(0.0015)	(0.0014)	(0.0013)	(0.0013)	(7.8798)	(7.979)	(0.4831)	(0.4904)
Pre 65 Mean	0.014	0.014	0.016	0.016	20.146	20.293	1.951	1.966
No. of obs.	345,993	341,524	345,993	341,524	345,993	341,524	345,993	341,524
Bandwidth=24 months								
Parametric (Linear)	0.0002	0.0002	0.0008	0.0009	-11.5655**	-11.8314**	-0.9129***	-0.9302***
	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(4.6328)	(4.7028)	(0.3370)	(0.3412)
Parametric (Quadratic)	0.0014	0.0012	0.0019	0.0017	-15.7805**	-16.3353**	-0.4013	-0.4127
	(0.0014)	(0.0014)	(0.0012)	(0.0012)	(7.2254)	(7.3431)	(0.4518)	(0.4607)
Parametric (Cubic)	-0.0004	-0.0006	0.0011	0.0009	-19.7414*	-20.3683*	-0.6726	-0.7006
	(0.0018)	(0.0017)	(0.0016)	(0.0016)	(10.2207)	(10.3634)	(0.5842)	(0.5924)
Pre 65 Mean	0.015	0.015	0.016	0.016	21.649	21.813	1.905	1.920
No. of obs.	231,739	228,761	231,739	228,761	231,739	228,761	231,739	228,761
Bandwidth=12 months								
Parametric (Linear)	0.0008	0.0006	0.0014	0.0013	-18.1770**	-18.8498**	-0.3821	-0.4134
	(0.0013)	(0.0013)	(0.0011)	(0.0011)	(7.2535)	(7.3824)	(0.4682)	(0.4820)
Parametric (Quadratic)	0.0000	-0.0000	0.0017	0.0017	-11.1041	-11.4725	-1.2723	-1.3001*
	(0.0019)	(0.0018)	(0.0016)	(0.0016)	(9.2074)	(9.2719)	(0.7508)	(0.7561)
Parametric (Cubic)	-0.0024	-0.0026	0.0001	0.0000	15.5767*	15.8280*	0.7291	0.7242
	(0.0029)	(0.0029)	(0.0028)	(0.0028)	(8.1682)	(8.1341)	(0.6800)	(0.6801)

Pre 65 Mean	0.014	0.014	0.016	0.016	23.559	23.742	1.810	1.824
No. of obs.	116,842	115,337	116,842	115,337	116,842	115,337	116,842	115,337
Non-parametric	0.0011*		0.0008		-7.0158***		0.1385	
	(0.0007)		(0.0007)		(2.3470)		(0.4005)	
	241,721		182,916		388,377		212,317	
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: In all models, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The means of the variables are reported for those who are younger than 65. The signs * and *** denote the statistical significance at 10 and 1 percent levels, respectively.

Table 1.8. RD estimates of change in emergency department visits at age 65: Alternative samples

	Prob. of Visit	No. of visit	Total payment	Out of pocket payment
Female	0.0036*	0.0059**	-18.9821	-0.5323
	(0.0019)	(0.0024)	(12.3195)	(0.7734)
No. of obs.	124,087	124,087	124,087	124,087
Male	-0.0016	-0.0030	-13.4050	-0.2885
	(0.0023)	(0.0027)	(12.1746)	(0.6095)
No. of obs.	104,674	104,674	104,674	104,674
White	0.0021	0.0012	-22.0537**	-0.8095
	(0.0015)	(0.0012)	(9.5325)	(0.5883)
No. of obs.	142,708	142,708	142,708	142,708
Hispanic	0.0043	0.0032	10.9674	-1.6421
	(0.0053)	(0.0060)	(11.9171)	(2.0258)
No. of obs.	33,178	33,178	33,178	33,178
Black	-0.0018	-0.0049	2.9595	2.9101**
	(0.0055)	(0.0055)	(10.4280)	(1.2042)
No. of obs.	37,814	37,814	37,814	37,814
Retired	0.0021	0.0036	-6.6876	-1.1032
	(0.0025)	(0.0033)	(9.2631)	(1.0817)
No. of obs.	80,144	80,144	80,144	80,144
Not Retired	0.0002	0.0000	-22.7847*	-0.1642
	(0.0024)	(0.0021)	(11.5250)	(0.5805)
No. of obs.	146,334	146,334	146,334	146,334
Married	0.0014	0.0024	-16.1845*	-0.6755
	(0.0016)	(0.0016)	(8.7981)	(0.7129)
No. of obs.	145,453	145,453	145,453	145,453
Poor/near poor	0.0009	-0.0003	-21.8750	-1.8163
	(0.0042)	(0.0045)	(24.3243)	(1.3848)
No. of obs.	76,051	76,051	76,051	76,051
Middle/high income	0.0014	0.0025	-14.1150*	0.0847
	(0.0011)	(0.0015)	(8.1073)	(0.5707)
No. of obs.	152,710	152,710	152,710	152,710

Notes: Estimates from parametric RD models with an age bandwidth of two years are reported. All models contain a quadratic polynomial of the forcing variable that is also fully interacted with the treatment variable. All models contain a set of control variables as discussed in the text. In all regressions, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The signs * and ** denote statistical significance at 10 and 5 percent levels, respectively.

Table 1.9. RD estimates of change in inpatient hospital stays at age 65

	Prob. of stay		No. of admision		Length of stay		Total payment		Out of pocket cost	
	(1)	(2)	(3)	(4)	(3)	(4)	(5)	(6)	(7)	(8)
Bandwidth=36 months										
Parametric (Linear)	0.0004	0.0006	0.0012	0.0014	-0.0001	0.0023	-36.9174*	-38.3736*	-4.1970*	-4.5380**
	(0.0010)	(0.0010)	(0.0011)	(0.0011)	(0.0059)	(0.0060)	(21.8792)	(22.4710)	(2.1792)	(2.2654)
Parametric (Quadratic)	-0.0003	-0.0002	-0.0002	0.0000	0.0026	0.0053	3.7633	0.3101	1.4102	1.2833
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0081)	(0.0083)	(25.7689)	(25.9165)	(2.6641)	(2.7638)
Parametric (Cubic)	-0.0010	-0.0010	-0.0005	-0.0004	-0.0102	-0.0104	-13.7848	-17.6335	2.5764	2.9536
	(0.0019)	(0.0019)	(0.0020)	(0.0020)	(0.0124)	(0.0128)	(38.3248)	(38.4694)	(2.7249)	(2.7309)
Pre 65 Mean	0.0134	0.0134	0.0145	0.0145	0.0658	0.0653	206.1655	206.9803	8.2426	8.2787
No. of obs.	345,993	341,524	345,993	341,524	278,001	274,573	277,989	274,563	277,989	274,563
Bandwidth=24 months										
Parametric (Linear)	-0.0000	0.0002	0.0005	0.0007	0.0012	0.0040	-6.8693	-9.1019	0.3845	0.0145
	(0.0012)	(0.0012)	(0.0013)	(0.0013)	(0.0063)	(0.0065)	(21.5830)	(22.0527)	(2.7360)	(2.8675)
Parametric (Quadratic)	-0.0006	-0.0005	-0.0004	-0.0002	-0.0088	-0.0078	-16.7338	-20.5725	-0.5140	-0.1709
	(0.0017)	(0.0017)	(0.0018)	(0.0018)	(0.0097)	(0.0101)	(34.9047)	(34.7138)	(3.0350)	(2.9192)
Parametric (Cubic)	-0.0010	-0.0011	0.0002	0.0000	0.0216	0.0208	-11.5788	-18.0804	4.7698	5.0498
	(0.0023)	(0.0023)	(0.0026)	(0.0026)	(0.0137)	(0.0144)	(31.8635)	(32.2892)	(5.2727)	(5.2499)
Pre 65 Mean	0.0139	0.0139	0.0151	0.0151	0.0667	0.0661	212.9772	214.0775	9.3788	9.4126
No. of obs.	231,739	228,761	231,739	228,761	186,089	183,828	186,083	183,823	186,275	184,007
Bandwidth=12 months										
Parametric (Linear)	0.0004	0.0005	0.0007	0.0009	0.0040	0.0060	-27.7933	-30.1667	3.3408	3.1887
	(0.0019)	(0.0019)	(0.0020)	(0.0020)	(0.0083)	(0.0088)	(28.1434)	(28.0893)	(3.1540)	(3.0745)
Parametric (Quadratic)	-0.0035	-0.0037	-0.0023	-0.0025	0.0089	0.0065	11.5315	6.0442	0.1641	0.1553
	(0.0022)	(0.0022)	(0.0025)	(0.0025)	(0.0140)	(0.0143)	(35.2110)	(35.6835)	(4.7414)	(4.8500)
Parametric (Cubic)	-0.0066**	-0.0069**	-0.0059*	-0.0063**	0.0017	-0.0033	24.1720	16.9909	-7.9735	-8.6139
	(0.0027)	(0.0027)	(0.0030)	(0.0030)	(0.0108)	(0.0118)	(59.2391)	(60.4530)	(6.2187)	(6.3832)

Pre 65 Mean	0.0142	0.0142	0.0152	0.0152	182.7878	0.0680	182.7878	183.8941	7.8184	7.8743
No. of obs.	116,842	115,337	116,842	115,337	94,438	93,277	94,432	93,273	94,432	93,273
Non-parametric	-0.0005		0.0002		0.0097		-9.7863		0.7195	
	(0.0008)		(0.0009)		(0.0064)		(23.0600)		(0.9059)	
	202,480		202,480		115,894		170,539		115,889	
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: In all models, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The means of the variables are reported for those who are younger than 65. The signs *, **, and *** denote the statistical significance at 10, 5, and 1 percent levels, respectively.

Table 1.10. RD estimates of change in inpatient hospital stays at age 65: Alternative samples

	Prob. of stay	No. of admission	Length of stay	Total payment	Out of pocket payment
Female	-0.0002	0.0001	0.0054	-3.1060	1.2924
	(0.0024)	(0.0025)	(0.0172)	(48.8806)	(3.8448)
No. of obs.	124,087	124,087	99,188	99,187	99,187
Male	-0.0009	-0.0006	-0.0237	-42.2252	-1.7709
	(0.0027)	(0.0026)	(0.0203)	(52.1597)	(4.1781)
No. of obs.	104,674	104,674	84,639	84,636	84,636
White	-0.0006	-0.0004	-0.0104	-32.3511	-0.0284
	(0.0021)	(0.0023)	(0.0128)	(40.5119)	(3.7033)
No. of obs.	142,708	142,708	119,597	119,592	119,592
Hispanic	0.0040	0.0031	0.0523	112.3109	-0.5266
	(0.0029)	(0.0031)	(0.0327)	(80.5006)	(2.2212)
No. of obs.	33,178	33,178	25,037	25,037	25,037
Black	0.0007	0.0004	-0.0247	-27.1035	0.1163
	(0.0029)	(0.0036)	(0.0365)	(68.6393)	(2.4202)
No. of obs.	37,814	37,814	28,879	28,880	28,880
Retired	0.0017	0.0022	0.0266	43.3324	0.5129
	(0.0021)	(0.0025)	(0.0201)	(57.8356)	(3.2067)
No. of obs.	80,144	80,144	66,210	66,207	66,207
Not Retired	-0.0017	-0.0017	-0.0286**	-61.1857	-0.1981
	(0.0026)	(0.0026)	(0.0122)	(51.2399)	(3.9358)
No. of obs.	146,334	146,334	115,488	115,487	115,487
Married	-0.0009	-0.0006	-0.0093	-16.0654	1.0801
	(0.0015)	(0.0018)	(0.0109)	(37.4876)	(3.0381)
No. of obs.	145,453	145,453	118,644	118,643	118,643
Poor/near poor	0.0056	0.0073	-0.0027	18.0895	-6.7249
	(0.0043)	(0.0045)	(0.0346)	(96.4384)	(5.2176)
No. of obs.	76,051	76,051	60,574	60,572	60,572
Middle/high income	-0.0026	-0.0027	-0.0086	-31.7525	1.8970
	(0.0022)	(0.0025)	(0.0161)	(45.6916)	(4.0138)
No. of obs.	152,710	152,710	123,253	123,251	123,251

Notes: Estimates from parametric RD models with an age bandwidth of two years are reported. All models contain a quadratic polynomial of the forcing variable that is also fully interacted with the treatment variable. All models contain a set of control variables as discussed in the text. In all regressions, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The signs ** and *** denote statistical significance at 5 and 1 percent levels, respectively.

Table 1.11. RD estimates of change in medical utilization: Insured vs. not insured before age 65

	Prob. of visit		No. of visits		Total payment		Out of pocket cost	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Office based and outpatient visit								
Parametric (Linear)	0.120***	0.001	0.445***	-0.006	183.659***	-17.574	15.113**	-15.301***
	(0.021)	(0.006)	(0.079)	(0.019)	(22.278)	(17.719)	(7.143)	(4.323)
Parametric (Quadratic)	0.071***	0.014	0.376***	0.028	158.416***	24.918	-2.462	-7.682
	(0.023)	(0.009)	(0.088)	(0.021)	(28.625)	(18.237)	(7.936)	(4.971)
Parametric (Cubic)	0.056**	-0.013*	0.196	-0.052	134.332***	-53.187	-13.366	-10.198
	(0.024)	(0.007)	(0.124)	(0.036)	(27.248)	(35.931)	(8.572)	(7.925)
Pre-65 Mean	0.217	0.383	0.366	0.856	63.971	242.879	18.453	31.690
No. of obs.	8,786	61,242	8,786	61,242	8,786	61,242	8,786	61,242
Inpatient visit								
Parametric (Linear)	0.003	-0.000	0.003	0.001	144.974**	-22.203	7.028*	-2.706*
	(0.005)	(0.002)	(0.005)	(0.002)	(61.233)	(33.560)	(3.686)	(1.473)
Parametric (Quadratic)	-0.006	-0.005*	-0.004	-0.003	153.747*	36.117	0.730	0.599
	(0.005)	(0.002)	(0.006)	(0.003)	(75.585)	(36.169)	(3.417)	(2.311)
Parametric (Cubic)	-0.004	-0.010***	0.003	-0.007*	84.628	27.371	-5.128	0.801
	(0.008)	(0.003)	(0.009)	(0.004)	(142.937)	(68.200)	(6.098)	(3.676)
Pre-65 Mean	0.008	0.016	0.009	0.017	65.889	208.336	2.427	4.566
No. of obs.	8,786	61,242	8,786	61,242	7,132	50,568	7,132	50,568
Emergency Department visit								
Parametric (Linear)	0.003	0.001	-0.001	0.003	-5.978	-11.768	-0.486	-1.171**
	(0.004)	(0.002)	(0.006)	(0.002)	(5.046)	(7.808)	(0.418)	(0.553)
Parametric (Quadratic)	0.003	-0.001	0.001	0.003	-28.768	-14.678	0.435	-0.650
	(0.005)	(0.002)	(0.006)	(0.003)	(19.357)	(12.189)	(1.154)	(0.624)
Parametric (Cubic)	-0.003	-0.006*	0.004	-0.002	2.741	-9.876	-1.526	-0.298
	(0.009)	(0.003)	(0.012)	(0.004)	(17.845)	(17.066)	(1.428)	(1.205)

Pre-65 Mean	0.009	0.014	0.011	0.016	14.694	22.191	0.427	1.478
No. of obs.	8,786	61,242	8,786	61,242	8,786	61,242	8,786	61,242
Not insured before age 65	Yes	No	Yes	No	Yes	No	Yes	No
Insured before age 65	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Estimates from parametric RD models with an age bandwidth of one year are reported. All models contain a set of control variables as discussed in the text. In all regressions, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The signs *, ** and *** denote statistical significance at 10, 5, and 1 percent levels, respectively.

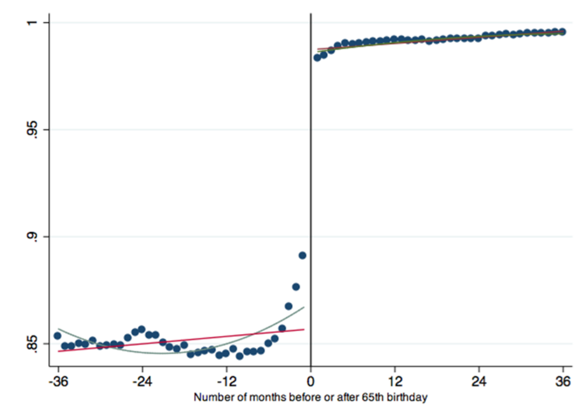
Table 1.12. RD estimates of change in medical utilization: Selected diagnosis types

	Office/Outpatient		Inpatient		Emergency	
	Prob.	No.	Prob.	No.	Prob.	No.
	(1)	(2)	(3)	(4)	(5)	(6)
Diabetes						
Parametric (Linear)	0.0038**	0.0077***	0.0003*	0.0003	0.0003	0.0003
	(0.0015)	(0.0027)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Parametric (Quadratic)	0.0032*	0.0147***	0.0007***	0.0008***	0.0004	0.0004
	(0.0018)	(0.0035)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Parametric (Cubic)	-0.0037*	0.0090*	0.0004	0.0003	0.0002	0.0004
	(0.0020)	(0.0047)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
Pre 65 Mean	0.0361	0.0495	0.0004	0.0004	0.0003	0.0004
No. of obs.	228,761	228,761	228,761	228,761	228,761	228,761
Hypertension						
Parametric (Linear)	0.0033*	0.0055*	0.0003	0.0003	0.0001	0.0000
	(0.0019)	(0.0028)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Parametric (Quadratic)	0.0091***	0.0109***	0.0004	0.0005*	0.0001	0.0001
	(0.0026)	(0.0038)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Parametric (Cubic)	0.0090***	0.0173***	0.0001	0.0000	-0.0006**	-0.0006***
	(0.0029)	(0.0038)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Pre 65 Mean	0.0443	0.0523	0.0005	0.0004	0.0006	0.0006
No. of obs.	228,761	228,761	228,761	228,761	228,761	228,761
Heart Disease						
Parametric (Linear)	-0.0007	-0.0057	-0.0004	-0.0005	-0.0001	-0.0003
	(0.0017)	(0.0035)	(0.0005)	(0.0006)	(0.0003)	(0.0003)
Parametric (Quadratic)	0.0003	0.0014	-0.0007	-0.0008	-0.0002	-0.0004
	(0.0026)	(0.0051)	(0.0008)	(0.0010)	(0.0003)	(0.0004)
Parametric (Cubic)	0.0062**	0.0177***	-0.0007	-0.0015	-0.0001	-0.0001
	(0.0026)	(0.0042)	(0.0013)	(0.0014)	(0.0005)	(0.0006)
Pre 65 Mean	0.0237	0.0361	0.0022	0.0024	0.0019	0.0017
No. of obs.	228,761	228,761	228,761	228,761	228,761	228,761

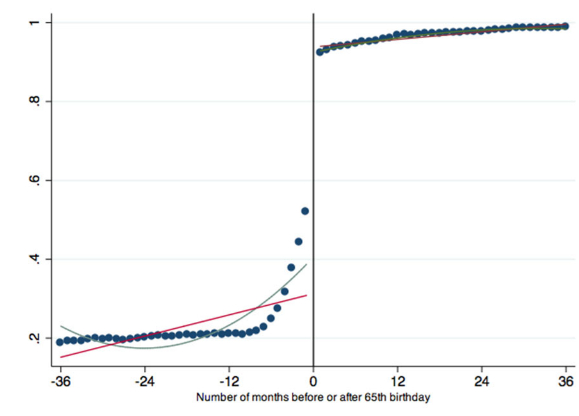
Notes: Estimates from parametric RD models with an age bandwidth of two years are reported. All models contain a quadratic polynomial of the forcing variable that is also fully interacted with the treatment variable. All models contain a set of control variables as discussed in the text. In all regressions, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The signs *, **, and *** denote statistical significance at 10, 5, and 1 percent levels, respectively.

Figure 1.1. The change in health insurance coverage status at age 65

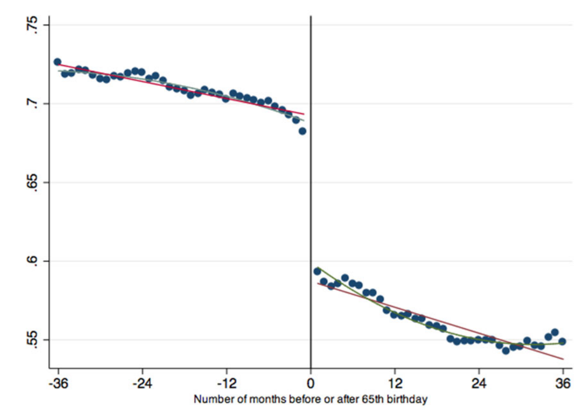
A. Any insurance



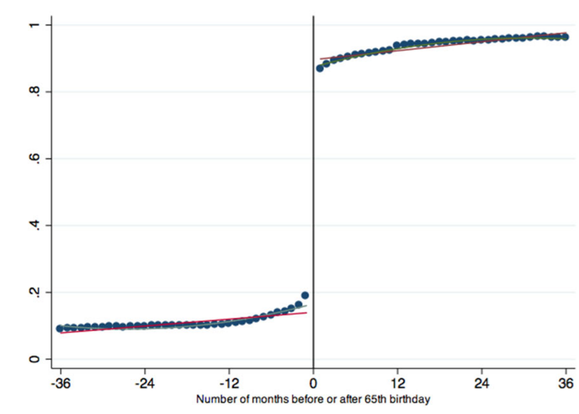
B. Public insurance



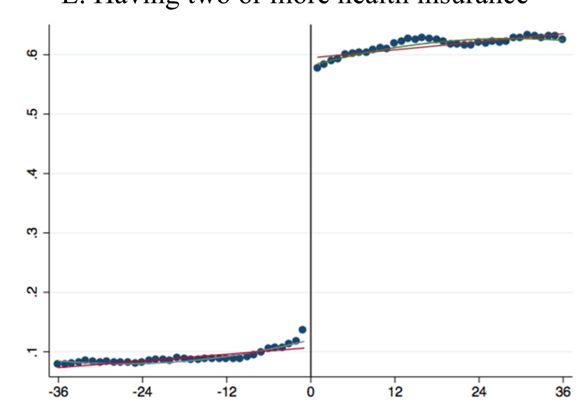
C. . Private insurance



D. Medicare



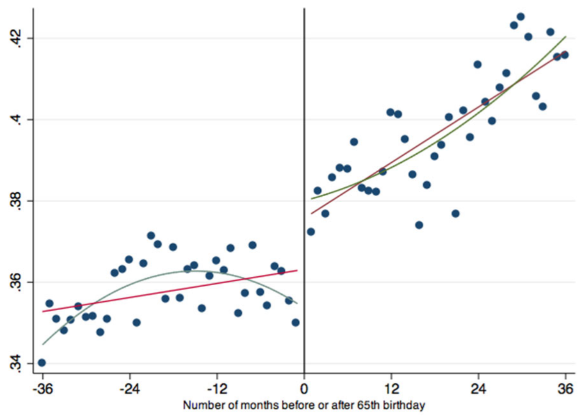
E. Having two or more health insurance



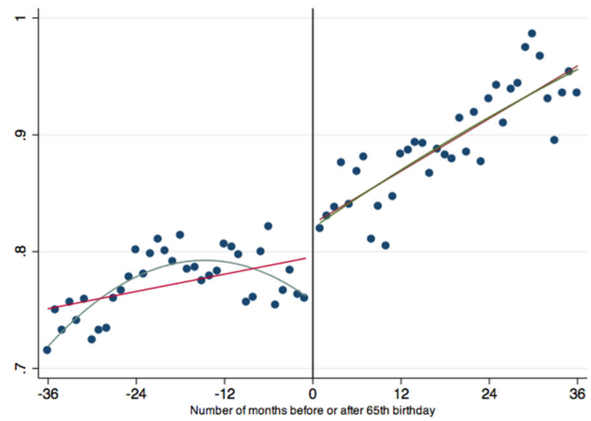
Notes: Mean of the outcome variables for 1-month intervals three years before and after the 65[th] birthday are plotted. The solid lines are the first and second order polynomials fitted on individual observations on both sides of the age-65 cutoff.

Figure 1.2**.** The change in medical care utilization and spending at age 65: office and outpatient visits

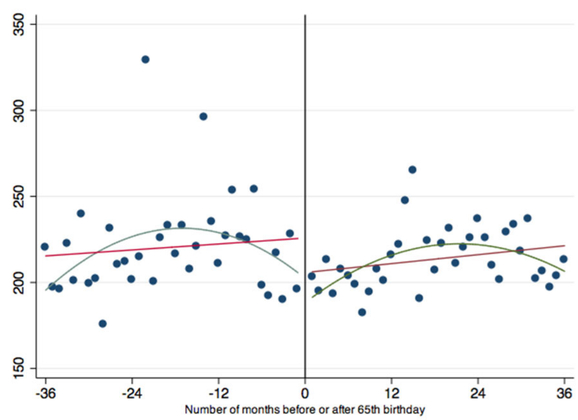
A. Probability of visit



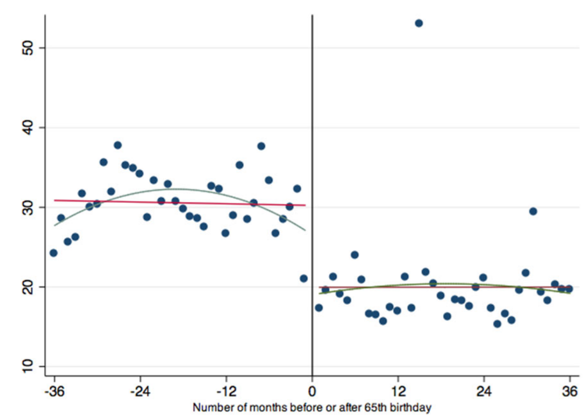
B. Number of visits



C. Total payment

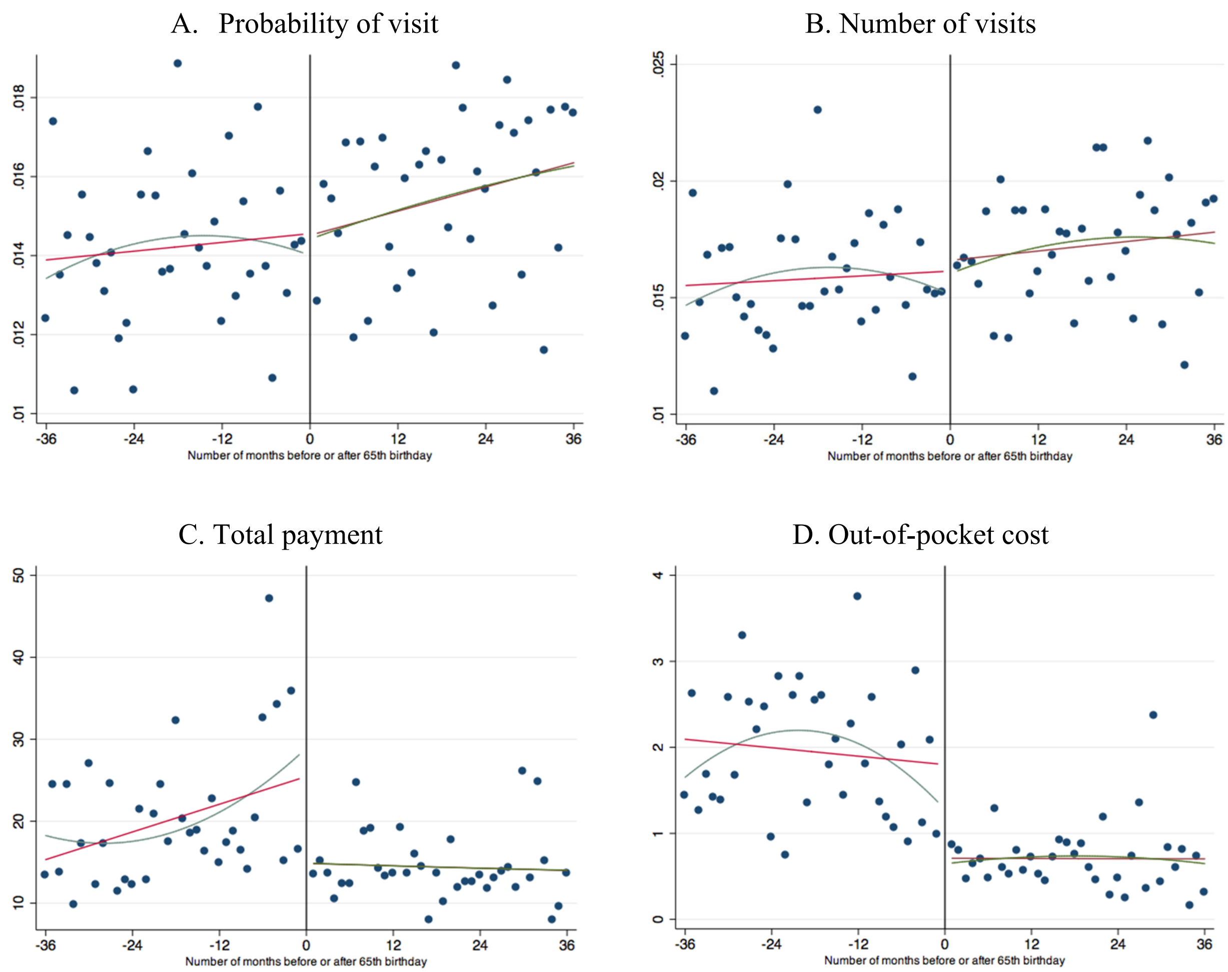


D. Out-of-pocket cost



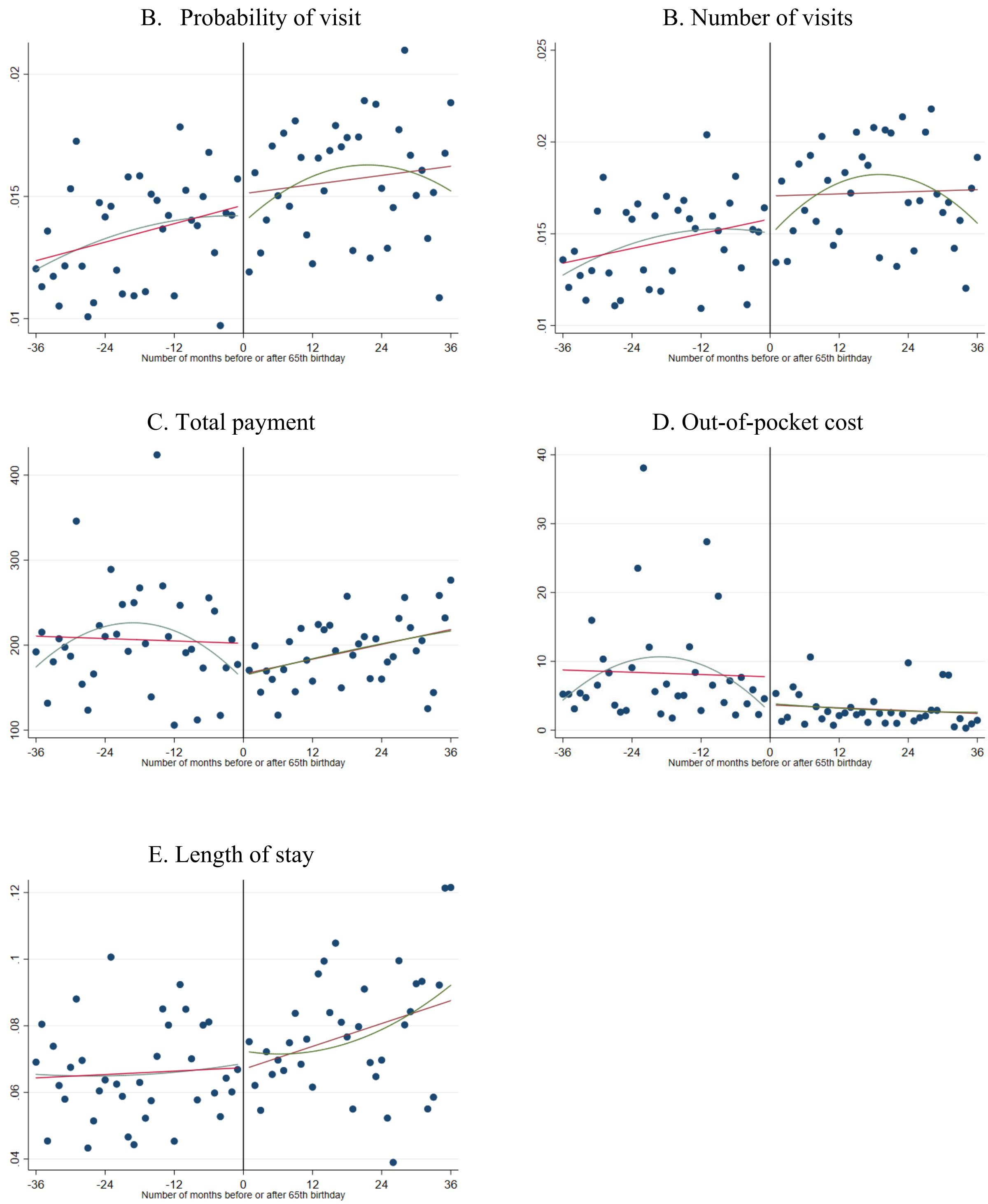
Notes: Mean of the outcome variables for 1-month intervals three years before and after the 65th birthday are plotted. The solid lines are the first and second order polynomials fitted on individual observations on both sides of the age-65 cutoff.

Figure 1.3. The change in medical care utilization and spending at age 65: emergency department visits



Notes: Mean of the outcome variables for 1-month intervals three years before and after the 65th birthday are plotted. The solid lines are the first and second order polynomials fitted on individual observations on both sides of the age-65 cutoff.

Figure 1. 4. The change in medical care utilization and spending at age 65: inpatient stays



Notes: Mean of the outcome variables for 1-month intervals three years before and after the 65th birthday are plotted. The solid lines are the first and second order polynomials fitted on individual observations on both sides of the age-65 cutoff

Appendix Table 1.1: Summary Statistic for sample of Insured vs. not insured before age 65

	No Insurance before 65		Always have ins before 65	
	Mean	Std	Mean	Std
White	0.681	0.466	0.806	0.396
Black	0.113	0.317	0.099	0.299
Hispanic	0.138	0.345	0.048	0.214
Less than HS	0.306	0.461	0.157	0.364
High school	0.522	0.500	0.533	0.499
Bachelor	0.106	0.308	0.159	0.365
Gradudate	0.054	0.226	0.145	0.353
Employed	0.413	0.493	0.442	0.497
Married	0.411	0.492	0.705	0.456
Female	0.533	0.499	0.506	0.500
Fam size	2.141	1.405	2.030	0.884
Poor	0.151	0.358	0.080	0.271
Near poor	0.079	0.270	0.036	0.185
Low income	0.212	0.409	0.108	0.311
Middle income	0.307	0.461	0.269	0.444
High income	0.250	0.433	0.507	0.500
N	4,400		30,656	

Note: The statistic is calculated for a sample of seniors who always report having health insurance vs. who consistently report having no insurance before age 65.

Appendix Table 1.2. RD estimates of change in office and outpatient visits at age 65: Alternative care types

	Checkup		Diagnosis/ Treatment		Mental health cousel	
	Prob.	No.	Prob.	No.	Prob.	No.
	(1)	(2)	(3)	(4)	(5)	(6)
Bandwidth= 36 months						
Parametric (Linear)	0.009***	0.009***	0.010***	0.030***	-0.002**	-0.002
	(0.002)	(0.003)	(0.003)	(0.010)	(0.001)	(0.002)
Parametric (Quadratic)	0.009**	0.003	0.022***	0.067***	-0.000	-0.002
	(0.003)	(0.005)	(0.004)	(0.010)	(0.001)	(0.004)
Parametric (Cubic)	0.008*	0.001	0.021***	0.088***	0.000	-0.008**
	(0.004)	(0.006)	(0.005)	(0.015)	(0.002)	(0.004)
Pre 65 Mean	0.131	0.164	0.189	0.388	0.013	0.024
No. of obs.	341,524	341,524	341,524	341,524	341,524	341,524
Bandwidth= 24 months						
Parametric (Linear)	0.008***	0.006	0.018***	0.053***	-0.000	-0.000
	(0.003)	(0.004)	(0.003)	(0.010)	(0.001)	(0.003)
Parametric (Quadratic)	0.010**	0.002	0.018***	0.076***	-0.001	-0.008**
	(0.004)	(0.006)	(0.005)	(0.012)	(0.001)	(0.003)
Parametric (Cubic)	0.001	-0.004	0.014***	0.076***	-0.004***	-0.022***
	(0.005)	(0.008)	(0.005)	(0.019)	(0.001)	(0.003)
Pre 65 Mean	0.132	0.165	0.191	0.395	0.012	0.023
No. of obs.	228,761	228,761	228,761	228,761	228,761	228,761
Bandwidth= 12 months						
Parametric (Linear)	0.007*	0.001	0.017***	0.081***	-0.002	-0.009***
	(0.003)	(0.005)	(0.004)	(0.012)	(0.001)	(0.003)
Parametric (Quadratic)	0.007	0.005	0.020***	0.057***	-0.003**	-0.021***
	(0.004)	(0.007)	(0.005)	(0.019)	(0.001)	(0.003)
Parametric (Cubic)	-0.000	0.004	0.019**	0.027	-0.008**	-0.023***
	(0.006)	(0.006)	(0.007)	(0.021)	(0.003)	(0.007)
Pre 65 Mean	0.132	0.168	0.190	0.387	0.010	0.021
No. of obs.	115,337	115,337	115,337	115,337	115,337	115,337
Non-parametric	0.009***	0.007	0.009***	0.029***	0.000	-0.004**
	(0.003)	(0.005)	(0.003)	(0.008)	(0.001)	(0.002)
	339,102	339,102	202,480	163,306	280,709	241,721

Notes: In all models, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The means of the variables are reported for those who are younger than 65. The signs *, **, and *** denote the statistical significance at 10, 5, and 1 percent levels, respectively.

Appendix Table 1.3. Donut RD estimates of change in office visits

	Prob. of Visit	No. of visit	Total payment	Out of pocket cost
Bandwidth=36 months				
Parametric (Linear)	0.009**	0.018	-30.190**	-11.373***
	(0.004)	(0.016)	(12.583)	(2.784)
Parametric (Quadratic)	0.027***	0.051*	-39.620*	-7.869**
	(0.006)	(0.028)	(20.145)	(3.432)
Parametric (Cubic)	0.042***	0.162***	11.889	-23.858**
	(0.011)	(0.037)	(34.848)	(10.213)
Pre-65 Mean	0.359	0.774	221.010	30.654
No. of obs.	312,545	312,545	312,545	312,545
Bandwidth=24 months				
Parametric (Linear)	0.021***	0.047**	-33.281**	-10.786***
	(0.005)	(0.021)	(16.140)	(2.585)
Parametric (Quadratic)	0.033***	0.083**	-16.511	-18.446**
	(0.009)	(0.034)	(31.285)	(8.717)
Parametric (Cubic)	-0.001	0.183***	21.184	0.541
	(0.019)	(0.062)	(51.526)	(8.951)
Pre-65 Mean	0.362	0.788	227.126	30.479
No. of obs.	199,782	199,782	199,782	199,782
Bandwidth=12 months				
Parametric (Linear)	0.023***	0.108***	-12.900	-8.787*
	(0.008)	(0.033)	(21.743)	(4.607)
Parametric (Quadratic)	0.042*	0.232**	120.739*	12.186
	(0.023)	(0.080)	(66.538)	(9.665)
Parametric (Cubic)	-0.112*	0.056	-290.729	-23.976
	(0.063)	(0.270)	(180.276)	(33.124)
Pre-65 Mean	0.361	0.783	219.212	29.972
No. of obs.	86,358	86,358	86,358	86,358

Notes: Observations for three months before and after the 65th birthday are excluded in all models. In all models, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The means of the variables are reported for those who are younger than 65. All models include a set of control variables as discussed in the text. The signs *, **, and *** denote the statistical significance at 10, 5, and 1 percent levels, respectively.

Appendix Table 1.4. RD estimates of the change in office visits: Sample is restricted to include only actual interview months

	Prob. of visit	No. of visits	Total payment	Out of pocket cost
Bandwidth 36 months				
Parametric (Linear)	0.021***	0.061**	-24.805	-3.276
	(0.007)	(0.028)	(20.103)	(6.396)
Parametric (Quadratic)	0.032***	0.044	-72.518**	-9.443
	(0.011)	(0.040)	(29.412)	(6.275)
Parametric (Cubic)	0.024*	0.099*	-60.894**	-21.315*
	(0.013)	(0.051)	(29.468)	(12.670)
Pre-65 Mean	0.365	0.790	231.473	28.165
No. of obs.	71,493	71,493	71,493	71,493
Bandwidth 24 months				
Parametric (Linear)	0.029***	0.057*	-29.447	-5.931
	(0.009)	(0.032)	(28.662)	(5.075)
Parametric (Quadratic)	0.025**	0.068	-100.789***	-20.749*
	(0.012)	(0.045)	(33.105)	(12.316)
Parametric (Cubic)	0.013	0.098*	-92.125***	-2.491
	(0.018)	(0.054)	(34.104)	(10.495)
Pre-65 Mean	0.366	0.791	240.769	28.382
No. of obs.	47,828	47,828	47,828	47,828
Bandwidth 12 months				
Parametric (Linear)	0.026**	0.093**	-56.373**	-7.885
	(0.010)	(0.043)	(24.871)	(6.925)
Parametric (Quadratic)	0.013	0.073	-78.770**	-1.933
	(0.016)	(0.051)	(29.552)	(9.206)
Parametric (Cubic)	0.021	-0.011	-195.192***	-10.917
	(0.028)	(0.095)	(49.231)	(14.591)
Pre-65 Mean	0.367	0.797	231.309	29.282
No. of obs.	23,915	23,915	23,915	23,915

Notes: All models are estimated using sample weights and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The means of the variables are reported for those who are younger than 65. All models include a set of control variables as discussed in the text. The signs *, **, and *** denote the statistical significance at 10, 5, and 1 percent levels, respectively.

Appendix Table 1.5. RD estimates of change in dental visits at age 65

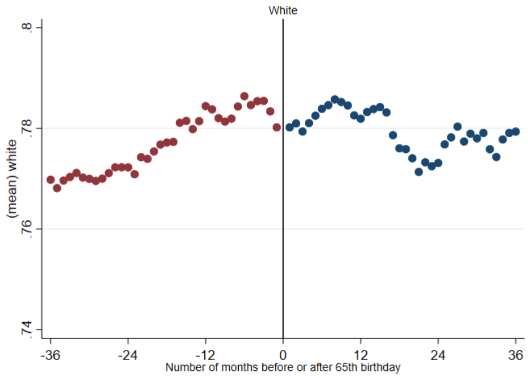
	Prob. of visit		No. of visits		Total payment		Out of pocket cost	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bandwidth=36 months								
Parametric (Linear)	0.0019	0.0013	0.0023	0.0016	-3.1173	-3.2139	0.1950	0.0904
	(0.0021)	(0.0021)	(0.0027)	(0.0027)	(1.9685)	(1.9783)	(1.5160)	(1.5210)
Parametric (Quadratic)	-0.0032	-0.0040	-0.0037	-0.0046	-2.5471	-2.7420	0.8428	0.7220
	(0.0029)	(0.0030)	(0.0042)	(0.0044)	(2.7751)	(2.8060)	(2.0117)	(2.0380)
Parametric (Cubic)	-0.0035	-0.0032	-0.0026	-0.0021	-0.2576	0.1069	2.8630	3.0344
	(0.0041)	(0.0041)	(0.0062)	(0.0063)	(3.1950)	(3.1162)	(2.4041)	(2.4043)
Pre 65 Mean	0.091	0.092	0.110	0.111	35.687	35.861	19.697	19.805
No. of obs.	345,993	341,524	345,993	341,524	345,993	341,524	345,993	341,524
Bandwidth=24 months								
Parametric (Linear)	0.0008	0.0000	0.0004	-0.0005	-1.2384	-1.4817	1.5066	1.3280
	(0.0026)	(0.0026)	(0.0034)	(0.0035)	(2.2504)	(2.2796)	(1.6422)	(1.6609)
Parametric (Quadratic)	-0.0060*	-0.0060	-0.0056	-0.0055	-4.7735	-4.6488	-0.2533	-0.2483
	(0.0035)	(0.0036)	(0.0056)	(0.0057)	(2.9538)	(2.9595)	(2.1753)	(2.2027)
Parametric (Cubic)	0.0004	-0.0055	-0.0037	-0.0020	0.5684	1.6124	4.9536*	5.4760*
	(0.0034)	(0.0046)	(0.0072)	(0.0070)	(3.5421)	(3.4122)	(2.9326)	(2.9250)
Pre 65 Mean	0.092	0.092	0.111	0.111	36.178	36.327	20.218	20.318
No. of obs.	231,739	228,761	231,739	228,761	231,739	228,761	231,739	228,761
Bandwidth=12 months								
Parametric (Linear)	-0.0055*	-0.0052	-0.0064	-0.0058	-3.4403	-3.0442	1.8743	1.6875
	(0.0032)	(0.0032)	(0.0051)	(0.0052)	(2.7637)	(2.7536)	(1.6767)	(2.0795)
Parametric (Quadratic)	-0.0064	-0.0058	-0.0014	-0.0005	-1.4640	-0.6018	2.8383	2.8980
	(0.0044)	(0.0043)	(0.0063)	(0.0063)	(3.8293)	(3.7137)	(2.3462)	(2.7939)
Parametric (Cubic)	0.0134**	0.0146**	0.0305***	0.0320***	3.1489	4.5182	4.7750	6.1175
	(0.0061)	(0.0060)	(0.0060)	(0.0059)	(5.9537)	(5.7831)	(3.8723)	(4.9539)

Pre 65 Mean	0.091	0.092	0.110	0.111	33.998	35.057	19.758	19.881
No. of obs.	116,842	115337	116,842	115337	116,842	115337	116,842	115337
Non-parametric	0.0006		-0.0007		-3.3485**		0.6837	
	(0.0014)		(0.0019)		(1.5949)		(1.2110)	
	437509		290482		417903		290,482	
Controls	No	Yes	No	Yes	No	Yes	No	Yes

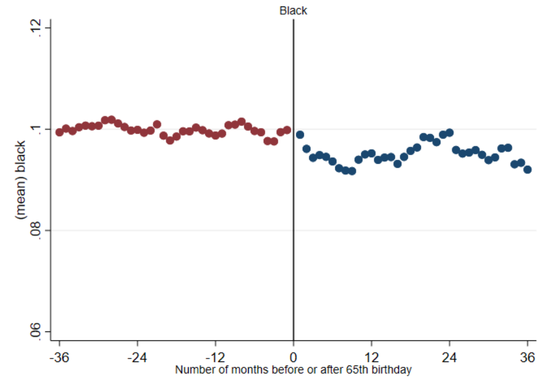
Notes: In all models, sample weights are used and standard errors are clustered by the forcing variable. Standard errors are reported in parentheses. The means of the variables are reported for those who are younger than 65. The signs *, **, and *** denote the statistical significance at 10, 5, and 1 percent levels, respectively.

Appendix Figure 1.1. Trends in control variables before and after the 65th birthday

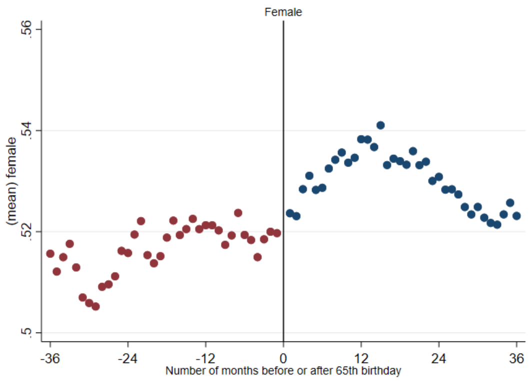
A. White



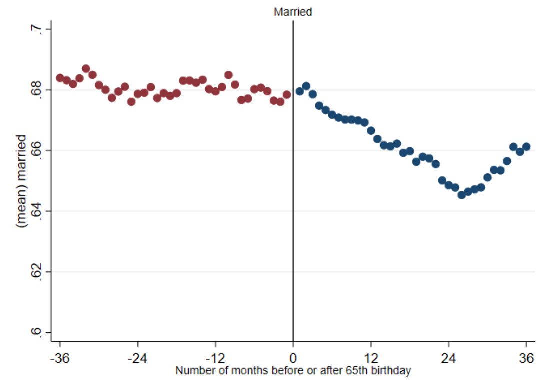
B. Black



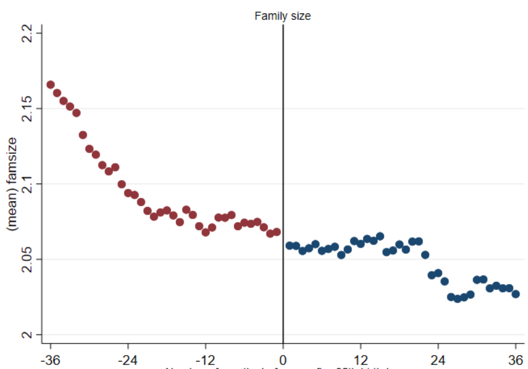
C. Female



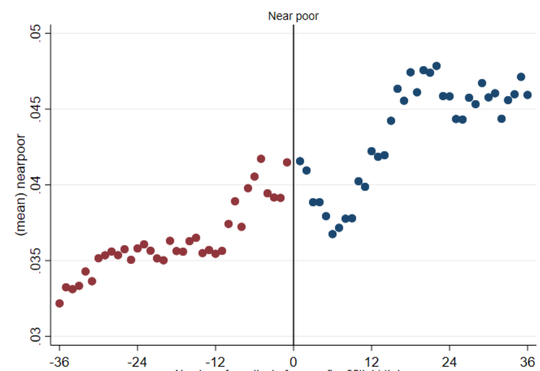
D. Married



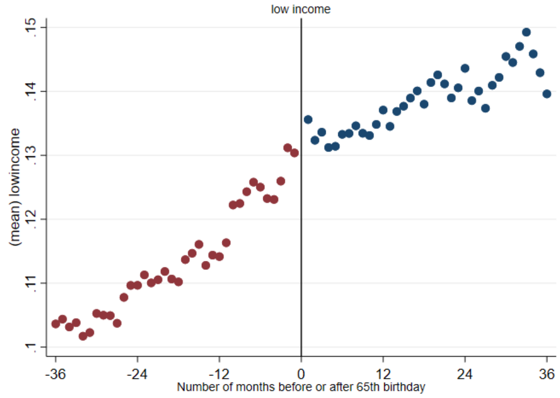
E. Family size



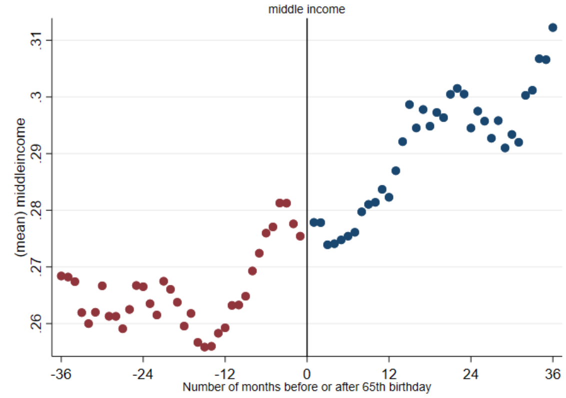
F. Near poor



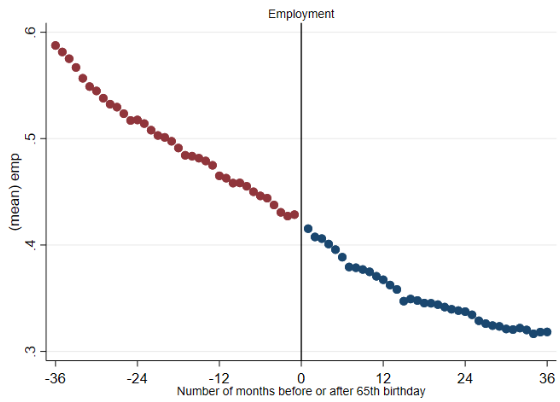
G. Low income



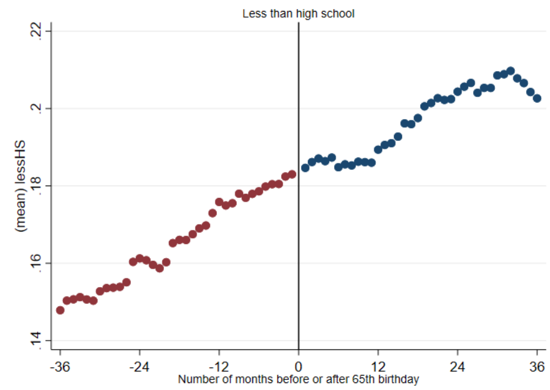
H. Middle Income



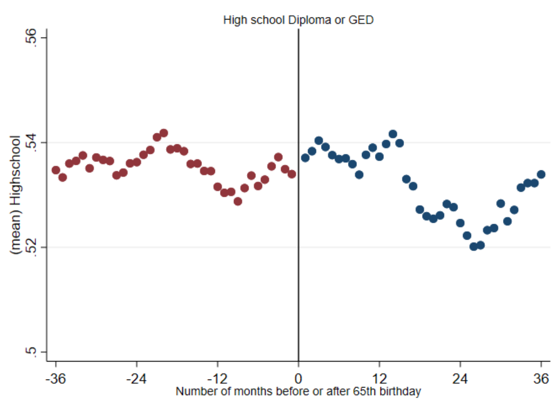
I. Employed



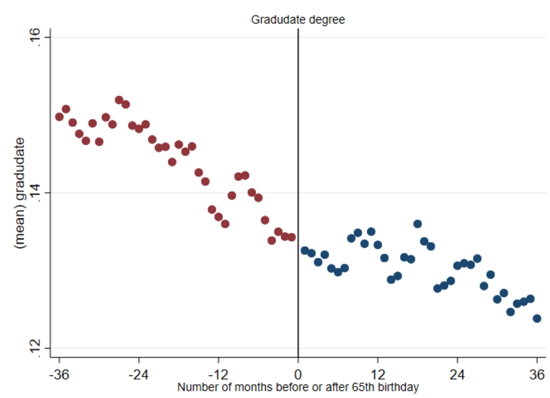
J Less than high school



K. High school, GED, or some college

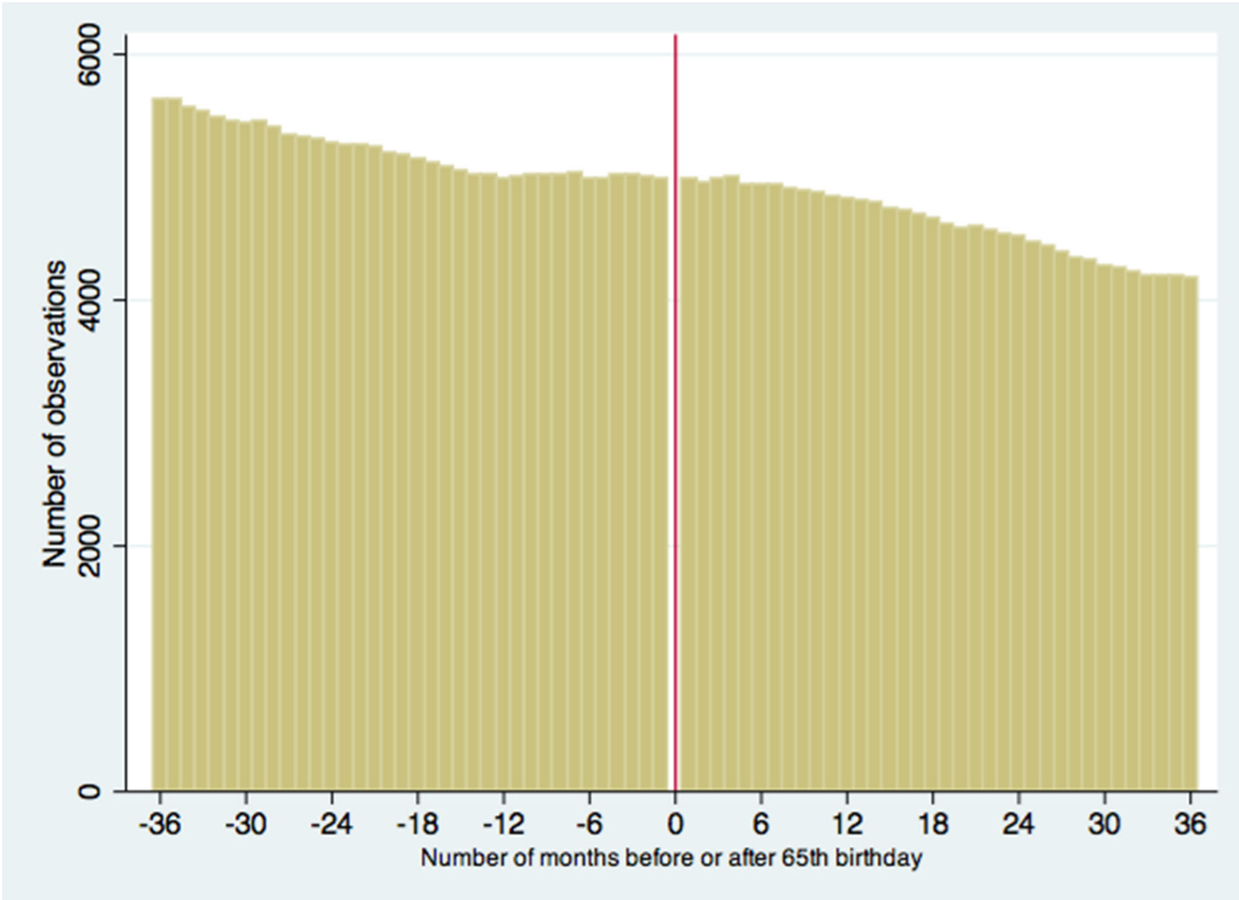


L. Graduate degree



Notes: Mean of the variables for 30-day intervals are plotted for three years before and after the month of the 65th birthday. The solid line indicates the month of the 65th birthday.

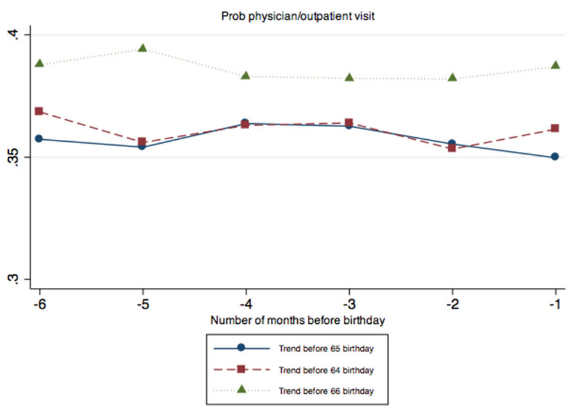
Appendix Figure 1.2. Distribution of number of observations around age 65



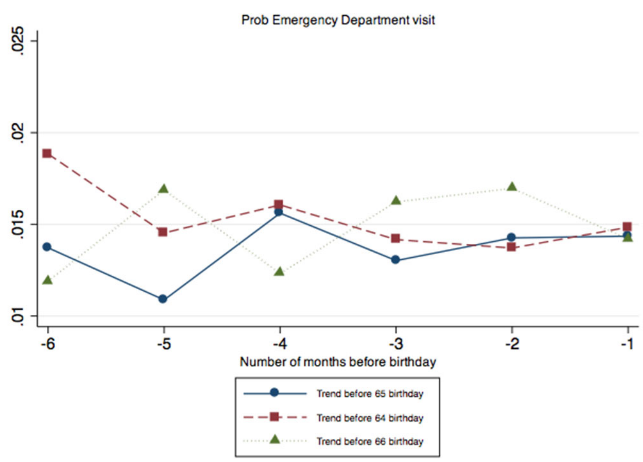
Notes: Total number of observations for each 30-day period around age 65 is plotted. Those who are interviewed in the month of their 65th birthday are not plotted.

Appendix Figure 1.3. Probability of using medical care up to six months before the 64th, 65th, and 66th birthdays

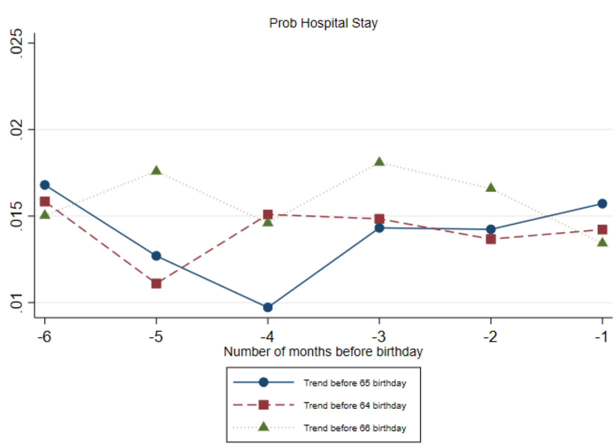
A. Office and outpatient visits



B. Emergency department visits



C. Inpatient stays



Chapter 2 The impact of prescription drug coverage on food access among the elderly: Evidence from Medicare Part D

2.1. Introduction

Food insecurity is an important indicator of individuals' well-being (Schmidt et al., 2015) and has a strong correlation with overall health problems and chronic conditions (Moran, 2017; Seligman et al., 2019; Heflin et al., 2005; Gundersen and Ziliak, 2015). However, the food insecurity rates in the United States remain high: 11 % of Americans and 7.7% of the senior population reporting food insecurity at some point in 2017 (Feeding America, 2017). Previous research documented evidence of the reversed relationship between medical care and food spending and food due to limited resources (Berkowitz et al., 2014; Weinfield et al., 2014). According to Hunger America 2014, the households who used charitable food programs reported that they have to make difficult choices among basic needs like food, utilization, and medical care. Specifically, 60% have to choose between food and medical spending. That demonstrates medical care burden can be a significant cause of the food access shortage, especially among individuals with high risk of medical spending.

Medicare is a federal health insurance program for seniors aged over 65 and certain groups of younger, disabled individuals. Initially, the focus of Medicare was to provide coverage for hospital services (Part A) and physician services (Part B) for the elderly. At its inception, Medicare did not include coverage for prescription drugs. Over time, as drug prices rapidly increased and many treatments for chronic disease required medications, elderly individuals became increasingly burdened by the out-of-pocket cost of prescription drugs. In 1982 prescription drugs accounted for about 4.5% of health expenditures, that share had more than doubled, to about 10.1% by 2005 (Duggan and Morton, 2010). Thus, the burden of medication weighs heavily on elderly individuals with multiple chronic conditions but lacking prescription drug insurance. The financial hardship due to medication expenditure burden can reduce access to other necessities among people with a high risk of medical expenditures.

Medicare Part D, initiated by the 2003 Medicare Modernization Act and implemented in 2006, was initiated to provide prescription drug coverage to Medicare beneficiaries. As of 2018, Medicare Part D provided drug coverage to 43 million of the 60 million Medicare beneficiaries in the United States (Cubanski et al., 2018). Studies have indicated that Medicare Part D has substantially increased prescription drug coverage and reduced out-of-pocket spending on prescription drugs among the elderly (Engelhardt and Gruber 2011; Dugan and Morton, 2010). Engelhardt and Gruber (2011) suggested that the effects on financial strain were concentrated among elderly individuals with chronic conditions, who have the most to gain from prescription drug coverage. As Medicare prescription drug coverage reduces medical spending, it may leave more financial resources available for the purchase of food, thus provide a mechanism to improve food access among the beneficiaries. Understanding the extent to which prescription drug coverage affects elderly households' food security is important for policymaker because the inadequacy access of food adversely affect health and well-being, especially among the less healthy population.

An extensive literature has investigated the effect of food-safety programs on food insecurity among families in the US. However, less is known about how non-food public programs affect food insecurity. In this paper, we test whether Medicare Part D improves food security and food stamp participation among senior adults, especially among individuals with the worst health status. We use data from The Health and Retirement Study wave 2000- 2014, and employ a difference-in-difference-in-difference approach to estimate the effect of Medicare Part D on out-of-pocket medication spending, food access related outcomes by exploiting the variation across age group and over time, and between groups with the burden of the medication spending.

This chapter is structured as follows: the next section presents a background in Medicare Part D and reviews the literature. Section 2.3 describes the primary data source and analysis sample. Section 2.4 presents the empirical framework. Section 2. 5 presents the main results. Section 2.6 provides falsification tests and sensitivity checks. Section 2.7 concludes.

2.2. Background

2.2.1. Medicare Part D

Medicare Part D is voluntary prescription drug coverage for Medicare beneficiaries. Medicare Part D was enacted under the Modernization Care Act in 2003, and it went into effect in 2006. Individuals who are in Medicare Part A and Medicare Part B plans can enroll in Part D with a monthly premium. Beneficiaries can choose to sign up in either stand-alone prescription drug plans (PDPs) to supplement traditional Medicare or Medicare Advantage prescription drug plan (MA-PDs), including HMOs and PPOs that cover all Medicare benefits including drugs (Kaiser Family Foundation, 2017). The average monthly premium for 2008 is $34, and the amount varies across states. The Part D standard benefit has a $275 deductible and 25% coinsurance up to an initial coverage limit of $2,510 in total drug costs, followed by a coverage gap. When entering the gap, beneficiaries have to pay a higher percentage of their total drug costs than in the initial coverage period, until their total out-of-pocket spending reaches $4,050[20] (in 2008). After beneficiaries reach that threshold, they become eligible for catastrophic coverage, that they pay the greater of 5% coinsurance, or $2.65 for generic drugs and $6.60 for brand-name drugs (Kaiser Family Foundation, 2008).

Medicare Part D is the largest expansion of Medicare since its introduction in 1966. Part D has been estimated to cost $780 billion over its first ten years (2006–2015) (Duggan and Morton, 2010. Elderly who have limited income and resources can apply for Medicare Part D low-income subsidies. Specifically, the elderly with limited incomes (below 150 % FPL) and assets can get help to pay monthly premiums, annual deductible, and coinsurance by applying for the "Extra Help" program. More than one-third of Medicare Part D enrollees receive a low-income subsidy in 2010 (Kaiser Family Foundation, 2010). Dual-eligible who enrolled in both Medicare and Medicaid automatically get enrollment in the Medicare drug coverage without paying a monthly premium and paying very little on deductible and coinsurance. Although drug coverage is an optional benefit in Medicaid programs, all states currently provide for all beneficiaries. Medicare Part D will be responsible for paying the prescription drug before Medicaid, and Medicaid may still cover some drugs that Medicare doesn't (Medicaid, 2017). The medication in the covered list may vary among different Part D plans and Medicaid programs.

2.2.2 Previous studies on public health insurance expansions health-related outcomes and well-being.

A vast literature has investigated the impact of Medicare Part D, but most of the studies focused on the effect on medication utilization, medical expenditures, and health outcomes.

---

[20] The premium, deductible, and coverage gap change by year

Previous research has shown that Medicare Part D increase the prescription filled while reducing out of pocket cost of medication. Duggan and Morton (2010) found evidence of increasing medication just one year after the policy implementation. They also suggested evidence of a new drug plan decreasing the medication price. Ketcham and Simon (2008) showed that the out of pocket cost reduced statistically among seniors who are eligible for Medicare, reduced the elderly medication out of pocket costs by 21 percent, and increased the use of prescription drugs by 4.7 percent. Engelhardt and Gruber (2011) suggested that Part D benefit was associated with 75 percent crowd-out of both prescription-drug insurance coverage and expenditures of those on Medicare. They found that the impact on out of pocket spending is concentrated among a small proportion of seniors with the highest risk of medical cost.

There are relatively few studies on the impact of Medicare part D on non-heath related outcomes. In respect of effect on financial outcomes, Ayyagari and He (2016) showed that the introduction of Medicare Part D was associated with 2.2 percentage point increase in the probability of having a risky investment that includes stocks, mutual funds, investment trusts, individual retirement accounts, and Keogh accounts among Medicare beneficiaries. The result implied that a decrease in health care spending risk through drug coverage protection increases the willingness to bear financial risk among seniors. Moulton et al. (2017) found evidence that Medicare Part D is associated with an increase of 0.5 percentage point in probability in self-employment among seniors aged 65-69. Wettstein (2016) reported that seniors aged over 65 without any retiree drug insurance coverage decreased the full-time job by 8.4 percentage point after the implementation of Medicare Part D.

Other studies explore the impact of health insurance on non-health outcomes under other public health insurance expansions. Barcellos and Jacobson (2015) used a regression discontinuity design to examine the effect of Medicare on medical expenditures risk and financial wellbeing using the Medical Expenditure Panel Survey and Health Tracking Household survey. They provided evidence of a reduction in out of pocket expenditures and the probability of having a problem of paying the medical bill as well as medical bill amount. These results suggest that Medicare coverage not only affecting health-related outcomes but also improves financial well-being. Himmelstein (2019) indicated that the ACA Medicaid expansion improved in food security among the low-income family in the states expanding Medicaid.

This chapter contributes to the literature of Medicare Part D by exploring whether the Medicare prescription drug can improve food security and weight outcome among the elderly. Since food access impacts the life quality and ultimately affect health outcomes, it is critical to understand how prescription drug insurance coverage may have an effect on well-being besides health care access among senior.

2.2.3. The mechanism that Medicare prescription drug coverage affects food access and Supplemental Nutrition Assistance Program (SNAP) participation

Previous research found evidence of the reversed relationship between medical care and food spending due to limited resources. Berkowitz et al. (2014) suggested evidence that people need to make decisions between buying food or necessary medications. Weinfield et al. (2014) found that 66% of clients from Feeding America reported having to tradeoff between buying food and paying medical bills. Medicare part D focuses on improving access to prescription drugs and reduce the financial burden from medical expenditure; it could provide a mechanism to improve food access.

Through the changes in medical expenditure, the prescription drugs insurance coverage may also affect the participation in safety-net programs such as SNAP. SNAP provides household food assistance based on household size and resources, income, expenditure, employment, and immigration status (USDA, 2017). Medical expenses for elderly aged over 60 or disabled members that are more than $35 for the month are allowed for deduction when considering for SNAP benefits if they are not paid by insurance or someone else (USDA, 2017). Thus, decreasing the unreimbursed medical expenditure would affect the eligibility for seniors who have significant spending on health care. There are many recent studies on the take-up of food assistance programs, and the effects of food assistance programs on food insecurity, and other outcomes (Gunderson et al. 2011; Bitler et al., 2016). Little is known of how the nonfood policies affect the eligibility and participation of food assistance programs (Chatterji et al., 2018; Schmidt et al., 2015). Thus, the results of this study are highly policy-relevant in this respect.

2.2.4. Chronic disease and out of pocket medical spending among the elderly

Chronic diseases are the major public health problem in the U.S, which incur the highest cost to treatment as well as the indirect social-economics cost. Having multiple chronic conditions is also associated with substantial health care expenditure. Among Medicare fee-for-service beneficiaries, people with multiple chronic conditions account for 93% of total Medicare spending (CMS, 2012). People with multiple chronic conditions also face substantial out-of-pocket costs of their care, including higher costs for prescription drugs (CDC, 2013).

A report by Paez et al. (2009) based on the Medical Expenditure Panel Survey (MEPS) 2005 showed that people aged over 65 were most likely to be burdened by multiple chronic conditions and least likely to report no chronic disease. 45.3 percent in aged 65–79 and 54.2 percent in aged 80 and older reported having at least three chronic conditions. The statistic clearly shows a correlation between spending and chronic conditions. These facts demonstrate less healthy populations who are suffering from multiple chronic diseases incur a substantial burden from medication spending.

2.3. Data

This paper uses data from the 2000-2014 waves of the Health and Retirement Study (hereafter HRS). The HRS is a longitudinal survey of a representative sample of Americans over age 50 and their spouses. The study interviews approximately 20,000 respondents every two years on a variety of subjects like health care, housing, assets, pensions, employment, and disability, health insurance, health-related variables. We combine data from the raw HRS files with RAND HRS data, which is a longitudinal data file containing cleaned versions of the most frequently used HRS variables. The Household Asset and Income Section from the HRS data provides information on household assets, income, and food security outcomes. The rich information on health status indicators, demographics, and food access-related and asset-related variables allow us to analyze the impact of Medicare Part D on seniors' well-being. They also have the identification of the chronic disease presence of individuals, enabling us to construct treatment and control groups to be used in a triple differences design. We obtained the restricted data from HRS for state identification for our analysis, so that we can better control for the state and state-time difference factors.

To provide a mechanism of how Medicare Part D can impact non-health related outcomes, we first estimate the impact of the policy on prescription coverage and out of pocket medication costs. Consequently, we are investigating the effect of Medicare Part D on the food access related variables. Lastly, we consider the weight variables as measures of health outcomes. Lacking food access can lead to less food intake and increase the probability of being underweight. In another scenario, people lacking resources for food can replace good food with cheap and unhealthy food, which can potentially result in a lot of health problems, including obesity.

The first group of variables that we study is prescription coverage and out of pocket spending: (1) binary indicator for RX coverage, and (2) total out of pocket spending for prescription drugs. The Health Services and Insurance section contains the variable to indicate prescription drug coverage and prescription drug spending. Individuals are first asked if they regularly take prescription drugs. Persons who answer yes are then asked whether the costs of their medications are covered by insurance. We create a binary indicator that takes the value one if the person reports that they are either fully or partially covered and zero if they are not covered at all. They are asked of how much is the total prescription drug expenditure in the past month. For people without any prescription filled, we recode the out of pocket cost for medication as zero.

The second group of outcome variables is the food access related variables from the financial and assets section in HRS. The financial respondent of the family will be answering the question related to this topic, and the answers are recorded at the family level. Food access related variables including: (1) Probability of always having enough money to buy food [21], (2) Binary indicator for eating less due to there is not enough money[22], (3) Binary indicator for receiving food stamp in the past two years [23], (4) Amount spend on food on an average week[24], and (5) the log amount of spending on food.

The third group of the outcome variable is weight-related outcome including (1) Body Mass Index (BMI), (2) Binary indicator for being overweight, (3) binary indicator for being underweight

For outcomes variable at the family level, we conduct the analysis separately on lone senior families and couple senior families. The lone senior family sample includes all the seniors aged 66-70 reported living by themselves, excluding 65 years old and senior below 65 years old with Medicare without any missing value of control variables (N=10,826[25]). Regarding couple family subsample, we include all the families with both spouses age 66-70 and families with both spouses aged 60-64 (N= 5,140). We exclude the families of a couple with one spouse over 65, and one spouse below 65 because it is unclear to assign those families to the treatment or the control group. The total observations vary across different outcome variables since there are missing reported value in the original HRS data files.

Multiple chronic condition Indicators

[21] Financial respondent is asked if they always have enough money to buy food

[22] For respondents who answered that they do not have enough money for food will be asked: "if they eat less due to not having enough money for food". We recode the variable takes the value 1 if they answer yes, 0 otherwise.

[23] . Respondents are asked "Do you receive food stamp since the last wave?"

[24] Respondents are asked "How much do your family spend on food on an average week?" I use this number and adjust the value of this variable with the CPI to represent the 2014 equivalent value

[25] The observation for each specific outcome can be different depending the number of missing value

As presented in Section 2.2, the impact of Medicare Part D on financial strain weighs heavily on the group with comorbidity who incur the highest risk of medical spending (Engelhardt and Gruber, 2011). As the medical expenditure is endogenous with the provision, we use a proxy that is invariant by the policy implementation but highly correlated with medical risk spending. That is the number of chronic diseases that respondents have. In Table 2.1, we report the average of total out of pocket spending for prescription medication along with the number of chronic conditions. We can see the total out of pocket expenditure is increasing as the number of chronic diseases increase. Therefore, test whether the impact of Medicare Part D on food security concentrate among the individuals who had multiple chronic conditions. In the HRS, respondents are asked about their current presence of any of the following chronic conditions: hypertension, diabetes, stroke, psychiatric, lung disease, cancer, arthritis, and heart disease. We divide this population into two groups: those who reported presenting at least three chronic diseases (TCC =1), and those with 0-2 chronic conditions (TCC = 0). There are about 33% of the HRS sample aged 60 -70 falls to the group of having at least three chronic conditions. In the main finding, we present the results based on this classification; we also report estimations from using different classifications based on different thresholds of the number of chronic conditions in our robust check analysis in section 2.6.1.

2.4. Methodology

Since Medicare Part D is a voluntary program, senior adults need to enroll in the program and pay a monthly premium for their coverage. Therefore, the sample of seniors with Medicare Part D drug coverage is subjected to the self-selection problem in that Medicare Part D beneficiaries are different from the group of people without Medicare Part D coverage. Regression against the Medicare Part D coverage indicator will encounter the endogeneity problem. Our empirical strategy exploits the variation in drug prescription potential benefits between Medicare beneficiaries and younger seniors before and after the implementation of Medicare Part D. Firstly; we adopt the difference-in-difference (DD) method, which compares the outcome of older seniors (aged 66-70) with that of younger seniors (aged 60-64) for the pre and post 2006.

As we discussed in Section 2.2, the impact of Medicare Part D on out of pocket spending weighs heavily on individuals with high risk of medication spending (Engelhardt and Gruber, 2011). The weaker individuals with multiple chronic conditions who incur large spending on medication before the policy are more likely to rely on prescription drugs and benefit more from drug insurance coverage. Therefore, we will allow for the differential in effect across different groups with different health expenditures. Since healthcare expenditure is endogenous and changing after the implementation of Medicare Part D, we cannot use them as the indicator to differentiate the effect. Instead, we use chronic conditions as a proxy indicator for high medication spending as they are highly correlated with out of pocket spending and, and they remain by the policy. Hence, we allow for differential effects of the policy changes across health status. Our preferred model is a difference-in-difference-in-difference design that compares outcomes before and after Medicare Part D was implemented among seniors aged 60-64 and aged 66-70 and between the high and lower burden of medication spending groups.

One more advantage of the DDD design is that it can help to reduce potential endogenous timing of Medicare Part D (Huh, 2017)[26] since the divergence in the impact across health status

---

[26] In Huh(2017) , he used DDD model to estimated the impact of Medicaid expansion on Medical provider supply in poor county in expansion states, by exploit the variation across state and time, and between the poor counties and non-poor counties.

group within the Medicare beneficiaries is more likely the consequence of health insurance policy rather than the economics plunge.

We first estimate the intent-to-treat effect of Medicare Part D on the prescription drugs coverage and the out-of-pocket drug expenditure. For this analysis, we run the regression at the respondent level since those variables are recorded at the person-level outcome. This result will provide evidence of how Medicare Part D impact prescription drug coverage and one financial strain outcome and provide the mechanism of how the health insurance coverage affects food access related outcomes.

The food-related variables family-level outcomes, as they are the joint outcome of two individual spouses who live in the same family, or the individual outcome if the seniors live by themselves. Thus, we analyze these outcome variables at the family level, and we estimate the impact separately for lone senior families and couple seniors families sample. We include the covariates of the respondent for the family of lone senior or covariates of both spouses for the couple senior families in the regression. For the lone senior sample, we cluster standard errors at the age level. For the couple families, we cluster standard error at the age of the older spouse in the household.

Individuals under 65 can be eligible for Medicare if they are receiving Social Security Disability Insurance (SSDI)[27], a program that provides income supplement and health insurance to people who are physically restricted in their ability to work. Therefore, we exclude all the people aged 60-64 with Medicare from our analysis.

[27] Regardless to person's age they will be eligible for Medicare after receiving SSDI benefits for 24 months.

2.4.1 Econometric Model

We estimate the intent-to-treat effect with linear regression difference-in-difference design and difference-in-difference-in-difference design. For the analysis of outcomes at the person level including RX coverage, RX out of pocket spending, BMI, the indicator for overweight/underweight, we use data at the personal level in the following regression:

The difference-in-difference model:

$$y_{iat} = \beta_0 + \beta_1(Post_t \times Age6670_{iat}) + \beta_2 \times X_{iat} + \tau_t + \phi_a + \theta_s \times t + \epsilon_{iat} \quad (1)$$

The difference-in-difference-in-difference model:

$$\begin{aligned} y_{iat} = \beta_0 + \beta_1(Post_t \times Age6670_{iat}) + \beta_2(Post_t \times Age6670_{iat} \times TCC) \\ + \beta_3(Post_t \times TCC_i) + \beta_4 \times (Age6670_{iat} \times TCC) + \beta_5 \times TCC + \beta_7 \times X_{iat} \\ + \tau_t + \phi_a + \theta_s \times t + \epsilon_{iat} \quad (2) \end{aligned}$$

In the equations above, i, a, t indicates the individual[28], age group, and year. y_{iat} are the outcomes of interest we discussed in Section 2.3. $Age6670_{iat}$ is a binary indicator, takes value of 1 if individuals aged 66-70, takes value of 0 if individuals age 60-64. *Post* is the dummy variable, takes the value of 1 if the interview year is after 2006, and takes value 0 if the interview year before 2006. TCC is the binary indicator for if the respondent having three chronic conditions or more that is defined in section 2.3. X_{iat} is a vector of characteristics including race, marital status, gender, age, education, and health status, income, employment[29], including

[28] The unit of analysis of family or individual depends on outcome variables. For the food-related access,
[29] The economic downturn possibly affects Medicare and non-Medicare group differently since the elderly population who are over 65 are less likely to be impacted by the employment situation and economic conditions than the younger group. We account for respondent employment status, family income level to account for respondents' economic-related standing. People can argue that income and employment variable are endogenous to the policy.

indicators for each chronic condition. ϵ_{iat} is the error term. Person weight is used in the regression.

For the analysis of outcomes of food-related variables outcomes, the unit of the regression is at the family level. Thus, we do the regression for lone senior and couple senior families separately.

The difference-in-difference model:

$$y_{fat} = \beta_0 + \beta_1(Post_t \times Age6670_{fat}) + \beta_2 \times Age6670_{fat} + \beta_3 \times X_{fat} + \tau_t + \phi_a + \theta_s \times t + \epsilon_{fat} \quad (3)$$

The difference-in-difference-in-difference model:

$$y_{fat} = \beta_0 + \beta_1(Post_t \times Age6670_{fat}) + \beta_2(Post_t \times Age6670_{fat} \times TCC) + \beta_3(Post \times TCC) + \beta_4 \times (Age6670_{fat} \times TCC) + \beta_5 \times TCC + \beta_6 \times Age6670_{fat} + \beta_7 \times X_{fat} + \tau_t + \phi_a + \theta_s \times t + \epsilon_{fat} \quad (4)$$

f, a, t indicates the family, age group, and year. y_{fat} is the outcome of interest, including a binary indicator for having enough money for food, a binary indicator of eating less due to lack of money, a binary indicator for SNAP participation, and dollar amount and log dollar amount spending on food on an average week. $Age6670_{fat}$ is a binary indicator, take the value of one if family f has both spouses aged over 66-70 years old (for couple senior families) or the only lone

However, we do the robust check that include/exclude the income and employment variables and, the results are similar senior aged 66-70 years old (for lone senior family). *Post* is the dummy variable, take the value of 1 if the interview year is after 2006, and takes the value 0 if the interview year before 2006. TCC is the binary indicator that takes the value of 1 if the lone senior has at least three chronic conditions (in the lone senior family), or if the couple senior family has at least one spouse with at least three chronic conditions that we defined in the sections 2.3. X_{fat} is a vector of characteristics of both spouses in the family (for couple senior family sample), or of one lone senior (for lone senior sample) including race, marital status, gender, age, education, and health status, including indicators for each chronic condition. ϵ_{fat} is the error term.

We also include year fixed effect, state linear time trend to control for unmeasured state-level, time-varying factors that can impact outcome variables. Standard errors clustered at the age level of respondents (lone seniors) or the age of the older spouse in the family (for couple senior family sample) to allow for correlation within an age group. Household weight is included in the regression.

In the above specifications, the coefficient of interest is the coefficient of $Post_t \times Aged6670$ and $Post_t \times Aged6670 \times TCC,$ which indicates the impact of Medicare part D on senior individuals over 65 and seniors who are over 65 and have at least three chronic conditions (for lone senior family) or family of couple seniors with both spouses aged over 65. For the DDD design, we will include all the interaction terms of aged 66-70 indicator, post-Part D implementation indicator, and indicator TCC defined in section 2.

2.4.2. Parallel trend assumption

The identifying assumption for DD and DDD design is that trends outcome would have been similar between the treatment and control group in the absence of the policy interventions.

We test for the common trend presumption by running the regression on the pre-treatment period controlling for the interaction of aged 66-70, TCC indicator, and linear trend variable for the period before 2000-2004 Medicare Part D implementation:

$$y_{iat} = \gamma_0 + \gamma_1(Linear\ Trend\ \times\ Aged66-70) + \gamma_2(Lineartrend\ Aged6670 \times TCC)) + \gamma_3\ (Linear\_Trend\ \times TCC) + \gamma_4 \times (Aged66-70 \times TCC) + \gamma_5 \times\ TCC\ + \gamma_7 \times X_{iat} + \tau_t + \phi_a + \theta_s \times t + \epsilon_{iat} \quad (5)$$

For the family level outcome:

$$y_{fat} = \gamma_0 + \gamma_1(Linear\ Trend\ \times\ Aged66-70) + \gamma_2(Lineartrend\ Aged6670 \times TCC)\ + \gamma_3\ (Linear\_Trend\ \times TCCs) + \gamma_4 \times (Aged66-70 \times TCC) + \gamma_5 \times\ TCC + \gamma_7 \times X_{fat} + \tau_t + \phi_a + \theta_s \times t + \epsilon_{fat} \quad (6)$$

The parallel trend presumption between control and treatment group implies that all coefficients $\gamma_1, \gamma_2, \gamma_3$ are equal to zero. We present the estimations for outcome form HRS in Appendix Table 2.1 and Appendix Table 2.2 and Appendix Table 2.3, which support our assumption. The estimates show that the interaction term of the $(Linear\ Trend\ \times\ Aged66-70)$ and $(Lineartrend\ Aged6670 \times TCC)$ are small and not statistically significant. That provides us with confidence in the assumption of a similar trend between individuals aged 60-64 and aged 66-70 as well as across health status groups in the absence of the policy change.

Descriptive Statistics of Control Variables

Table 2.2 and Table 2.3 present the weighted mean of control variables and outcomes variables for lone seniors and couple seniors for the sample from HRS data, respectively. We present the weight mean for four different sub-groups in the order: aged 66-70 with at least three chronic conditions (TCC), aged 66-70 without TCC, aged 60-64 with TCC, and aged 60-64 without TCC. The statistics from Table 2.2 and Table 2.3 indicate that the sample with TCC has a slightly higher portion of the minority than the healthier sample. They are less likely to have a college degree or advanced degree, less likely to work full time, and has a lower income, compared with the healthier group. The TCCs group has a higher prevalence of all chronic conditions, which is based on the definition of this group. This is known in the previous literature that the low social-economics status and minority have a higher prevalence of chronic conditions.

2.5. Results

2.5.1 Effect of Medicare Part D on prescription coverage and out of pocket prescription expenditures:

Table 2.4 reports the DD and DDD estimation for the impact of Medicare part D on the prescription coverage and prescription out of pocket cost. Panel A reports the coefficient from the interaction term of the DD model. The estimations indicate that Medicare Part D is associated with an increase in the prescription drug coverage among seniors aged over 65 by 16 percentage points and a decrease of $25 on monthly out of pocket medication expenditure on average. Our DD estimation of prescription coverage is comparable with the finding in Ayyagari & Shane[30] (2016).

Panel B reports the DDD interaction terms' coefficients. The coefficient of $Post \times Aged6670$ indicates that Medicare Part D is associated with an average reduction of $5

[30] Ayyagari, & Shane (2016) used HRS data 2000-2010 for their analysis

in monthly out of pocket prescription drug spending among all the Medicare beneficiaries. The coefficient of the term $Post \times Aged6670 \times TCC$ implies that Medicare Part D led to an additional decrease of $67 in the monthly prescription out of pocket cost among senior-aged 66-70 with more than two chronic conditions compared to the 'healthier' group in the post-Medicare Part D period. In contrast, we still find that Medicare Part D leads to an increase of 16 percentage point increase in the probability of having prescription coverage in every senior on average, but there is no discrepancy in the Medicare Part D take-up rate between the 'weaker' and the 'healthier' group. Figure 2.1 illustrates these findings. In the figures, we present average out of pocket drug expenditure and prescription drug coverage of the group with and without three chronic conditions among the older group (aged 66-70) in comparison to the younger senior adult (60-64) for the period 2000-2014. The graph clearly shows that the prescription drug coverage increases sharply for the aged 6670 group (both TCC and without TCC), however, the out of pocket only decrease significantly among the group aged 66-70 with TCC.

2.5.2 Effect of Medicare Part D on food access- related variables and SNAP program participation

Table 2.5 reports the impact of Medicare Part D on the food-security related outcomes for lone seniors. Panel A shows the estimation for the interaction term from the difference-in-difference model. All the coefficients of the interaction term in the difference-in-difference model are not statistically significant. That implies there is no effect from prescription drugs on food access and SNAP participation among lone seniors aged 66-70 on average.

In Panel B, we report the estimation of the interaction terms from the DDD model for five outcomes variables in columns (1) – (5), respectively. The estimate on the interaction terms of $Post \times Aged6670 \times TCC$ indicates that Medicare Part D led to a 6.8 percentage point increase of the probability of having enough money for food among the elderly who have at least three chronic conditions. However, the coefficient of the term $Post \times Aged6670$ is small and not statistically significant, implying that Medicare part D does not affect the probability of having enough money for food among the elderly population aged 65-70. The coefficient of $Post \times Aged6670 \times TCC$ term suggests that Medicare part D is associated with 4.8 percentage point decrease in the probability of eating less due to money deficiency, and $14 increase in weekly amount spending for food among seniors age over 65 with more than two chronic conditions in comparison with the "healthier" group. The estimation also suggests that SNAP participation reduces by 10 percentage points. However, the coefficient on the $post \times Aged6670$ is not statistically significant in all the analysis of the five outcomes variables, implying that there is no statistically significant effect on 'healthier' seniors. That suggests the impact of Medicare Part D on the food-related outcomes is substantial among the weaker population who are at higher quantiles of medical spending. Although the lower quantiles of medical spending group can experience a reduction in medical expenditures, this group may be less likely to suffer from food deficiency, so their food-related outcome is not impacted by prescription drug coverage.

Table 2.6 displays estimation from the DD and DDD model on the food-security related outcomes for the families of couple seniors. In Panel A, the estimates from column (1) to (5) indicate that Medicare Part leads to D leads to 3.2 percentage point increase in the probability of having enough money for food, and 1.4 percentage point decrease in the likelihood of eating less due to lacking of money among family with both spouses age over 65. These estimations are statistically significant. The impact on the average weekly spending on food has the expected sign. However, it is small, not statistically significant. The effect on SNAP participation is small and not statistically significant among families of couple seniors sample.

Figure 2.2 and Figure 2.3 confirm our finding above. The graph presents the aggregate trends of the food-related variables of the families of lone seniors and families of couple seniors. The trends of the outcomes of interest between Medicare and non-Medicare and across health status remain parallel before the year 2006. On the other hand, the discrepancy between the Medicare group with TCC and the non-Medicare group with TCC getting larger after the implementation of Medicare Part D among lone senior families. That pattern implies Medicare Part D provides the older seniors with Medicare the financial protection, the protection is more substantial among the ones with multiple chronic conditions.

2.5.3. Effect of Medicare Part D on BMI/Overweight/Underweight

Table 2.7 reports the DiD estimation and DiDiD estimation of Medicare Part D on the weight-related outcome. Although we found that the effect on BMI is statistically significant for the general elderly population aged 66-70, we don't find evidence that the policy impacts the probability of being overweight or underweight for the Medicare beneficiaries.

2.6. Sensitivity Check

2.6.1. Sensitivity check using different thresholds of the number of chronic conditions in the difference-in-difference-in- difference model

In the main specification for DDD design, we use a binary indicator of having at least three chronic conditions as the threshold to differentiate between the weaker and the healthier group. In the sections, we use one chronic condition, two chronic diseases, four chronic conditions as a threshold to differentiate the TCC group, and the number of chronic conditions to interact with the difference-in-difference terms. The results for lone seniors are presented in Table 2.8. We find that if using one chronic condition as the threshold, we don't find any clear effect among the weaker group, which has at least one chronic condition. This can be explained by the fact that the portion of the population has at least one chronic condition is large, and the impact on this group is small. Panel C reports the estimation using two chronic conditions as the threshold. The estimates for most of the outcomes are similar to our main results, except the estimate on SNAP participation. The coefficient is now smaller and not statistically significant. Panel D reports the estimation using four chronic conditions as the threshold. The estimation is larger in magnitude and statistically significant for the triple interaction.

Table 2.9 reports the results for couple senior families sample. We find that using different numbers of chronic conditions as a threshold does not change the result much. The estimations suggest that prescription drug coverage increase the probability of having enough money for food among the general senior population, but not the seniors with more chronic condition among couple senior families.

2.6.2. Sensitivity Check with different covariates

We conducted various sensitivity checks of the main findings for the impact of Medicare Part D on food-related outcomes. The results from these checks are shown in Table 2.10 (food access outcomes – lone senior family) and Table 2.11 (food access outcomes – couple seniors families). These robust checks included: (1) add to the original model the interactions of the age group with the state linear trend to account for the difference in trend among different age group across states (Panel A), (2) using the interaction of state-year fixed effect instead of state linear trend effect (Panel B); (3) No control for income and employment in the regression(Panel C), (4) dropping the Medicaid population[31] (Panel D), (5) estimating un-weighted models (Panel E). Our estimates are robust across these estimations. In the Panel E, when we exclude the Medicaid population from our analysis, the effect on food access related variables is stronger than the main result, however, the effect on SNAP is smaller and not statistically significant.

2.6.3. Falsification test

To perform the falsification test, we restrict the HRS sample to seniors aged 55-64 years old. We estimated the similar models to the main models that falsely assumed that Part D coverage became available to persons aged 60–64 since 2006 but not for the younger cohort aged 55–59. The estimations from the DD model and DDD model on food access related outcomes for lone senior family and couple senior family on are reported in Table 2.12 and Table 2.13, respectively. The coefficients $Post \times Aged6164 \times TCC$ and $Post \times Aged6164$ from the estimations using falsification treatment group are small and not statistically significant. These results give us more confidence that the observed effect on food access outcomes that we found from the Medicare beneficiaries aged 66-70 after the implementation of Medicare Part D is the result of prescription drug coverage. From the falsification test, we did not find evidence that other factors can affect the older group more favorably compared with the younger group. That gives us more confidence that the impact we find in our main analysis on the seniors who are eligible for Medicare Part D come from the prescription drug coverage.

2.7. Conclusion

[31] Medicaid population can have prescription covered under the Medicaid program, although the coverage can be different from Medicare

Medicare Part D is the largest expansion of the Medicare program since it initiated in 1966. Previous literature has documented that Medicare Part D is associated with higher utilization and better financial stability among the elderly. In this chapter, we examine if Medicare prescription drug coverage has a spillover effect on food security among the beneficiaries. Understanding the spillover effect on food access among the elderly due to the change in prescription drug coverage is critical to evaluate the cost and benefit of the program.

We present the DD and DDD estimates to indicate the effects of Medicare Part D implementation on the out of pocket cost for medication, food access related outcomes, and weight outcomes. Our analysis based on the HRS waves 2000-20014 suggests that Medicare Part D increases the prescription drug coverage for the Medicare beneficiaries by 16 percentage points. Also, the program decreases the burden of out of pocket medication, and the effect is more substantial among the beneficiaries with multiple chronic conditions. As a result, Medicare Part D statistically improve the food access related outcomes lone senior family and reduces the participation of food assistance program among lone seniors who have multiple chronic conditions that incur a high risk of medication spending. Among the couple seniors family sample, we found evidence that Medicare reduces the probability of self-reported not having enough money for food among the general group; but we did not find further effect among the families of couple seniors with at least one spouse with comorbidity. Regarding the weight outcomes, we find some evidence that Medicare increase BMI but no clear evidence that that the program impacts the probability of being overweight or underweight among seniors.

These findings suggest that Medicare Part D improve food access among the elderly population as a consequence of reducing financial strain from medication expenditure. Thus, the prescription drug coverage provides one additional pathway that prescription drugs can impact overall well-being as well as mental health outcomes and physical health outcomes.

Table 2. 1. Monthly RX out of pocket expenditure by the number of chronic conditions

	Out-of-Pocket RX cost	Sample	Sample Percentage
	(1)	(2)	(3)
0 chronic condition	$25.98	1,089	12.60%
1 chronic condition	$58.6	2,300	26.70%
2 chronic condition	$102.94	2321	26.90%
3 chronic condition	$140.42	1,702	19.70%
4 chronic condition	$246.84	759	8.80%
5+ chronic condition	$180.45	454	5.30%

Note: The sample size and RX OOP is calculated from senior age 66-70 from HRS 2000-2004.

Table 2. 2. Summary Statistics

	All	Age 60-64		Age 66-70	
		TCCs = 0	TCCs =1	TCCs = 0	TCCs =1
	(1)	(2)	(3)	(4)	(5)
Age	64.92	61.889	62.003	67.964	67.984
Female	0.63	0.629	0.706	0.654	0.745
Black	0.161	0.156	0.198	0.149	0.161
Asian/mixed	0.027	0.026	0.031	0.017	0.037
Hispanic	0.089	0.079	0.113	0.087	0.092
High school/GED graduate	0.587	0.597	0.603	0.583	0.566
Some college	0.114	0.145	0.095	0.119	0.071
College graduate	0.084	0.112	0.071	0.078	0.057
More than college	0.024	0.025	0.018	0.027	0.021
Log earned income	10.027	10.075	9.737	10.203	9.926
Work part time	0.057	0.08	0.061	0.048	0.027
Unemployed	0.029	0.044	0.028	0.02	0.016
Partly retired/	0.112	0.093	0.096	0.153	0.103
Retired	0.464	0.265	0.425	0.554	0.701
Disabled	0.028	0.019	0.064	0.012	0.036
Not in labor force	0.042	0.037	0.048	0.044	0.045
Diabetes	0.217	0.08	0.428	0.075	0.474
Heart disease	0.204	0.049	0.4	0.074	0.485
Hypertension	0.573	0.399	0.875	0.405	0.858
Lung disease	0.125	0.032	0.27	0.042	0.279
Cancer	0.137	0.05	0.247	0.082	0.271
Arthritis	0.589	0.367	0.856	0.491	0.884
Psychiatric	0.239	0.115	0.503	0.096	0.438
Stroke	0.052	0.009	0.103	0.018	0.127
Dependent variables					
Enough money for food	0.894	0.923	0.815	0.942	0.843
Eat less	0.066	0.041	0.139	0.034	0.097
Food Stamp	0.119	0.069	0.236	0.065	0.189
Food Spending	79.646	80.553	78.334	78.307	80.829
Log food spending	3.81	3.862	3.737	3.815	3.77
N Observations	10,903	3,520	1,586	3,212	2,585

Note: Weighted mean is calculated from HRS 2000-2014.

Table 2. 3. Summary Statistic for couple seniors families

	All samples	TCC = 0	TCC =1	TCC = 0	TCC =1
	(1)	(2)	(3)	(4)	(5)
Age	65.127	62.468	62.705	68.495	68.646
Female	0.313	0.323	0.332	0.298	0.295
Black	0.054	0.043	0.058	0.049	0.07
Asian/mixed	0.02	0.019	0.024	0.017	0.021
Hispanic	0.07	0.069	0.085	0.058	0.067
High school/GED graduate	0.552	0.481	0.644	0.521	0.615
Some college	0.191	0.261	0.123	0.215	0.127
College graduate	0.1	0.131	0.076	0.106	0.069
More than college	0.04	0.048	0.031	0.05	0.029
Log earned income	11.161	11.353	10.996	11.219	10.978
Work part time	0.05	0.067	0.06	0.033	0.03
Unemployed	0.02	0.025	0.028	0.012	0.01
Partly retired/	0.137	0.117	0.107	0.209	0.14
Retired	0.452	0.298	0.378	0.557	0.665
Disabled	0.007	0.005	0.015	0.006	0.004
Not in labor force	0.041	0.051	0.038	0.034	0.035
Diabetes	0.194	0.088	0.287	0.107	0.339
Heart disease	0.211	0.097	0.285	0.107	0.398
Hypertension	0.548	0.384	0.698	0.439	0.745
Lung disease	0.073	0.017	0.127	0.032	0.141
Cancer	0.121	0.057	0.158	0.083	0.212
Arthritis	0.527	0.368	0.664	0.426	0.722
Psychiatric	0.119	0.058	0.223	0.036	0.182
Stroke	0.039	0.012	0.055	0.009	0.089
Younger Spouse					
Age	63.851	61.247	61.42	67.293	67.242
Work part time	0.074	0.119	0.075	0.047	0.028
Unemployed	0.013	0.015	0.022	0.008	0.007
Partly retired/	0.107	0.097	0.081	0.14	0.119
Retired	0.417	0.247	0.338	0.563	0.63
Disabled	0.013	0.011	0.037	0.002	0.005

Not in labor force	0.095	0.087	0.105	0.104	0.089
High school/GED graduate	0.595	0.504	0.645	0.579	0.649
Some college	0.17	0.223	0.138	0.176	0.115
College graduate	0.103	0.135	0.076	0.114	0.069
More than college	0.026	0.042	0.008	0.031	0.012
Black	0.056	0.044	0.064	0.052	0.071
Asian/mixed	0.019	0.018	0.024	0.018	0.016
Hispanic	0.069	0.07	0.083	0.059	0.066
Dependent variables					
Enough money for food	0.964	0.973	0.931	0.983	0.963
Eat less	0.014	0.006	0.034	0.005	0.016
Food Stamp	0.028	0.019	0.048	0.012	0.036
Food Spending	123.798	126.82	127.959	117.405	120.724
Log food spending	4.385	4.414	4.398	4.336	4.369
N Observations	5,140	1,594	1032	1,114	1,400

Note: Weighted mean is calculated from HRS 2000-2014.

Table 2. 4. DD and DDD estimation on prescription drug coverage and out-of -pocket expenditure

	RX Coverage	RX OOP cost
	(1)	(2)
Panel A : Difference in Difference		
Post * Age66-70	0.164***	-27.149***
	(0.015)	(7,258)
Observations	30,207	35,582
Panel B: Triple Difference		
Post*Age66-70 *TCC	-0.016	-67.372**
	(0.011)	(29.456)
Post * Age66-70	0.167***	-5.061
	(0.017)	(8.181)
Age66-70 *TCC	0.027	57.906*
	(0.015)	(28.903)
Post*TCC	0.024***	6.041
	(0.005)	(18.733)
TCC	-0.016	-9.587
	(0.013)	(17.626)
Observations	30,207	35,582

Notes: The panel A presents the coefficient and standard error of the interaction term from DD estimation Panel B presents coefficient and standard error of the interaction term from DDD estimation All the models contain a set of control variables discussed in the text. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 2. 5. DD and DDD estimation on food-related variables among lone seniors

	Enough money for food	Eat less	SNAP	Spending on food	Log food spending
	(1)	(2)	(3)	(4)	(5)
Panel A : Difference in Difference					
Post * Age66-70	-0.000	-0.003	-0.020	2.119	0.021
	(0.016)	(0.010)	(0.012)	(3.093)	(0.026)
Panel B: Triple Difference					
Post*Age66-70 *TCCs	0.064**	-0.054**	-0.100***	9.830**	0.160*
	(0.022)	(0.017)	(0.011)	(3.586)	(0.074)
Post * Age66-70	-0.016	0.012	0.012	-1.746	-0.036
	(0.019)	(0.013)	(0.011)	(3.316)	(0.039)
Age66-70 *TCC	-0.035**	0.001	0.038*	-3.751	-0.045
	(0.014)	(0.016)	(0.019)	(2.593)	(0.055)
Post*TCC	-0.035**	0.001	0.038*	-3.751	-0.045
	(0.014)	(0.016)	(0.019)	(2.593)	(0.055)
TCC	0.059***	-0.039	-0.016	6.650	0.028
	(0.016)	(0.022)	(0.019)	(4.106)	(0.065)
Observations	10,826	10,821	10,799	9,812	9,812

Notes: The panel A presents the coefficient and standard error of the interaction term from DD estimation Panel B presents coefficient and standard error of the interaction term from DDD estimation All the models contain a set of control variables discussed in the text. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age of the lone seniors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 2. 6. DD and DDD estimation on food access related variables among couple seniors

	Enough money for food	Eat less	SNAP	Spending on food	Log food spending
	(1)	(2)	(3)	(4)	(5)
Panel A : Difference in Difference					
Post * Age66-70	0.032***	-0.014***	-0.009	1.563	0.031
	(0.009)	(0.004)	(0.008)	(4.120)	(0.030)
	5,146	5,145	5,138	4,599	4,599
Panel B: Triple Difference					
Post*Age66-70 *TCC	0.018	-0.009	0.003	4.52	0.03
	(0.017)	(0.011)	(0.014)	(4.085)	(0.041)
Post * Age66-70	0.026***	-0.01	-0.013	-1.635	0.009
	(0.007)	(0.007)	(0.012)	(5.309)	(0.048)
Age66-70 *TCC	0.004	-0.009	-0.011	-3.826	0.011
	(0.010)	(0.007)	(0.011)	(3.361)	(0.028)
Post*TCC	-0.040*	0.014	0.030**	3.693	0.026
	(0.018)	(0.008)	(0.013)	(3.147)	(0.025)
TCC	0.004	0.005	-0.017	0.439	-0.021
	(0.013)	(0.006)	(0.011)	(2.562)	(0.022)
Observations	5,146	5,145	5,138	4,599	4,599

Notes: The panel A presents the coefficient and standard error of the interaction term from DD estimation Panel B presents coefficient and standard error of the interaction term from DDD estimation All the models contain a set of control variables discussed in the text. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age of the older senior in the family are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 2.7. DD and DDD estimation on weight-related outcomes

	Overweight	Underweight	BMI	Log BMI
	(1)	(2)	(3)	(4)
Panel A : Difference in Difference				
Post * Age66-70	-0.001	0.021	0.285***	0.011***
	(0.003)	(0.014)	(0.073)	(0.003)
Panel B: Triple Difference				
Post*Age66-70 *TCC	0.002	0.01	-0.081	-0.001
	(0.006)	(0.023)	(0.287)	(0.011)
Post * Age66-70	-0.002	0.018	0.271**	0.010**
	(0.004)	(0.016)	(0.112)	(0.004)
Age66-70 *TCC	-0.003	0.025	0.033	0.003
	(0.002)	(0.015)	(0.172)	(0.006)
Post*TCC	-0.001	-0.014	0.353	0.007
	(0.005)	(0.019)	(0.275)	(0.010)
TCC	0.000	-0.012	-0.094	-0.003
	(0.003)	(0.007)	(0.152)	(0.005)
Observations	37,587	37,587	37,587	37,587

Notes: All the models contain a set of control variables discussed in the text. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age of the senior are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 2.8. Robust check with different thresholds of the number of chronic conditions among lone seniors

	Enough money for food	Eat less	SNAP	Spending on food	Log food spending
	(1)	(2)	(3)	(4)	(5)
Pane A: Using number of chronic condition					
Post*Age66-70 *Number of chronic cons	0.017**	-0.013*	-0.025**	3.461**	0.051**
	(0.007)	(0.007)	(0.008)	(1.101)	(0.018)
Post * Age66-70	-0.024	0.015	0.026*	-4.696	-0.075
	(0.021)	(0.017)	(0.014)	(3.980)	(0.050)
Obs	10,826	10,821	10,799	9,812	9,812
Panel B: Using Indicator of having at least one chronic condition					
Post*Age66-70 *(at least 1 chronic condition)	-0.001	-0.010	-0.039	1.478	-0.035
	(0.017)	(0.015)	(0.028)	(7.543)	(0.118)
Post * Age66-70	0.005	0.001	0.012	0.535	0.051
	(0.024)	(0.013)	(0.021)	(6.622)	(0.105)
Obs	10,826	10,821	10,799	9,812	9,812
Panel C: Using Indicator of having at least two chronic condition					
Post*Age66-70 *(at least 2 chronic condition)	0.063**	-0.050**	-0.035	9.560**	0.128**
	(0.020)	(0.018)	(0.019)	(3.506)	(0.047)
Post * Age66-70	-0.033	0.023	-0.000	-3.986	-0.060
	(0.019)	(0.014)	(0.014)	(2.889)	(0.038)
Obs	10,826	10,821	10,799	9,812	9,812
Panel D: Using Indicator of having at least four chronic condition					
Post*Age66-70 *(at least 4 chronic condition)	0.092*	-0.034	-0.096**	16.241*	0.289***
	(0.044)	(0.042)	(0.036)	(8.496)	(0.080)
Post * Age66-70	-0.008	-0.002	-0.006	0.415	-0.016
	(0.015)	(0.011)	(0.009)	(3.995)	(0.033)
Obs	10,826	10,821	10,799	9,812	9,812

Notes: All the models contains a set of control variables discussed in the text. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 2.9. Robust check with different thresholds of the number of chronic conditions among couple seniors

	Enough money for food	Eat less	SNAP	Spending on food	Log food spending
	(1)	(2)	(3)	(4)	(5)
Panel A: Using Indicator of having at least one chronic condition					
Post*Age66-70 *(at least 1 chronic condition)	-0.003	-0.004	0.018	-16.887	-0.085
	(0.016)	(0.008)	(0.018)	(15.768)	(0.113)
Post * Age66-70	0.036**	-0.011	-0.026*	18.285	0.115
	(0.015)	(0.007)	(0.014)	(15.146)	(0.102)
Obs	5,146	5,145	5,138	4,599	4,599
Panel B: Using Indicator of having at least two chronic condition					
Post*Age66-70 *(at least 2 chronic condition)	0.007	-0.012	0.012	-5.536	-0.008
	(0.012)	(0.007)	(0.015)	(4.720)	(0.038)
Post * Age66-70	0.027**	-0.005	-0.021	5.434	0.033
	(0.008)	(0.007)	(0.016)	(5.714)	(0.034)
Obs	5,146	5,145	5,138	4,599	4,599
Panel C: Using Indicator of having at least four chronic condition					
Post*Age66-70 *(at least 4 chronic condition)	0.010	-0.015	0.016	9.543	0.062
	(0.031)	(0.018)	(0.015)	(6.196)	(0.069)
Post * Age66-70	0.030**	-0.009	-0.012	-0.322	0.017
	(0.011)	(0.006)	(0.009)	(4.942)	(0.043)
Obs	5,146	5,145	5,138	4,599	4,599

Notes: All the models contains a set of control variables discussed in the text. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 2.10. Robust Check – DDD estimates among lone seniors

	Enough money for food	Eat less	SNAP	Spending on food	Log food spending
	(1)	(2)	(3)	(4)	(5)
Panel A: Including State#Age#linear trend fixed effect					
Post*Age66-70 *TCCs	0.066**	-0.058***	-0.112***	13.794**	0.188**
	(0.025)	(0.016)	(0.011)	(5.159)	(0.075)
Post * Age66-70	0.024	-0.03	-0.004	-10.545	-0.036
	(0.023)	(0.022)	(0.031)	(10.164)	(0.090)
Obs	10,826	10,821	10,799	9,812	9,812
Panel B: No control for income and employment					
Post*Age66-70 *TCCs	0.061**	-0.051**	-0.102***	9.655**	0.155*
	(0.022)	(0.018)	(0.011)	(3.325)	(0.070)
Post * Age66-70	-0.010	0.007	0.007	-1.588	-0.023
	(0.018)	(0.013)	(0.010)	(3.095)	(0.039)
Obs	10,826	10,821	10,799	9,812	9,812
Panel C: Using state#year fixed effect					
Post*Age66-70 *TCCs	0.067**	-0.059***	-0.109***	13.399**	0.176**
	(0.025)	(0.015)	(0.012)	(5.254)	(0.077)
Post * Age66-70	-0.011	0.008	0.009	-3.728	-0.033
	(0.019)	(0.023)	(0.032)	(10.303)	(0.098)
Obs	10,826	10,821	10,799	9,812	9,812
Panel D: Remove Medicaid population					
Post*Age66-70 *TCCs	0.089***	-0.062***	-0.046*	7.496	0.098
	(0.026)	(0.019)	(0.025)	(4.219)	(0.081)
Post * Age66-70	-0.026	0.013	0.001	-2.658	-0.027
	(0.017)	(0.010)	(0.011)	(2.542)	(0.034)
Obs	9,182	9,179	9,163	8,396	8,396
Panel E: Unweighted					
Post*Age66-70 *TCCs	0.062**	-0.075***	-0.083***	4.702	0.119*
	(0.027)	(0.017)	(0.019)	(4.615)	(0.059)
Post * Age66-70	0.004	0.007	0.013	-2.777	-0.041
	(0.018)	(0.010)	(0.013)	(2.782)	(0.037)
Obs	10,955	10,950	10,935	9,813	9,813

Notes: All the models contains a set of control variables discussed in the text. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 2.11. Robust Check – DDD estimates among couple seniors

	Enough money for food	Eat less	SNAP	Spending on food	Log food spending
	(1)	(2)	(3)	(4)	(5)
Panel A: Including State#Age#linear trend fixed effect					
Post*Age66-70 *TCCs	0.035	-0.016	0	6.652	0.032
	(0.020)	(0.009)	(0.017)	(5.708)	(0.043)
Post * Age66-70	-0.005	0.008	0.015	-0.65	0.039
	(0.010)	(0.014)	(0.013)	(11.658)	(0.086)
	5,146	5,145	5,138	4,599	4,599
Panel B: No control for income and employment					
Post*Age66-70 *TCCs	0.024	-0.011	-0.004	4.418	0.028
	(0.017)	(0.010)	(0.014)	(2.984)	(0.030)
Post * Age66-70	0.020**	-0.008	-0.012	-1.964	0.007
	(0.007)	(0.006)	(0.011)	(4.591)	(0.037)
	5,376	5,375	5,368	4,807	4,807
Panel C: Using state#year fixed effect					
Post*Age66-70 *TCCs	0.019	-0.011	0.003	0.960	0.032
	(0.016)	(0.010)	(0.017)	(3.440)	(0.049)
Post * Age66-70	0.025**	-0.007	-0.015	1.617	-0.01
	(0.008)	(0.007)	(0.014)	(4.444)	(0.102)
	5,146	5,145	5,138	4,599	4,599
Panel D: Remove Medicaid population					
Post*Age66-70 *TCCs	0.007	0.004	0.019*	3.559	0.014
	(0.016)	(0.010)	(0.010)	(4.269)	(0.042)
Post * Age66-70	0.027***	-0.012**	-0.009	-0.114	0.025
	(0.008)	(0.005)	(0.009)	(5.510)	(0.051)
	4,872	4,871	4,865	4,361	4,361
Panel E: Unweighted					
Post*Age66-70 *TCCs	0.024*	-0.022**	0.004	4.623	0.039
	(0.013)	(0.009)	(0.015)	(3.133)	(0.032)
Post * Age66-70	0.020***	-0.003	-0.022	1.004	0.039
	(0.005)	(0.006)	(0.013)	(3.875)	(0.039)
	5,379	5,378	5,371	4,807	4,807

Notes: All the models contains a set of control variables discussed in the text. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 2.12. Placebo Test – Effect of Medicare Part D on food access among younger lone seniors

	Enough money for food	Eat less	SNAP	Spending on food	Log food spending
	(1)	(2)	(3)	(4)	(5)
Panel A : Difference in Difference					
Post * Age61-64	0.001	-0.004	-0.002	-7.393	-0.063
	(0.016)	(0.010)	(0.021)	(4.106)	(0.046)
	9,177	9,175	9,164	8,530	8,530
Panel B: Triple Difference					
Post*Age61-64 *TCCs	-0.029	0.009	0.042	0.117	-0.017
	(0.024)	(0.033)	(0.026)	(5.431)	(0.067)
Post * Age61-74	0.010	-0.009	-0.018	-7.429	-0.059
	(0.018)	(0.009)	(0.016)	(4.117)	(0.049)
Age61-64 *TCC	0.046	0.005	-0.012	-1.850	-0.036
	(0.027)	(0.032)	(0.027)	(2.244)	(0.060)
Post*TCC	-0.052**	0.080**	0.055*	-2.145	-0.033
	(0.015)	(0.027)	(0.025)	(3.150)	(0.048)
TCC	0.027	-0.062	-0.032	0.031	0.027
	(0.027)	(0.038)	(0.026)	(2.883)	(0.042)
Observations	9,177	9,175	9,164	8,530	8,530

Notes: In this placebo test est, we use the sample of younger seniors aged 55-64 for our analysis. We run a similar regression as the main estimation with the placebo treatment group to be elderly age 61-64 and control group to be age 66-59. Panel A presents the coefficient, and standard error of the interaction term from DD estimation. Panel B presents coefficient and standard error of the interaction term from DDD estimation. All the models contain a set of control variables discussed in the text. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

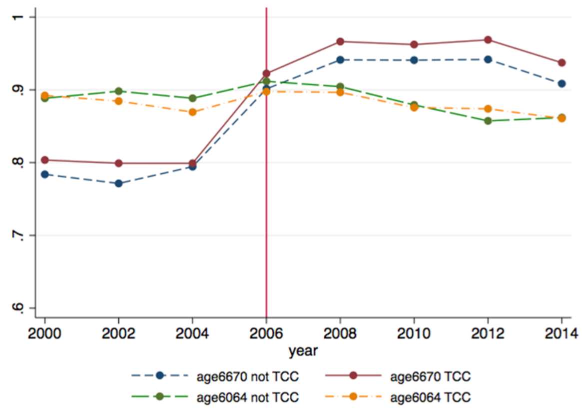
Table 2.13. Placebo Test – Effect of Medicare Part D on food access among younger couple seniors

	Enough money for food	Eat less	SNAP	Spending on food	Log food spending
	(1)	(2)	(3)	(4)	(5)
Panel A : Difference in Difference					
Post * Age61-64	0.020	-0.012	0.007	3.442	0.002
	(0.016)	(0.008)	(0.006)	(21.372)	(0.034)
	8,136	8,134	8,130	7,553	7,553
Panel B: Triple Difference					
Post*Age61-64 *TCCs	0.059	-0.044*	-0.017	-4.448	0.092
	(0.035)	(0.019)	(0.019)	(22.529)	(0.077)
Post * Age61-74	0.005	0.000	0.007	0.192	-0.040*
	(0.011)	(0.008)	(0.005)	(27.307)	(0.020)
Age61-64 *TCC	-0.001	-0.008	-0.011	27.614	0.013
	(0.013)	(0.010)	(0.013)	(23.291)	(0.044)
Post*TCC	-0.073***	0.050**	0.047***	6.652	-0.021
	(0.011)	(0.015)	(0.007)	(18.844)	(0.053)
TCC	0.040**	-0.025**	-0.036***	-17.717	0.031
	(0.014)	(0.010)	(0.009)	(29.176)	(0.040)
Observations	8,158	8,156	8,151	7,574	7,574

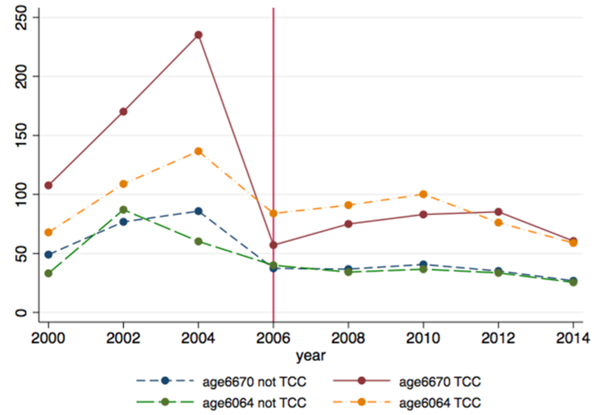
Notes: In this placebo test, we use the sample of younger seniors aged 55-64 for our analysis. We run a similar regression as the main estimation with the placebo treatment group to be elderly age 61-64, and control group to be age 66-59. Panel A presents the coefficient, and standard error of the interaction term from DD estimation Panel B presents coefficient and standard error of the interaction term from DDD estimation. All the models contain a set of control variables discussed in the text. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Figure 2. 1**.** Prescription coverage and prescription out of pocket cost

A. RX coverage



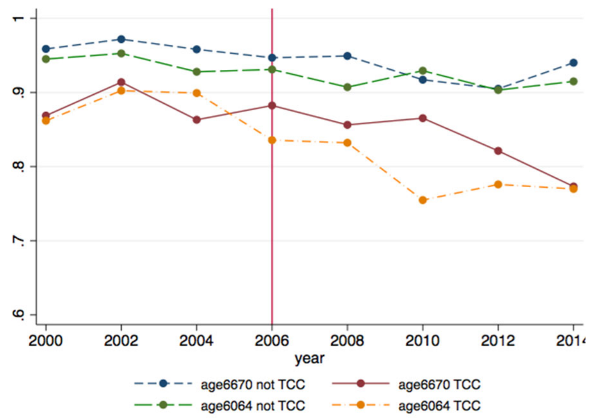
B. RX out-of-pocket cost



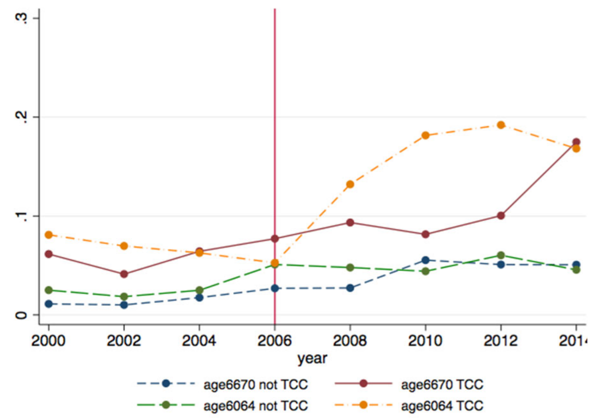
Notes: Mean of the outcome variables are plotted.

Figure 2. 2. Trend in food-related outcomes among lone seniors

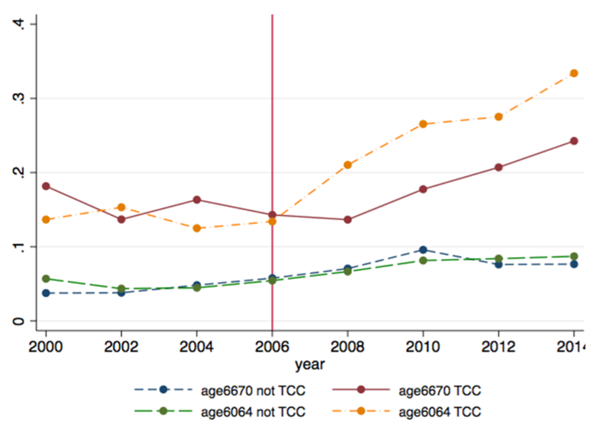
C. Prob. of having enough money for food



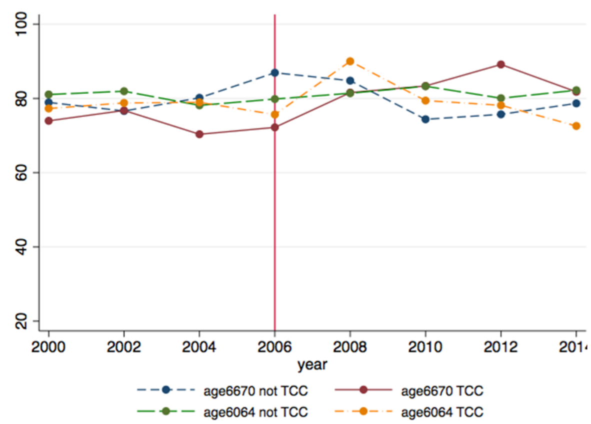
D. Prob. of eating less due to lack of money



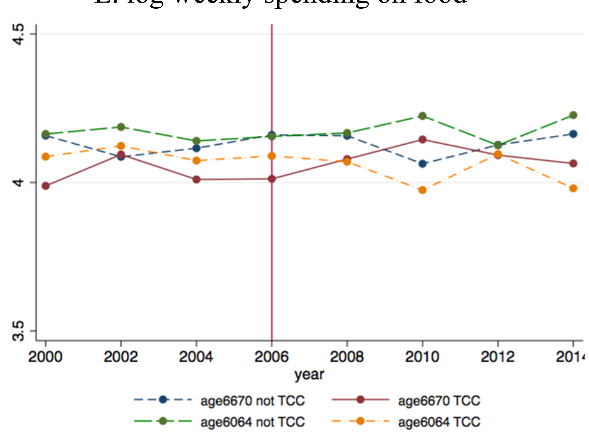
C. SNAP participation



D. Weekly spending on food



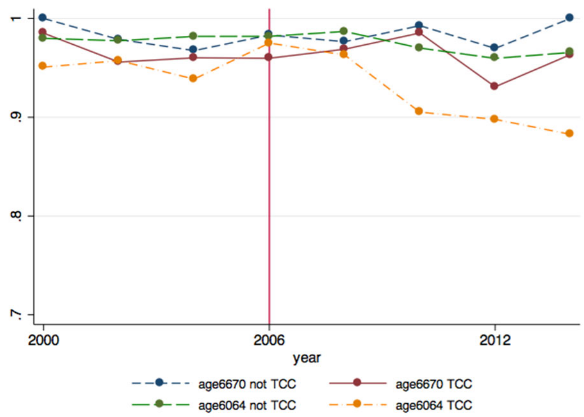
E. log weekly spending on food



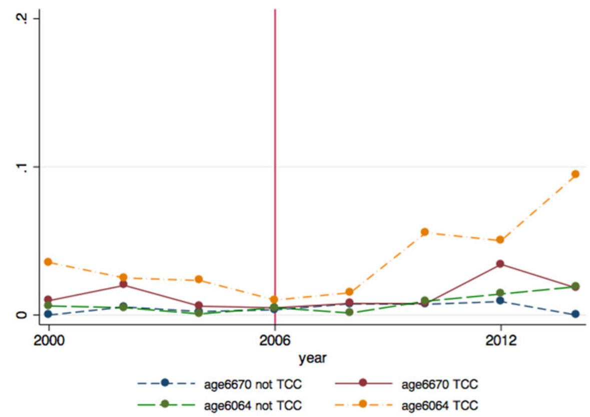
Notes: Mean of the outcome variables are plotted.

Figure 2. 3. Trend in food-related outcomes among couple seniors

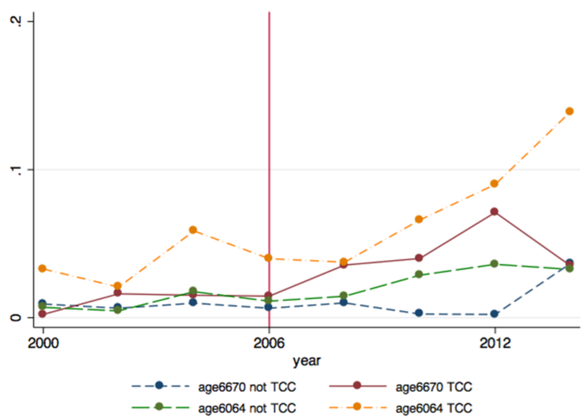
A. Prob. of having enough money for food



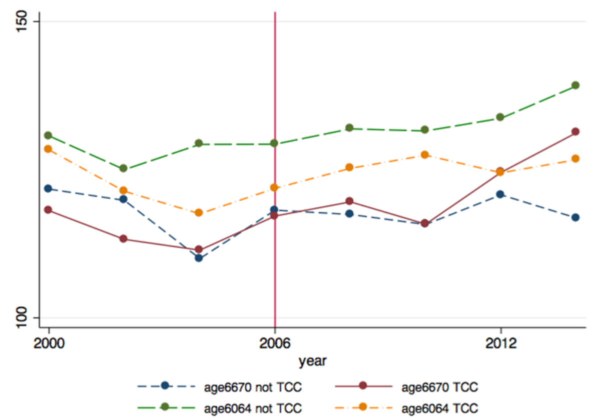
B. Prob. of eating less due to lack of money



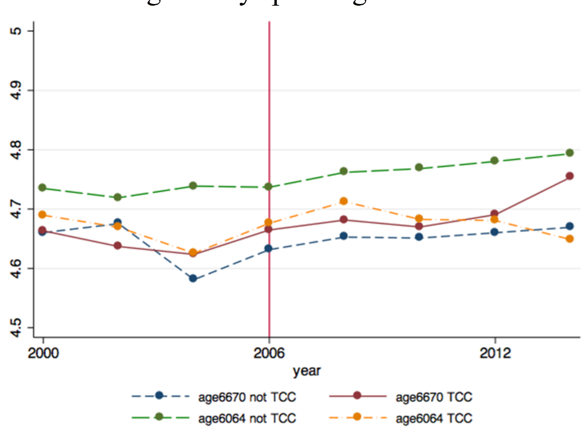
C. SNAP participation



D. Weekly spending on food

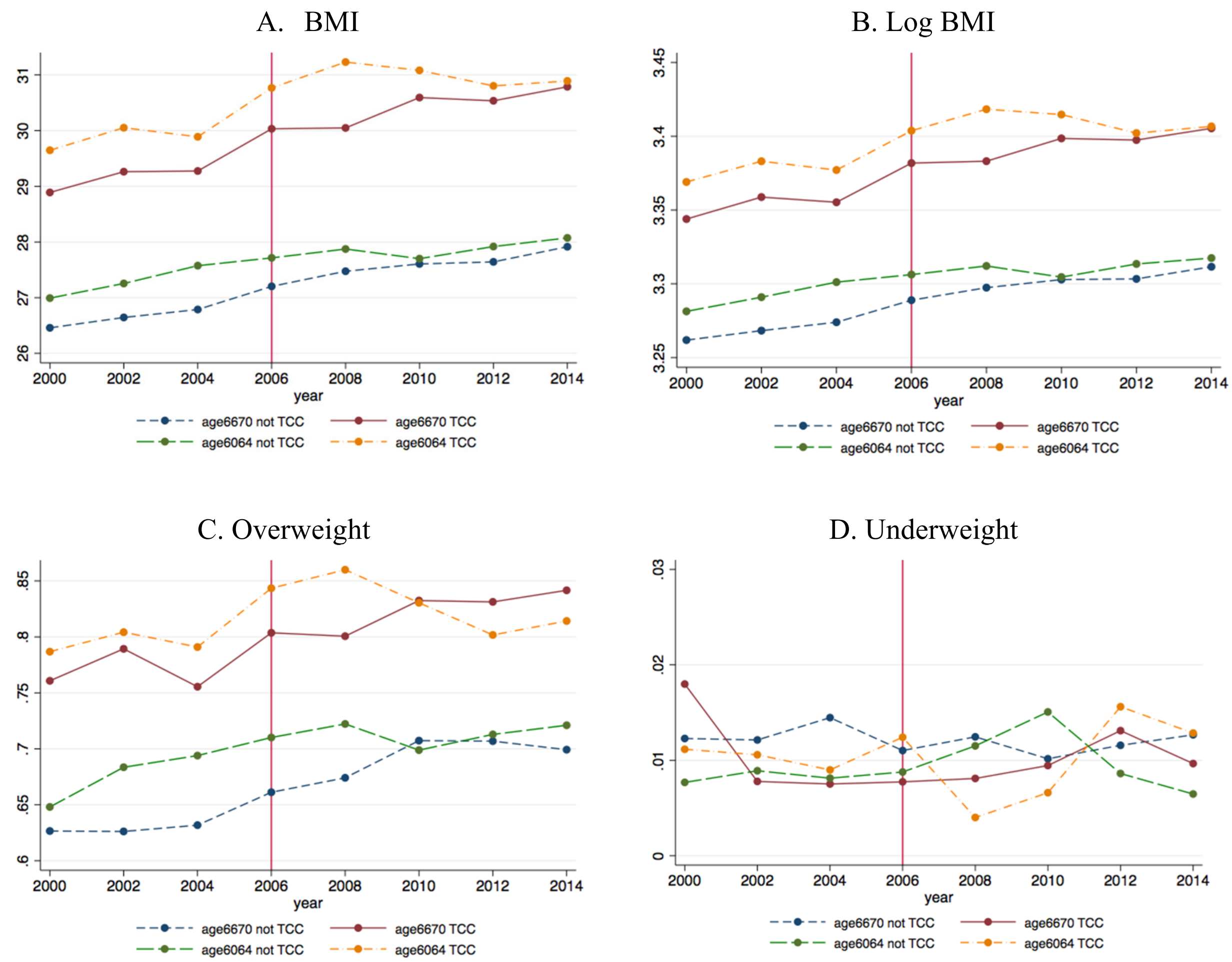


E. log weekly spending on food



Notes: Mean of the outcome variables are plotted.

Figure 2. 4. Trend in weight related outcomes.



Notes: Mean of the outcome variables are plotted.

Appendix Table 2. 1. Tests for differences between treatment and comparison groups in pre-policy period trends prescription drug coverage and OOP cost.

	RX coverage	OOP RX spending
	(1)	(2)
Panel A: Difference in Difference		
Lineartrend *Age66-70	0.002	16.145
	(0.012)	(12.938)
Panel B: Triple Difference		
Lineartrend *Age66-70 *TCCs	-0.000	28.079
	(0.017)	(37.197)
Lineartrend *Age66-70	0.003	2.938
	(0.012)	(6.585)
Observations	14,503	17,471

Notes: Panel A presents the coefficient and standard error of the interaction term from difference in difference estimation. Panel B presents coefficient, and standard error of the interaction term from triple difference estimation 0 All the models contain a set of control variables for both spouses discussed in the text. In regression, person sample weight is used, and standard errors are clustered at the age-in-year level. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age are in parentheses. The sign of *, **, *** denotes for the significance at 10, 5, and 1 percent level, respectively.

Appendix Table 2. 2. Tests for differences between treatment and comparison groups in prepolicy period trends for food-related outcome variables among lone seniors

	Enough money for food	Eat less	SNAP	Spending on food	Log food spending
	(1)	(2)	(3)	(4)	(5)
Panel A: Difference in Difference	-0.006	0.007*	0.013	0.204	-0.013
Lineartrend *Age66-70	(0.005)	(0.004)	(0.007)	(2.178)	(0.133)
	5,173	5,171	5,167	4,639	4,639
Panel B: Triple Difference					
Lineartrend *Age66-70 *TCCs	-0.030	-0.000	0.004	-2.153	0.064
	(0.022)	(0.011)	(0.014)	(5.906)	(0.080)
Lineartrend *Age66-70	0.002	0.007*	0.012*	0.962	-0.035
	(0.008)	(0.004)	(0.007)	(2.985)	(0.028)
Observations	5,173	5,171	5,167	4,639	4,639

Notes: Panel A presents the coefficient and standard error of the interaction term from difference in difference estimation. Panel B presents coefficient, and standard error of the interaction term from triple difference estimation 0. All the models contain a set of control variables for both spouses discussed in the text. In all regression, household sample weight is used, and standard errors are clustered at the age-in-year level of the lone senior. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age are in parentheses. The sign of *, **, *** denotes for the significance at 10, 5, and 1 percent level, respectively.

Appendix Table 2. 3. Tests for differences between treatment and comparison groups in pre-policy period trends for food-related outcome variables among couple seniors

	Enough money for food	Eat less	SNAP	Spending on food	Log food spending
	(1)	(2)	(3)	(4)	(5)
Panel A: Difference in Difference	0.004	-0.001	0.005*	-1.028	-0.021
Lineartrend *Age66-70	(0.006)	(0.003)	(0.002)	(4.523)	(0.035)
	2,648	2,648	2,641	2,325	2,325
Panel B: Triple Difference					
Lineartrend *Age66-70 *TCCs	0.011	-0.010	0.016	1.673	0.019
	(0.011)	(0.006)	(0.011)	(7.988)	(0.063)
Lineartrend *Age66-70	-0.009	0.003***	-0.002	-1.772	-0.029
	(0.008)	(0.001)	(0.006)	(7.186)	(0.052)
Observations	2,648	2,648	2,641	2,325	2,325

Notes: Panel A presents the coefficient and standard error of the interaction term from difference in difference estimation. Panel B presents coefficient, and standard error of the interaction term from triple difference estimation .All the models contain a set of control variables for both spouses discussed in the text. In all regression, household sample weight is used, and standard errors are clustered at the age-in-year level of the older spouse in the family. All monetary variables are inflated to 2014 prices by the consumer price index. Robust standard errors clustered at the level of the age are in parentheses. The sign of *, **, *** denotes the significance at 10, 5, and 1 percent level, respectively.

Chapter 3 Effects of the ACA Medicaid expansions on health and health care utilization among the diabetics: Evidence from the BRFSS 2009-2017

3.1. Introduction

Diabetes has been a critical public health issue in the United States. In 2012, approximately 12.3 percent of the U.S. adult population had diabetes (Center for Disease Control and Prevention [CDC], 2014). People with diabetes have a high risk of developing severe complications such as heart attack, stroke, blindness, kidney failure, or lower limb amputation that lead to permanent disability. Also, diabetes is one of the leading causes of premature mortality in the United States. Hence, they impose on society a substantial burden of medical treatment cost and indirect cost of reduced work productivity (American Diabetes Association, 2013; CDC, 2014). The estimated total economic cost in 2012 is $245 billion for diabetes (CDC, 2014).

The concern about these chronic diseases is even more pronounced among socioeconomically disadvantaged groups. Respectively, people living in poverty or people with less education have had a higher prevalence of those diseases compared with more advantaged individuals (CDC, 2013a; CDC, 2013b). Given these significant impacts, promoting for adequate illness management to reduce the burden of these diseases is the particularly important goal for health policymakers that has been emphasized in Healthy People 2020 (US DHHS). And, the low-income population should be the most crucial target.

Medicaid expansion is one major component of the 2010 Affordable Care Act (ACA), which authorizes states to provide adults with income less than 138% Federal poverty level (FPL) with access to public health insurance regardless of parental, age, or disability status from

2014. Before ACA, only seniors, people with disabilities, or parents with minimal income were eligible for Medicaid. Medicaid expansions are expected to improve health insurance coverage or lower out-of-pocket cost of medical care. Thus, they can play an important role in encouraging more appropriate health care patterns, especially among people with a very limited financial resource. Therefore, it is important to examine if this passage of Medicaid expansions can enhance chronic conditions management among low-income childless adults who were typically excluded from the public health insurance program.

A growing literature is investigating the impact of nationwide ACA Medicaid expansions on health-related outcomes (Simon et al., 2016; Wherry and Miller, 2016; Na and Slusky, 2016). We add to the literature on the effect of ACA Medicaid expansions by studying how the policy affects diabetes-related care and health outcomes among low-income childless adults with diabetes. We also investigate the impact across ethnicity, education, and gender groups to find evidence if Medicaid expansions have a differential impact on each sub-group.

This paper is structured as follows: the next section presents a background in Medicaid expansions and related policy under ACA and reviews the literature on the effect of health insurance on health-related outcomes. Section 3.3 describes the primary data source and analysis sample. Section 3.4 presents the empirical framework. Section 3.5 presents the main results. Section 3.6 provides falsification tests and sensitivity checks. Section 3.8 concludes.

3.2.Background

3.2.1. ACA and Medicaid expansions

ACA has been the largest health care reform in the United States since the introduction of Medicaid and Medicare in 1965. ACA aims to provide universal health insurance coverage and more comprehensive healthcare plans for all Americans. One key component of ACA is the Medicaid expansion that targets to offer public health insurance coverage for the most disadvantaged adults who have income below 138% FPL. ACA initially requires all states to expand Medicaid to this population from 2014. However, in 2012 Supreme Court allowed states to opt-out of the expansion program. Up to December 2015, 31 states and the District of Columbia have decided to expand Medicaid to provide health insurance coverage to their low-income residents. For those states that opt-in the Medicaid expansions, all adults with income up to 138% FPL will be qualified for Medicaid regardless of age or parental status. District of Columbia, Minnesota, and Connecticut have higher income thresholds, at 215%, 200%, and 155%, respectively (Kaiser Family Foundation, 2016a). As of January 2014, there are 25 states and the District of Columbia adopted Medicaid expansions. These states include AZ, AR, CA, CO, CT, DE, DC, HI, IL, IA, KY, MD, MA, MI, MN, NV, NJ, NM, NY, ND, OH, OR, RI, WA, WV, VT. Four states MI, NH, PA, IN, AK, and LA adopted Medicaid expansions in April 2014, August 2014, January 2015, February 2015, August 2015, June 2016 respectively; WI covered childless adults up to 100% FPL in Medicaid but did not adopt the ACA expansion (Kaiser Family Foundation, 2016b).

Between 2010 and 2013, there are nine states that had early Medicaid expansion for childless adults. They include AZ, CA[32], CT, DE, DC, HI, MN, NY, and VT (Kaiser Family Foundation, 2016a). Massachusetts had health care reform in 2006 that offers universal health

[32] California had Low-Income Health Program (LIHP) in 2011 that allows counties to expand health insurance to low-income people.

insurance coverage to all low-income residents up to 150% FPL without any premium (Kaiser Family Foundation, 2007).

ACA also aims for more comprehensive health insurance plan coverage. All non-grandfathered health insurance plans, including Medicaid, are required to cover chronic condition management care and prescription drug as parts of ten categories of essential benefits. The relatively comprehensive benefits package aims to encourage adequate care for the uninsured population at a lower cost, especially less healthy adults.

3.2.2. Review of previous Literature: Effect of health insurance on health-related outcomes

3.2.2.1.Effect of health insurance on health care utilization and health outcomes

There is a voluminous literature on the effect of health insurance on health care utilization and health outcomes. Empirical studies show that the impact might vary in different contexts, types of services, and population targets.

Kolstad and Kowalski (2012) showed that the 2006 Massachusetts health reform increased preventive care and lowered the length of hospitalizations, and Miller (2011) suggested the reform reduced emergency room services. Finkelstein et al. (2012) investigate the 2008 Oregon health insurance experiment, which selects low-income adults randomly to the Medicaid program by lottery. They find evidence of an increase in a wide range of health care utilization, including hospitalization, outpatient, drug utilization, recommended preventive care, and an improvement in self-reported health outcomes among low-income adults who were selected into Medicaid. Card et al. (2004) find that Medicare eligibility increases health care access, hospitalization, and self-access health, but no clear evidence on preventive screening for seniors. Antwi et al. (2014) find that ACA dependent coverage provision, which allows young adults remains in their parent health plan until age 26, linked to an increase in health insurance coverage and hospital admissions among young adults. Barbaresco et al. (2015) suggest the evidence that ACA dependent coverage provision improved health care access but had no significant impact on preventive care and health outcomes.

Several studies examine the effect of health insurance coverage on chronic-conditions-related outcomes. Under the context of the Oregon health insurance experiment, Baicker et al. (2013) show that Medicaid coverage increased the probability of having medication for diabetes and depression but not for hypertension or hypercholesterolemia. However, they find no improvement in any clinical measures of those conditions. Finkelstein et al. (2012) do not focus on the population with chronic conditions but provide an additional investigation of how the Oregon Medicaid Lottery program affected hospital utilization among people with chronic diseases. They find that there was an increase in hospital admission for people with heart disease but no effect on people with other illnesses, including diabetes.

3.2.2.2.Effect of 2014 Affordable Care Act Medicaid Expansions

There are recent studies exploring the effect of health insurance in the context of nationwide 2014 ACA Medicaid expansions. Na and Slusky (2016) use the 2007-2014 NHANES with the health examination result to examine the impact of ACA Medicaid expansions on clinical measures, and they find that there was an improvement in blood pressure and cholesterol level but not blood sugar. They also indicate an increase in the probability of taking medication for hypercholesterolemia no impact on medication for blood sugar and hypertension.

Simon et al. (2016) examine the impact on preventive care and health behaviors among low-income adults and find that Medicaid expansions are associated with better health care access and an increase in preventive care utilization and but no apparent effect on health risk behaviors. Wherry and Miller (2016) find that 2014 ACA Medicaid expansions linked to an increase in hospital stays and general physician visits but no impact on emergency department visits and self-accessed health outcomes.

Although Na and Slusky (2016) provide evidence about the drug utilization for those chronic conditions, less is known about how the health insurance coverage affects other specific utilization related to diabetes, which is also a significant concern. In addition, we might not be certain to generalize the results from other studies to the effect of Medicaid expansions on the care of chronic conditions for several reasons. First, a relatively large increase in the number of beneficiaries by Medicaid expansions may exceed the capacity of the state's health care providers. Thus, Medicaid expansions may not guarantee new enrollees to have adequate care for some specific illnesses. Second, chronic conditions like diabetes differ from acute diseases in the way that they require continuing medical care and illness management in the long-term instead of one-time treatment. Hence, individuals with illness may not be aware of obtaining the appropriate utilization, even with health insurance coverage.

3.3.Data

In this study, the main data source comes from the Behavior Risk Factor Surveillance System (BRFSS) waves 2009-2017, including five years of pre-expansion and four years of post-expansion. BRFSS is the state-based telephone survey conducted by state health departments. BRFSS is the largest telephone survey in the world, interviews more than 400,000 people every year, and contains a wide range of information on health care access, health care utilization, and health risk behaviors. BRFSS questionnaire includes core sections and optional modules. Core contents include queries about current health-related perceptions, conditions, self-accessed health, behaviors, and demographic questions. The optional BRFSS modules include variables in specific health care topics that states can elect to use in their questionnaire or not.

To explore the effect of Medicaid expansions on health outcomes and health care utilization among the diabetic population, we utilize variables from core sections as well as variables from the diabetes module. Diabetes module has variables specifying appropriate care for diabetes. Unlike the core sections that are always collected by BRFSS common questionnaire by combined landline and cellphone survey[33], diabetes module, or other optional modules, data can be collected by landline telephone. In addition, if states decide to use an optional module, they may collect it as a common module (by interviewing their entire samples with a common version of questionnaire); or they can divide their samples and used different modules in the subsamples that were distinguished by the version of the surveys (maximum 3) (BRFSS Module Data for Analysis 2009-2017). In each state, the core sections and modules interviewed by the common version will be recorded in BRFSS questionnaire data, while the modules interviewed with multiple version questionnaires will be recorded in the data set named based on the questionnaire versions[34]. Therefore, we need to collect data for diabetes-related care analysis through the following steps. Firstly, we identify the states that include diabetes modules in each year and determine the version of the questionnaire that they use for the diabetes module[35]. Secondly, from each BRFSS combined landline and cellphone/landline only and multiple-

[33] Before 2011, BRFSS only have landline telephone survey

[34] From 2011-2014 BRFSS group data into 8 data sets: BRFSS combined landline telephone and cellular telephone, BRFSS combined landline telephone and cellular telephone v1/v2/v3, BRFSS landline telephone data, BRFSS landline telephone datav1/v2/v3. From 2015, BRFSS don't have landline telephone only survey anymore.

[35] The information for this can be obtain from BRFSS Combined Landline Telephone and Cellular Telephone Survey Multiple-Version Questionnaire Use of Data

questionnaire/common version questionnaire data, we collect all states which have diabetes module using that questionnaire version. Appendix A2 reported the list of BRFSS data sets used to extract data for diabetes-related care analysis by state and year used in this paper.

3.3.1. Control and Treatment states

The treatment group consists of low-income individuals from the states that the expansion state and the control group includes individuals from non-expansion states. However, to assure that the treatment effect is correctly measured, we exclude from our analysis ten states that have comprehensive Medicaid expansions or health care reform for low-income childless adults before 2014, including AR, CA, CT, DC, DE, HI, MA, MN, NY, VT.

Besides, we dropped the states that opt-in Medicaid expansion later than January 2014 [36] as the post-treatment period for these states is quite short compared to the state adopt the expansion from the beginning of 2014. All of 14 states dropped from the analysis, including AK, AR, CA, CT, DC, DE, HI, IN, MA, MN, MT, NH, NY, PA, VT.

As mentioned before, because the diabetes module is optional, states can decide to include it in their questionnaire every year or not. Hence, the diabetes module is not available in all states every year for the period 2009-2017. To ensure that we have observations before and after the Medicaid expansions for every state, we select all states that have diabetes modules at least two years in the pre-expansion period and at least two years in the post-expansion period. The treatment group for diabetes-related care analysis includes ten states: IA, KY, MI, NV, NJ, NM,

[36] Michigan (4/1/2014), New Hampshire (8/15/2014), Pennsylvania (1/1/2015), Indiana (2/1/2015), Alaska (9/1/2015), Montana (1/1/2016.

ND, OH, WV, WI. The control group in this analysis includes fifteen states: AL, FL, GA, KS, ME, NE, NC, OK, SC, SD, TN, TX, UT, VA, WY. Details are presented in Table 3.1.

3.3.2. Studied Sample: childless adults with household income below 138% FPL

Our study focuses on the low-income non-elderly childless adult population age 25-64 that are most likely to become newly eligible for Medicaid if their state expands Medicaid under the ACA. Accordingly, we restrict our sample to the adults without any children and have a household income below 138% FPL, the income cutoff level of Medicaid eligibility in most of the states.

Since FPL depends on both total income and number of members in the household, we use two variables to determine whether a childless adult belongs to the "low-income" population: household's annual income and the number of adults in the household. Since BRFSS only reports income as an interval [37], it is not possible to impute precisely whether a person belongs to the "low-income" group or not. To deal with this issue, we include a respondent in the low-income sample if the upper bound of the respondent's household income bracket is below or equal to the 138% FPL corresponding to his/her household size in a particular year [38]. That guarantees that our sample does not include any individuals with income too high for Medicaid eligibility[39]. The upper bound in each BRFSS income bracket matches quite well with 138% FPL of the family size of one, two, or three[40].

---

[37] BRFSS reports income in 8 brackets: (1) <10,000; (2) $10,000-$15,000; (3) $15,000-$20,000; (4) $20,000-$25,000; (5) $25,000-$35,000; (6) $35,000-$50,000; (7) $ 50,000-$75,000 and (8) above $75,000

[38] Please see Appendix A1 of 138% FPL by household size across year.

[39] However, we have one exception, we include individuals in a family of one in 2009 and 2010 if their income in $10,000-$15,000 bracket or below. Although 138% FPL for family of one ($14,945) is below the upper bound $15,000 of that bracket, the different is small enough to ignore.

[40] From appendix A3 we can see 138% FPL for family of one, two, three is quite matched with income bracket [$10,000-$15,000] , [$15,000-$20,000] and [$20,000-$25,000] . For examples, as 138% FPL for household with size of two in 2011 is

3.3.3. Outcome variables:

Firstly, we consider how Medicaid expansion affects health insurance coverage. Medicaid expansion can possibly impact the outcome of chronic conditions if individuals are aware of their conditions through checkup tests when they have access to health insurance coverage. The variable for health insurance coverage is a binary variable that indicates if a respondent has any type of health insurance coverage. In BRSS, there is no variable to indicate the type of health insurance coverage that the respondents, so we are not able to Two variables for chronic condition diagnosis include: 1) binary variable indicates respondent has ever been diagnosed with diabetes, 2) binary variable indicates respondent has ever been diagnosed with hypertension.

Second, among people with diagnosed diabetes, we examine relevant variables of the diabetes-related care and management from diabetes module:

1) binary variable indicates having at least one doctor visit for diabetes in the past 12 months[41]:

2) binary variable indicates having at least one A1C test in the past 12 months [42];

3) binary variable indicates having at least two A1c test in the past year;

4) binary variable indicates having at least one dilated eye examination in the past 12 months;

$20,300, we include all respondents who reported having two adult members living in the household only if that respondent's income belongs bracket $15,000-$20,000 or lower.

[41] Respondents with diagnosed diabetes are asked about how many times they see doctor/ health professional for their diabetes. We recode variable indicating if people have at least one doctor visit for diabetes;

[42] A one C test is the test for the average blood sugar level in the past 3 months, conducted by health professionals. The test result is an important indicator of how diabetes treatment plan is working as it shows how blood glucose control.

5) binary variable indicates having at least one foot examination during the past 12 months;

6) binary variable indicating if the respondent has ever taken a diabetes self-management class[43]. We have 14,797 observations from 25 states in our diabetes module sample. However, the number of observations for each outcome can vary since the number of missing values for each outcomes variables are different.

Third, we also consider the self-reported health outcomes on people with diabetes[44]: number of days with physical health in the past 30 days 2) number of days with poor mental health in the past 30 days ; 3) number of days with physical/mental health limit usual work in past 30 days; 4) having self- accessed poor or fair general health [45]. Although the variables indicating the self-reported health status belong to the core sections, we use data from the states in diabetes above for this analysis for consistency

The independent variables include dummy variables for each age group (each ten-year group of age), a dummy variable for gender (male/female), dummy variables for each race/ethnicity, dummy variables for each education level (less than high school, high school, some college, and college graduate); dummy variable for marital status; dummy variable for each household size (one adult, two adults, three adults, four adults, and five adults or more); dummy variable for each working status (currently employed, self-employed, not at work, retired and

[43] Diabetes self-management education (DSME) is program to training people with knowledge, skill, and ability necessary for diabetes self-care. Diabetes care requires a lot of corporation of the patients including self-control and adjust diet, behavior. As a result, diabetes self-management education (DSME) is a critical element of care for all people with diabetes and is necessary in order to improve patient outcomes. Studies have shown that self-management class is cost-effective in helping patient control their conditions as diabetes requires patients to adjust diet, health behaviors.

[44] These outcomes overlap with the outcomes studied in Simon et al., 2016. However, they examine the effect on entire low-income population while we focus on the adults with diabetes only.

[45] The general health status in BRFSS has 5 categories: poor, fair, good, very good, excellent. We recode variable having poor of fair health to have value 1 if respondent report to have poor of fair health, 0 otherwise.

unable to work) and state-year unemployment rate. We include year and state fixed effects to control for the underlying difference through time and across states. The state-year unemployment rate from the Bureau of Labor Statistics is introduced as an explanatory variable to control for economic factors in each state because the variation in economic conditions across states and time can impact low-income adults in treatment and control states differently.

We also use cell phone dummy to control for whether respondents are from cell phone survey. BRFSS does not ask respondents from cellphone survey about the number of adults in the household, and missing this information does not allow us to determine if an individual belongs to a low-income sample or not. Thus, we cannot select respondents in cellular telephone surveys before 2014 into the sample. The inclusion of people from cellphone survey starts at the same year with Medicaid expansions can raise a concern about how whether the sample of cellular phone survey in treatment and control states are different and then may bias the impact of Medicaid expansions. Although we already account for all demographic and socioeconomic factor variables, controlling for cellphone survey indicator may provide a better account for differences in characteristics of cellphone and landline sample.

Descriptive Statistics of Control Variables

Table 3.2 presents the weighted mean of control variables for the treatment and control group separately. Although the t-test shows the statistically significant difference the characteristics in some categories of income, education, race, age groups, marital status, household size, and employment status, and unemployment rate between control and treatment states; the differences are small in most of the categories except for race proportion. Treatment states have a larger population of non-Hispanic whites, while control states have more Hispanic and African-Americans. Our regression with the control variables will account for those differences.

3.4.Empirical methodology

The average effect of Medicaid on health care coverage, health care utilization and health outcomes

Identify the causal impact of health insurance has the fundamental issue of self- selection problem. As there is variation in the Medicaid eligibility across states since 2014, we can adopt the difference-in-difference (DiD) method. We use the reduced-form regression to study the intent-to-treat effect of Medicaid expansions under ACA on health-related outcome variables.

$$y_{ist} = \beta_0 + \beta_1(Post_t \times Treat_s) + \beta_2 \times X_{ist} + \beta_3 \times Unem_{st} + \tau_t + \phi_s + \epsilon_{ist} \qquad (1)$$

i, s, t indicates the individual, state, and year. y_{ist} is the outcome of interest, including health insurance, each chronic condition diagnosis, specialized health care for diabetes or hypertension and self-accessed health outcomes. For all binary outcome variables, we use a linear probability model.

Post is the dummy variable, take the value of 1 if the year of the interview is 2014 or after. Treat is a dummy variable, equal to 1 if the state belongs to the treatment group presented in Table 1A/ Table 2A. X_{ist} is a vector of dummy indicators of individual characteristics including race, marital status, sex, age, education, household size, household income, employment status, and cellular phone survey. $Unem$ is the state-year unemployment rate. τ_t and ϕ_s are year fixed effect and state fixed effect, respectively. ϵ_{ist} is the error term. Standard errors clustered at the state level.

β_1 is the coefficient of interest in this study, which measures the magnitude of the average impact of Medicaid expansions on health-related outcomes. The difference-in-difference design is based on the assumption that the trend in health-related outcomes of the low-income population would be identical in the treatment and control states in the absence of ACA Medicaid expansions. Although this assumption cannot be tested directly, we provide some evidence of a similar trend between the treatment and control groups. We use data from 2009-2013 and estimate a similar model, but instead of using interaction terms of post-period dummy and treatment dummy, we employ the interaction of treatment dummy and year dummy or interaction of treatment dummy and linear time trend.

$$y_{ist} = \beta_0 + \sum_{k=2010}^{2013} \theta_k \times (Year_t \times Treat_s) + \beta_2 \times X_{ist} + \beta_3 \times Unemp_{st} + \tau_t + \phi_s + \epsilon_{ist} \qquad (2)$$

$$y_{ist} = \beta_0 + \theta_1 \times (t \times Treat_s) + \beta_2 \times X_{ist} + \beta_3 \times Unem_{st} + \tau_t + \phi_s + \epsilon_{ist} \qquad (3)$$

The coefficients of those interaction terms θ_k demonstrate whether the trend of outcome variables in treatment states diverge from the control states in the pre-treatment period. The parallel trend presumption between control and treatment states implies all coefficient θ_k are equal to zero. We present the estimations in Table 3A and 3B, which support our assumption.

The causal effect of health insurance coverage on health care utilization and health outcomes

In Equation (1), we estimate the intent to treat the effect of Medicaid expansions on the health-related outcome of the entire low-income childless adult population. We are also interested in measuring the causal effect of health insurance coverage on health-related outcomes by using $(Post_t \times Treat_s)$ as an instrumental variable for endogenous health insurance under the assumption that Medicaid expansions represent a source of exogenous variation in insurance coverage that is not correlated with the individual error term.

To estimate the effect of insurance on health care utilization, we adopt the 2SLS model that regresses the health-related outcome variables against the estimated health insurance coverage in the second stage.

$$y_{ist} = \gamma_0 + \gamma_1 \times \widehat{Insurance}_{ist} + \gamma_2 \times X_{ist} + \gamma_3 \times Unem_{st} + \tau_t + \phi_s + \epsilon_{ist} \quad (4)$$

Where $\widehat{Insurance}_{ist}$ is the health insurance coverage, estimated from the first-stage regression.

$$Insurance_{ist} = \alpha_0 + \alpha_1 \times (Post_t \times Treat_s) + \alpha_2 \times X_{ist} + \alpha_3 \times Unem_{st} + \tau_t + \phi_s + \epsilon_{ist} \quad (5)$$

This 2SLS model is just identified, so the coefficient γ_1 is equal to the ratio of the average impact of Medicaid expansions on health outcome and impact of Medicaid expansions on health insurance coverage ($\frac{\beta_1}{\alpha_1}$), where $\beta_1$is estimated from equation (1) and α_1 is estimated from equation (5). Coefficient γ_1 measures the causal effect of having health insurance on health-related outcomes among low-income childless adults who would not obtain the health insurance coverage if their states do not expand Medicaid.

The assumption that $(Post_t \times Treat_s)$ is not correlated with individual error term holds if health insurance coverage is the only pathway that Medicaid expansion affects health-related outcomes. However, Medicaid expansions under ACA may affect low-income people in other ways beyond increasing the extensive margin of health insurance coverage. First, Medicaid expansions may crowd out other types of health insurance or lead to dual health insurance eligibility. Switching from other health insurance plans to Medicaid or getting dual eligibility does not change the insured status reported in BRFSS [46] but may affect health care utilization due to the change in the plan generosity. Second, the individuals who had to purchase private health insurance before Medicaid expansion now can have free Medicaid coverage, so they use their income to increase health care or improve health outcomes (Barbaresco et al., 2015). BRFSS does not provide information on the respondent's health insurance plan name before 2014, so we can't estimate the crowd out rate. Leung and Mas (2016) use ACS 2010-2014 data, report that ACA Medicaid expansions were associated with a 3 percentage point decrease in private health insurance among low-income childless adults, in which two percentage point comes from private- own purchase. Third, if expansion states have more generous coverage beginning from 2014 together with Medicaid expansions, then people who are eligible for traditional Medicaid in those states possibly increase the utilization. Then, the change in health care utilization or health outcomes we observed may reflect not only those of the newly insured population. In those cases, the 2SLS estimation can be overestimated. Therefore, we interpret the causal impact of health insurance on health-related outcomes with caution.

3.5.Results

3.5.1. Test for parallel trend

We plot all the outcome variables for treatment and control states during 2009-2017 to demonstrate the trend of the two groups in Figure 3.1 and Figure 3.2 visually. The vertical lines mark the timeline of pre and post-Medicaid expansions. Overall, we can see all the outcomes of

[46] BRFSS only ask respondents if they have health insurance coverage but they do not ask how many health insurance coverage respondents have or what type of health insurance they have.

chronic condition outcomes and self-accessed health of people with diabetes exhibit a similar movement prior to Medicaid expansion. The diabetes-related care trend figures are slightly noisier and harder to interpret for several outcomes. The estimations of equation (2) and (3) provide more formal evidence about the parallel trend assumption.

Table 3.3 column (1) – (4) reports the estimates of coefficients of the interaction term of year dummy and treatment dummy variables from equation (2) including $year_{2010} \times treat$, $year_{2011} \times treat$, $year_{2012} \times treat$, and $year_{2013} \times treat$. Only three coefficients from all sixty coefficients exhibit statistical significance. These results lend support to the assumption on the parallel trend between treatment and control groups. Therefore, we have confidence in the validity of difference-in-difference estimates.

3.5.2. Main Results

i) Health insurance

The main results of the effect of Medicaid expansions are reported in Table 3.4. The column (1) presents the mean of outcome variables of treatment states before Medicaid expansions. The column (2) presents the reduced form DiD estimates β_1 in Equation (1) that measures the average treatment effect of Medicaid expansions on the health-related outcome on the low-income childless adult. We find that Medicaid expansions lead to an 8.8 percentage point increase in health insurance coverage among childless low-income adults. Before the Medicaid expansion, the average health insurance coverage is 75 percent. This estimation is comparable with the finding in Kaestner et al. (2016).

ii) Diabetes-related care

Figure 3.1 plots the trend of diabetes-related cares for the year 2009-2017 for expansion states and control states. For the treatment and care of diabetes, low-income childless adults in expansion states experience statistically significant increase the probability of having at least one doctor visit for diabetes by 1.9 percentage point, and this estimation is marginally significant at 10% level. Medicaid expansions increase the probability of having at least one A1c test by 4.4 percentage points and the probability of having at least two A1C tests by 3.5 percentage points. Before the expansion, there is about 80 percent of people with diabetes have at least one A1C test in the past year. The effect on the probability of having at least A1c test twice is smaller and not statistically significant. The impact on other utilization, including foot examination, eye examination, and diabetes education is smaller and not statistically significant.

iii) Self-reported health outcomes

Among all low-income childless adults with diabetes, Medicaid expansions lead to a decrease of 1.2 days of poor physical health, 1.4 days of poor mental health, and 1.1 days of poor health that limits usual activities. Medicaid expansions also decrease the probability of having poor or fair general health by 5.1percentage points. These results indicate evidence of health improvement among low-income diabetics.

3.5.3. Heterogeneity of Medicaid expansions effect

The Affordable Care Act aims to provide Americans with universal health insurance coverage to promote health care equity for the less advantaged population. Understanding the impact of Medicaid eligibility on health care utilization outcomes among different subgroups will be critical to evaluate the effectiveness of the policy in reducing inequality in health and health care access. However, the effect of Medicaid eligibility on health equity may not be evident. As it provides all individuals with equal access to health care, it can narrow health-related outcomes disparity across different groups (Card et al., 2008)[47]. However, more advantaged subgroups can take the benefit more efficiently than the others given the same input (Grossman, 1972; Sonchak, 2015; Barbaresco et al., 2015). If that is the case, Medicaid expansions may increase health disparities. The evidence that health insurance coverage expansions have a more favorable effect on health outcomes among men compared with women is also realized (Simons et al., 2016; Barbaresco et al., 2015). Therefore, we examine the heterogeneity of the effects of Medicaid expansion across education/racial/gender groups.

We report the average impact of Medicaid expansions from the reduced form DiD estimates for stratified race/education/gender samples.

i) White adults versus Non-white adults

Column (1) and (2) shows the estimation for subgroups white and the other race separately. The results in other panels are reported for white/non-white subgroups. The impact of Medicaid expansion on health insurance coverage is smaller among the non-white population than the white population. This is possibly due to the large portion of the nonwhite immigrant population are not eligible for Medicaid. The estimates show that Medicaid expansion is associated with a 9.6 percentage point increase in health insurance coverage among white and 8.0 percentage point increase among the non-white group. White individuals experience a higher probability of having an A1c test or at least two A1C tests than non-white populations. The impact on other utilization is both statistically insignificant among the two groups.

[47] Card et al., 2004 find the Medicare eligibility reduces disparity in health care coverage across ethnicity/ education group when people turn to 65.

ii) High school graduate adults versus at least some years of college adults

Column (3) and column (4) reports the estimation for two stratified samples: adults with less than or equal 12 years of education versus adults with at least a one-year college. We find that the Medicaid expansions are associated with a higher increase in health insurance coverage among the less educated subgroup with 10.8 percentage points and 5 percentage points among the high-educated group. The effects on the probability of having at least one doctor visit for diabetes and A1c test are higher among less educated compared with individuals with at least some college, and statistical significance is only observed among the less educated group. It is possibly due to improvement in health outcomes among this group (details below). Higher educated adults have experienced a marginally significant increase in taking the diabetes self-management class by 5.1 percentage points.

Regarding the self-accessed health outcome indicators, we find that Medicaid expansion significantly lowers the probability of having self-accessed fair or poor general health and the number of unhealthy days among less-educated adults. The effects sub-group of people with more than 12 years of education are smaller and not statistically significant. These results suggest that Medicaid expansions have a more favorable effect on health outcomes among less-educated groups, hence may reduce the disparity across education groups.

iii) Women versus men

Column(5) and column(6) report the results for males and females, respectively. The effect on health insurance coverage is higher for men than women, which are 13.4 vs. 6.8 percentage points. As a result, the impact on health care utilization is stronger among men. Specifically, Medicaid expansion is associated with an increase of 6.5 percentage point increase in the probability of having at least one A1C test, and 8.4 percentage point in the probability of having at least two A1C tests, and 5.1 percentage point increase in the probability of taking diabetes education. The impact on foot examination and dilated eye examination is not statistically significant. However, among women, we find that Medicaid expansion leads to an increase in the probability of having at least one A1C test by 3.7 percentage points, and the impact is not significant, among other utilization. These findings are quite consistent with Simon et al. (2016) and Barbaresco et al. (2015) which both find that there is a larger effect on self-accessed health among men than women from dependent ACA coverage provision and ACA Medicaid expansions, though our analysis focuses on a sample of adults with diabetes only.

3.5.4. Causal effect of health insurance health care utilization – Instrumental variable estimation

Previously section presents the intent-to-treat effect of Medicaid expansion on health care utilization. In this section, we report the estimation of the causal impact of health insurance on health care utilization for diabetes among people with diabetes from the instrumental variables method. Table 3.6 reports the IV estimates for the causal effect of having health insurance coverage on health care utilization. We report the estimation for the full sample and alternative demographic sample. We find that having insurance is associated with an increase in the probabilities of having at least one doctor visit for diabetes by 53 percentage points, having at least one A1c test by 43 percentage points, having at least two A1C tests by 52 percentage point. These estimations are large. Firstly, the low-income population may be very elastic to the price of medical services. Second, as we explained the caveat in the instrumental variable model, the increase in the utilization can reflect the intensive increase in the utilization due to the coverage generosity among the people in expansion states who already had health insurance before ACA Medicaid expansions. Thus, the instrumental variable estimation for the causal effect of health insurance can be subject to overestimation. The effects are not statistically significant for other outcomes.

With respect to the causal impact of health insurance on health care utilization among stratified samples, we find mixed evidence. The elasticity to the A1C test is quite comparable among all groups, but having health insurance has the highest impact on the probability of having an A1C test among the above high school subgroup (with 77.5 percentage points). The effect on foot examination, eye examination, and diabetes education are almost statistically insignificant among all the subgroups, except for the higher educated group with a 137.5 percentage point increase in foot exam and male group with a 38.9 percentage point increase in the diabetes educations.

3.6. Falsification Test and Sensitivity Check

3.6.1. Falsification Test

We provide falsification tests on two other different populations that are not likely to be affected by Medicaid expansions: high-income adults (with annual household income above $75,000) and senior adults (age over 65). Those groups are not supposed to be impacted by the Medicaid expansions since the high-income adults are not qualified for Medicaid eligibility, and seniors have already been covered by Medicare. That means the Difference-in difference estimation of Medicaid expansions effect on these samples would be zero. This placebo test can evaluate if treatment states have any other change in policy that may affect all residents with chronic conditions after January 2014 besides Medicaid expansions.

Table 3.7 reports the difference-in-difference estimates on the high-income population and older population. As expected, it shows that most of the coefficients are very small and statistically insignificant. The coefficient on health insurance coverage for high-income and seniors population is statistically significant but very small compared with the estimations we have for the low-income group in the main results. These results provide more evidence to support our argument that the effect we observed on low-income childless with chronic conditions in expansion states come from ACA Medicaid expansions, rather than any other potential policy or any divergent trend in the health-related outcome between treatment and control states.

3.6.2. Sensitivity Check

We perform several sensitivity checks of our primary results using different models or samples. The estimations from sensitivity analysis are shown in Table 3.8.

First, we estimate the linear probability regression using BRFSS weights and report results in column (2). As BRFSS changed the weighting method in 2011, we use estimation without weights in our main analysis. The magnitudes of the effect on the self-accessed number of poor physical/mental/health limited usual work, A1c test, and foot examination are now larger than the results without BRFSS weight, but the sign of all coefficients remains. These estimations do not affect our conclusion that Medicaid expansions improve diabetes-related management.

Second, we excluded the first six months in 2014 from analysis for all variables of diabetes-related care, indicating the utilization during the past years. We do not exclude the whole year 2014 since the sample of diabetes care comes from the year 2014. The results presented in column (2) remain for most of the coefficients.

Third, we drop all individuals from cell phone survey. As we discussed in the data section, the adults from the cell phone survey are included in our sample only from 2014 because we do not have information about the number of household members to select a respondent in the "low-income sample" before that point of time. In this sensitivity check, we used the sample only from the landline survey to examine to check if the results are driven by cell phone survey sample. The results provided in column (4) are quite similar to the main results.

3.7.Conclusion

Diabetes has caused a substantial burden for patients, especially less advantaged individuals with limited resources. Lack of affordable care may prevent people with these conditions from obtaining proper care. As a result, it will lead to worse health outcomes and impose a higher indirect cost on society. Improving health care access and health outcomes for low-income people with chronic conditions can be a critical goal of ACA Medicaid expansions. In this paper, using the difference-in-differences approach, we investigate the effect of Medicaid expansions after four years of implementation on health care utilization and health outcomes among low-income childless adults, focus on the less healthy population with diabetes. We also estimate the effect on a stratified sample of education, race, and gender groups to explore if there is heterogeneity in effect across sub-populations.

We find that Medicaid expansions improve the health insurance coverage for all low-income childless adults. Our estimations indicate that Medicaid expansions significantly increase the probabilities of having doctor visits for diabetes, probabilities of having A1c at least one or at least twice in the past year. These findings suggest that Medicaid expansions encourage more appropriate care patterns, improve self-accessed health outcomes among individuals with diabetes.

Our study has several limitations. First, our analysis based on cross-sectional data, so we can't follow the outcomes of the same individual before and after treatment time. Second, all of the health outcomes are self-reported, so we cannot evaluate the effect on clinical measures of blood sugar level and blood pressure, which provide a more objective picture of health outcomes among people with these chronic illnesses. Third, our analysis for diabetes care contains only 25 states; thus, it may not reflect the effect of Medicaid expansions in the states that are not included in the samples. Finally, we cannot rule out the possibility of changing health-related outcomes among people who already had health insurance before Medicaid expansion using BRFSS data. It can overestimate the causal impact of health insurance on health-related outcomes using the 2SLS model. Hence, the 2SLS estimation should be interpreted conservatively.

Table 3.1. Control and Treatment states list for diabetes-related care analysis

States for Analysis (25 states)		Excluded states (25 states and DC)	
Control States (15 states) Never expansion	Treatment states (10 states) Expand in 2014	Expand Early or Expand late (14 states)	Not enough year in pre or post treatment period (12 states)
(1)	(2)	(3)	(4)
Alabama	Iowa	Alaska	Arkansas
Florida	Kentucky	Arizona	Colorado
Georgia	Michigan	Connecticut	Maryland
Kansas	Nevada	Delaware	Rhode Island
Maine	New Jersey	District of Columbia	South Dakota
Nebraska	New Mexico	Hawaii	Oregon
North Carolina	North Dakota	Indiana	Mississippi
Oklahoma	Ohio	Massachusetts	Missouri
South Carolina	West Virginia	Minnesota	Idaho
Tennessee	Wisconsin	New Hampshire	Illinois
Texas		New York	Washington
Utah		Louisiana	
Virginia		Vermont	
Wyoming		Pennsylvania	
South Dakota		Montana	

Note: The source to categorize all states come from Kaiser Family Foundation, 2016a & 2016b, BRFSS Use of Multiple Version questionnaire data 2009-2017, BRFSS module by category 2009-2017; BRFSS Landline Telephone Survey Multiple-Version Questionnaire Use of Data. 2011-2014; BRFSS Combined landline and cellphone Survey Multiple-Version Questionnaire Use of Data. 2011-2017; BRFSS Multiple-Version Questionnaire Use of Data 2009-2010

Table 3.2. Weighted mean for control variables

	Control States	Expansion States
	(1)	(2)
Income between $10,000 &$15,000	0.322	0.337
Income between $15,000 &$20,000	0.261	0.217
Income between $20,000 &$25,000	0.088	0.098
Income above 25,000	0.013	0.005
12 year of education	0.350	0.393
Some college	0.246	0.253
College graduate	0.062	0.068
Black	0.269	0.162
Hispanic	0.218	0.118
Other race	0.061	0.083
2 adult	0.385	0.382
3 adult	0.212	0.216
4 adult	0.081	0.054
>=5 adults	0.051	0.018
Female	0.512	0.530
Currently married	0.356	0.300
Self-Employed	0.560	0.07
Not at work	0.171	0.28
Retired	0.178	0.06
Unable to work	0.36	0.33
Age from 35-44	0.113	0.102
Age from 45-54	0.330	0.347
Age from 55-64	0.518	0.527
Cell phone	0.227	0.172
Observations	9911	4886

Note: BRFSS weights are used.

Table 3.3. Test for parallel trend between expansion and non-expansion states in pre-expansion

	Year2010 x treat	Year2011 x treat	Year2012 x treat	Year2013 x treat
	(1)	(2)	(3)	(4)
Diabetes related care				
Health insurance coverage	0.012	0.049	0.019	0.006
N = 9,785	(0.031)	(0.030)	(0.026)	(0.030)
Prob. doctor visit for diabetes	0.006	0.018	-0.010	0.011
N = 9,368	(0.024)	(0.025)	(0.018)	(0.019)
Prob. A1c Test	-0.036	0.029	-0.014	-0.008
N = 8,890	(0.044)	(0.025)	(0.032)	(0.022)
Prob. Test Twice	-0.059	-0.029	-0.050	-0.019
N = 8,890	(0.036)	(0.042)	(0.031)	(0.028)
Prob. Foot examination	-0.038	0.003	-0.023	-0.911
N = 9,320	(0.029)	(0.041)	(0.025)	(0.973)
Prob. Dilated eye examination	0.003	-0.043	-0.016	-0.004
N = 9,576	(0.041)	(0.041)	(0.040)	(0.029)
Prob. Diabetes education	-0.023	-0.035	-0.013	-0.055**
N = 9,690	(0.025)	(0.039)	(0.034)	(0.020)
Panel D: Health Outcomes				
Have poor or fair general health	-0.048***	-0.092***	-0.051**	-0.012
N = 9435	(0.016)	(0.026)	(0.021)	(0.032)
Days bed physical health	-0.911	-0.852	-1.031	-0.127
N = 9,435	(0.973)	(0.790)	(0.688)	(0.780)
Days not in good mental health	0.041	-1.611	-1.275*	0.315
N = 9,540	(0.887)	(0.980)	(0.706)	(0.986)
Days health limited usual work	0.418	-0.706	-0.318	0.629
N = 9,045	(0.923)	(0.860)	(0.728)	(1.056)

Note: Results are drawn from BRFSS 2009-2013.
Coefficients of the interaction term of treat dummy and year dummy from 2010-2013) are reportede in column (1) - column (4). All regressions include state fixed effect, year fixed effect, state-year unemployment rate, and dummy variables for each category of gender, race, marital status, education, household size, household income, age, current employment status, and cell phone dummy indicator. *** p<0.01, ** p<0.05, * p<0.1

Table 3.4. Effect on health-related outcomes among low-income non-elderly childless adults

	Pre-treat mean	Estimation	
	(1)	(2)	(3)
Panel A: Health insurance coverage			
Health insurance coverage	0.746	0.094***	0.088***
N= 14,756		(0.014)	(0.016)
Panel B: Diabetes related care			
Prob. doctor visit for diabetes	0.876	0.020*	0.019*
N = 14111		(0.011)	(0.011)
Prob. A1c Test	0.800	0.042***	0.044***
N = 13,494		(0.014)	(0.015)
Prob. Test Twice	0.635	0.033*	0.034*
N = 13,494		(0.017)	(0.017)
Prob. Foot examination	0.687	0.018	0.018
N = 14,060		(0.021)	(0.021)
Prob. Dilated eye examination	0.586	0.011	0.006
N = 14,401		(0.023)	(0.025)
Prob. Diabetes education	0.525	-0.003	0.001
N = 14,593		(0.014)	(0.014)
Panel C: Health Outcomes			
Have poor or fair general health	0.697	-0.048***	-0.049***
N = 14,797		(0.016)	(0.016)
Days not in good physical health	10.221	-1.149**	-1.226***
N = 14,247		(0.415)	(0.393)
Days not in good mental health	11.446	-1.351***	-1.339***
N = 14,387		(0.350)	(0.339)
Days health limited usual work	14.413	-1.044**	-1.109**
N = 13,656		(0.472)	(0.492)
Control for covariates		N	Y

Note: Column (1) reports the mean of the dependent variable for treatment groups before Medicaid expansions, adjusted by BRFSS weights. Standard errors clustered at the state level are reported in parentheses. All regressions include state fixed effect, year fixed effect, state-year unemployment rate, and dummy variables for each category of gender, race, marital status, education, household size, household income, age, current employment status, and cell phone dummy indicator.

*** p<0.01, ** p<0.05, * p<0.1

Table 3.5. DiD estimation on diabetes-related care utilization - alternative sample

		White	Non White	College or above	high school	Female	Male
		(1)	(2)	(3)	(4)	(5)	(6)
Health insurance	Coef	0.096***	0.080***	0.050**	0.108***	0.068***	0.134***
	S.E	(0.019)	(0.021)	(0.019)	(0.019)	(0.015)	(0.026)
	Obs	8,478	6,243	5,074	9,647	9,490	5,248
Prob doctor visit for	Coef	0.020	0.013	0.014	0.021	0.018*	0.020
	S.E	(0.013)	(0.017)	(0.014)	(0.013)	(0.010)	(0.016)
	Obs	8,167	5,912	4,916	9,163	9,069	5,027
Prob. A1c Test	Coef	0.049**	0.036	0.037*	0.046**	0.037**	0.063***
	S.E	(0.018)	(0.023)	(0.021)	(0.019)	(0.018)	(0.018)
	Obs	7,868	5,595	4,769	8,694	8,706	4,773
Prob. A1c Test twice	Coef	0.046*	0.017	0.031	0.037	0.009	0.085***
	S.E	(0.024)	(0.024)	(0.025)	(0.024)	(0.022)	(0.027)
	Obs	7,868	5,595	4,769	8,694	8,706	4,773
Prob. foot examination	Coef	0.018	0.019	0.064**	-0.009	0.026	0.004
	S.E	(0.026)	(0.025)	(0.027)	(0.027)	(0.023)	(0.029)
	Obs	8,120	5,908	4,900	9,128	9,055	4,990
Prob. Dilated eye exam	Coef	0.002	-0.012	-0.027	0.019	0.002	0.017
	S.E	(0.038)	(0.023)	(0.027)	(0.032)	(0.032)	(0.031)
	Obs	8,263	6,107	4,962	9,408	9,287	5,099
Diabetes education eve	Coef	0.003	0.002	0.024	-0.012	-0.024	0.051**
	S.E	(0.020)	(0.020)	(0.031)	(0.019)	(0.017)	(0.023)
	Obs	8,387	6,174	5,013	9,548	9,394	5,184

Note: Estimation from BRFSS data 2009-2017. All regressions include state fixed effect, year fixed effect, state-year unemployment rate, and dummy variables for each category of gender, race, marital status, education, household size, household income, age, current employment status, and cell phone dummy indicator.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6. IV estimation on the causal impact of health insurance on health care utilization

		Full sample	White	Non White	A. High school	high school	Female	Male
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prob doctor visit for	IV est	0.214	0.201	0.178	0.276	0.201	0.299	0.112
	S.E	(0.138)	(0.142)	(0.207)	(0.287)	(0.140)	(0.212)	(0.115)
	Obs	14,046	8,145	5,901	4,906	9,140	9,054	4,992
Prob. A1c Test	IV est	0.527***	0.508***	0.524*	0.775*	0.453**	0.630*	0.439***
	S.E	(0.172)	(0.176)	(0.285)	(0.433)	(0.178)	(0.351)	(0.142)
	Obs	13,427	7,843	5,584	4,758	8,669	8,688	4,739
Prob. A1c Test twice	IV est	0.429**	0.496**	0.260	0.654	0.373	0.162	0.627***
	S.E	(0.199)	(0.239)	(0.336)	(0.486)	(0.223)	(0.361)	(0.214)
	Obs	13,427	7,843	5,584	4,758	8,669	8,688	4,739
Foot examination	IV est	0.233	0.187	0.277	1.375**	-0.080	0.418	0.039
	S.E	(0.216)	(0.253)	(0.316)	(0.623)	(0.270)	(0.331)	(0.211)
	Obs	13,991	8,096	5,895	4,888	9,103	9,038	4,953
Dilated eye exam	IV est	0.057	-0.025	-0.094	-0.659	0.230	-0.070	0.133
	S.E	(0.307)	(0.420)	(0.406)	(0.797)	(0.292)	(0.570)	(0.234)
	Obs	13,518	7,805	5,713	4,737	8,781	8,837	4,681
Diabetes education e	IV est	0.033	0.053	0.021	0.523	-0.111	-0.352	0.389**
	S.E	(0.165)	(0.219)	(0.251)	(0.649)	(0.182)	(0.255)	(0.183)
	Obs	14,522	8,361	6,161	5,002	9,520	9,374	5,148

Note: All regressions include state fixed effect, year fixed effect, state-year unemployment rate, and dummy variables for each category of gender, race, marital status, education, household size, household income, age, current employment status, and cell phone dummy indicator.
*** p<0.01, ** p<0.05, * p<0.1

Table 3.7. Falsification test on high income and senior populations

		High Income	Seniors
		(1)	(2)
Panel A: Health Insurance			
Health insurance coverage	Coef	0.004*	0.004*
	S.E	(0.002)	(0.002)
	Obs	40,068	62,547
Panel B: Diabetes related care			
Prob. doctor visit for diabetes	Coef	0.009	0.011
	S.E	(0.009)	(0.007)
	Obs	39,224	60,200
Prob. A1c Test	Coef	0.002	0.001
	S.E	(0.005)	(0.006)
	Obs	38,636	58,003
Prob. Test Twice	Coef	-0.011	-0.004
	S.E	(0.009)	(0.010)
	Obs	38,636	58,003
Prob. Foot examination	Coef	0.005	0.005
	S.E	(0.008)	(0.010)
	Obs	38,959	59,907
Prob. Dilated eye examination	Coef	-0.020*	0.002
	S.E	(0.010)	(0.012)
	Obs	39,302	61,244
Prob. Diabetes education	Coef	0.006	0.009
	S.E	(0.009)	(0.010)
	Obs	39,537	61,811
Panel C : Health Outcomes			
Have poor or fair general health	Coef	0.017*	0.016*
	S.E	(0.009)	(0.008)
	Obs	40,095	62,613
Days not in good physical health	Coef	0.030	0.153
	S.E	(0.191)	(0.190)
	Obs	39,429	60,316
Days not in good mental health	Coef	-0.403**	0.054
	S.E	(0.152)	(0.129)
	Obs	39,736	61,403
Days health limited usual work	Coef	-0.092	0.213
	S.E	(0.108)	(0.135)
	Obs	39,015	58,914

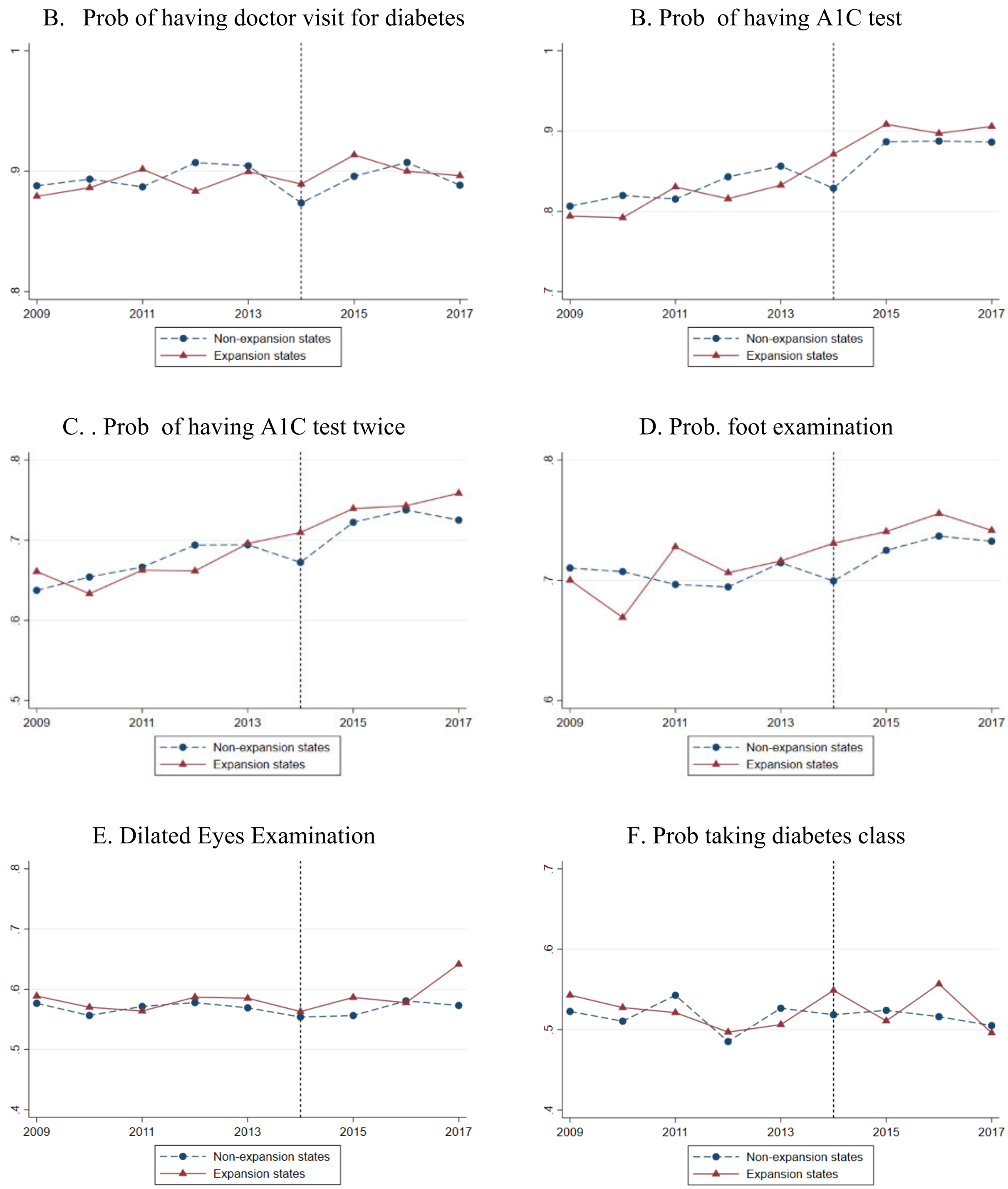
Note: All regressions include state fixed effect, year fixed effect, state-year unemployment rate, and dummy variables for each category of gender, race, marital status, education, household size, household income, age, current employment status, and cell phone dummy indicator. *** p<0.01, ** p<0.05, * p<0.1

Table 3.8. Sensitivity check

		Using weight	Excluded cellphone	Excluded 6 month
		(1)	(2)	(3)
Panel A: Health insurance coverage				
Health insurance coverage	Coef	0.102***	0.064***	0.100***
N= 14,756	S.E	(0.020)	(0.013)	(0.015)
	Obs	14,721	12,687	13,955
Panel B: Diabetes related care				
Prob. doctor visit for diabetes	Coef	0.004	0.033**	0.019*
	S.E	(0.011)	(0.014)	(0.011)
	Obs	14,079	12,190	13,342
Prob. A1c Test	Coef	0.044	0.038**	0.040**
	S.E	(0.027)	(0.016)	(0.016)
	Obs	13,463	11,624	12,756
Prob. Test Twice	Coef	0.050**	0.041**	0.036**
	S.E	(0.022)	(0.020)	(0.017)
	Obs	13,463	11,624	12,756
Prob. Foot examination	Coef	0.047	0.029	0.020
	S.E	(0.033)	(0.024)	(0.021)
	Obs	14,028	12,123	13,287
Prob. Dilated eye examination	Coef	0.002	-0.007	0.010
	S.E	(0.038)	(0.024)	(0.026)
	Obs	14,370	12,443	13,614
Prob. Diabetes education	Coef	0.029	0.003	0.001
	S.E	(0.025)	(0.019)	(0.015)
	Obs	14,561	12,594	13,799
Panel C : Health Outcomes				
Have poor or fair general health	Coef	-0.036	-0.050***	-0.039**
	S.E	(0.021)	(0.018)	(0.015)
	Obs	14,762	12,718	13,994
Days not in good physical health	Coef	-1.848**	-1.213**	-1.082**
	S.E	(0.762)	(0.568)	(0.465)
	Obs	14,213	12,244	13,481
Days not in good mental health	Coef	-1.469**	-0.956**	-1.110***
	S.E	(0.607)	(0.402)	(0.357)
	Obs	14,353	12,361	13,609
Days health limited usual work	Coef	-1.782***	-1.072	-1.049*
	S.E	(0.630)	(0.660)	(0.526)
	Obs	13,624	11,737	12,921

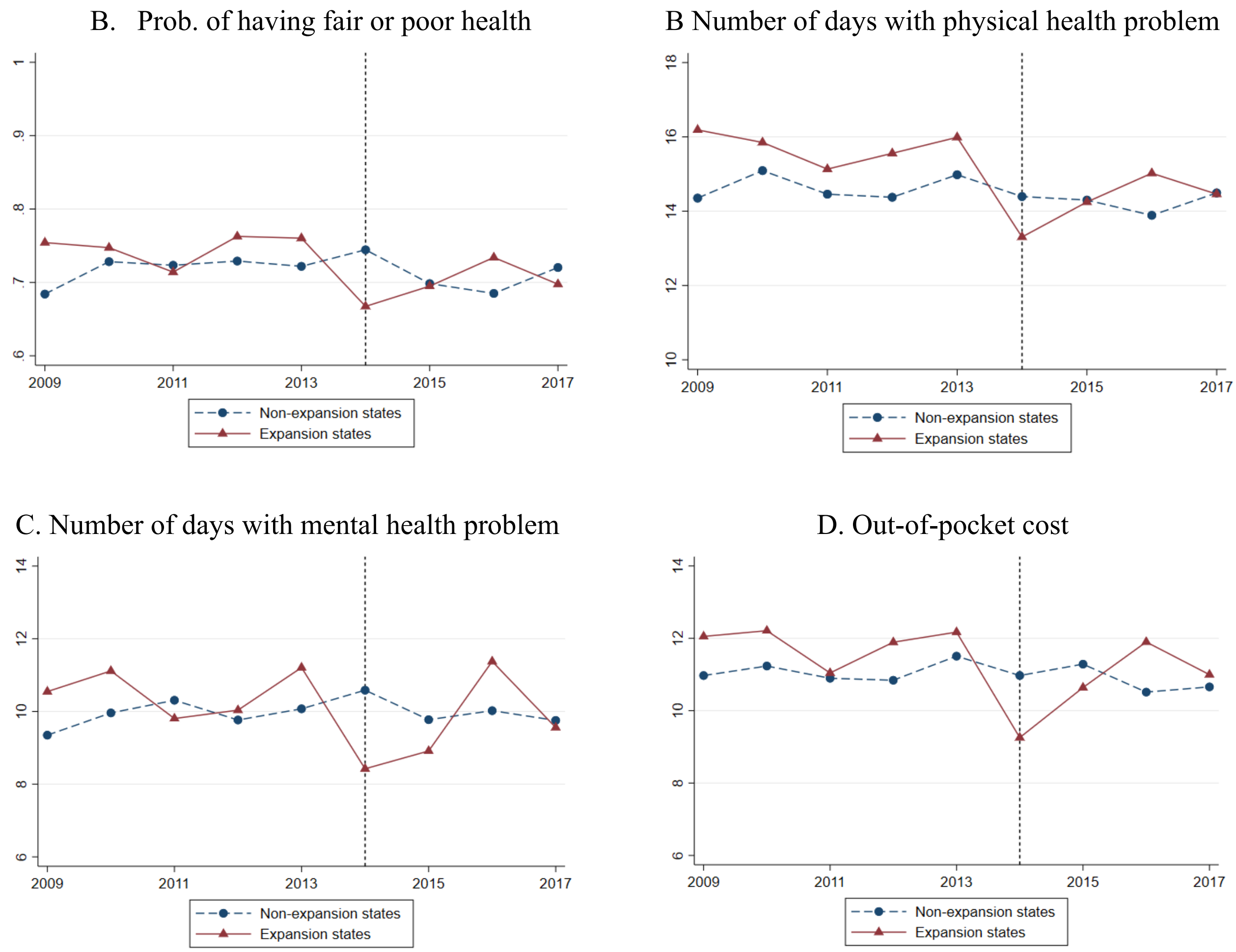
Note All regressions include state fixed effect, year fixed effect, state-year unemployment rate, and dummy variables for each category of gender, race, marital status, education, household size, household income, age, current employment status, and cell phone dummy indicator. *** p<0.01, ** p<0.05, * p<0.1

Figure 3.1. Trend diabetes-related care utilization among low-income adults with diabetes



Notes: Mean of the outcome variables by year is plotted.

Figure 3.2. Trend in self-accessed health outcomes among low income adults with diabetes,



Notes: Mean of the outcome variables by year is plotted.

Appendix Table 3.1. % FPL level by household size and year

Household size	Year 2009	2010	2011	2012	2013	2014	2015	2016	2017
1	$14,945	$14,945	$15,028	$15,415	$15,856	$16,105	$16,243	$16,394	$16,643
2	$20,107	$20,107	$20,300	$20,879	$21,404	$21,707	$21,983	$22,108	$22,411
3	$25,268	$25,268	$25,571	$26,344	$26,951	$27,310	$27,724	$27,821	$28,180
4	$30,429	$30,429	$30,843	$31,809	$32,499	$32,913	$33,465	$33,534	$33,948
5	$35,590	$35,590	$36,115	$37,274	$38,047	$38,516	$39,206	$39,247	$39,716
6	$40,751	$40,751	$41,386	$42,739	$43,594	$44,119	$44,947	$44,960	$45,485
7	$45,913	$45,913	$46,658	$48,203	$49,142	$49,721	$50,687	$50,687	$51,253
8	$51,074	$51,074	$51,929	$53,668	$54,689	$55,324	$56,428	$56,428	$57,022

Source: U.S. Department of Health & Human Services (USDHHS), Office of Assistant secretary for planning and evaluation, ASPE, 2009-2017. Poverty Guidelines

Appendix Table 3.2. BRFSS datasets for the diabetes module by state and year

State	FIPS	2017	2016	2015	2014	2013	2012	2011	2010[c]	2009[c]
1 Florida	12	LLCP		LLCPv1	LLCP	LLCP	LL	LL	LL	LL
2 Georgia	13	LLCP		LLCP	LLCP	LLCP	LLCP	LL	LL	LL
3 Iowa	19	LLCP		LLCP	LLCP	LLCP	N/A	LL	LL	LL v1
4 Kansas	20	NA		LLCP v1	N/A	LLCP v1	LLCP v1	LL v1	LL v1	LL v1
5 Kentucky	21	LLCP		LLCP	N/A	LLCP	LLCP	LL	LL	LL
6 Louisiana	22	LLCP	LLCP	LLCP	LLCP	LLCP	LL	LL	LL	LL
7 Maine	23	N/A		N/A	LLCP	LLV1	LLCP v1	LL v3	LL v1	NA
8 Michigan	26	LLCP		LLCP	N/A	LLCP v1	LLCP v1	LL v1	LL v1	LL v3
9 Montana	30	LLCP		LLCP	N/A	LLCP	N/A	LLCP	LL	LL
10 Nebraska	31	LLCPv1		LLCP v1	LLCP v1	LLCP v2	LLCP v2	LL v3	LL v1	LL v1
11 Nevada	32	LLCP		LLCP	N/A	LLCP	LLCP	N/A	LL	LL
12 New Jersey	34	LLCP	LLCP	LLCP	LLCP	LLCP	LLCP	LLCP	LLv1	LL
13 New Mexico	35	LLCP		LLCP	LLCP	LLCP	LLCP	LLCP	LL	LL
14 North Carolina	37	LLCP		LLCP	N/A	LLCP	LLCP	LL	LL	LL
15 North Dakota	38	LLCP		N/A	LLCP	LLCP	LL	LL	LL	LL
16 Ohio	39	LLCP	LLCPv1	N/A	LLCP	LLCP v1	LLCP	LL	LL	LL
17 Oklahoma	40	LLCPv1	LLCPv1	LLCP v2	N/A	LLCP v1	LLCP v1	LL v1	LL v1	N/A
18 South Carolina	45	LLCP		LLCP	LLCP	LLCP	LLCP	LLCP	LL	LL
19 Tennessee	47	N/A		LLCP	LLCP	LLCP	LLCP	LLCP	LL	LL
20 Texas	48	LLCP	LLCP{v1	LLCPv1	LLCPv1	LLCP v1	LLCP v1	LLV1	LL v1	LL
21 Utah	49	LLCPv1		LLCP 2	N/A	N/A	LLCPV2/3	LL	LL	LL
22 Virginia	51	LLCP		LLCP	LLCP	LLCP	LLCP	N/A	LL	LL
23 West Virginia	54	N/A		N/A	LLCP	LLCP	LLCP	LLCP	LL	LL
24 Wisconsin	55	LLCP		LLCP	N/A	LLCP	LLCP	LLCP	LL	LL
25 Wyoming	56	LLCP	LLCP	LLCP	LLCP	N/A	LLCP	LLCP	LL	LL

Notes: Source: BRFSS modules by category, BRFSS Combine Landline, and Cellphone, Multiple-Version Questionnaire use of data 2009-2017, BRFSS Combine Landline Multiple-Version Questionnaire use of data 2009-2017

[c] : In 2010 and 2009, BRFSS conduct the survey only on landline telephone

LLCP: questions of diabetes module are asked as common module on combined landline telephone and cellular telephone questionnaire

LL: questions of diabetes module are asked as common module on landline telephone survey only questionnaire

LLCP v1/v2/v3: questions of diabetes module are asked on combined landline telephone and cellular telephone version 1 or version 2 or version 3 only

LL v1/v2/ v3: questions of diabetes module are asked on landline telephone version 1 or version 2 or version 3 only

N/A: diabetes module is not available in that state at that time

References

Afendulis, C. C., He, Y., Zaslavsky, A. M., & Chernew, M. E. (2011). The Impact of Medicare Part D on Hospitalization Rates. *Health Services Research, 46(4),* 1022-1038.

Ai, C., & Norton, E. C. (2003). Interaction terms in logit and probit models. *Economics Letter*, 80(1), 123-129.

American Diabetes Association (2013). Economic costs of diabetes in the U.S. in 2012. *Diabetes Care,* Volume 36, pp. 1033–1046

Autor, D. H., & Duggan, M. G. (2003). The Rise in the Disability Rolls and the Decline in Unemployment. *The Quarterly Journal of Economics*, *118*(1), 157–206.

Ayyagari, P. and He, D. (2016). The role of medical expenditures risk in portfolio allocation decisions. *Health Economics*, vol. 26, no. 11, Sept. 2016, pp. 1447–1458.

Ayyagari, P., & Shane, D. M. (2015). Does prescription drug coverage improve mental health? Evidence from Medicare Part D. *Journal of Health Economics, 41*, 46-58.

Ayyagari, P., Shane, D. M., & Wehby, G. L. (2016). The Impact of Medicare Part D on Emergency Department Visits. *Health Economics, 26(4),* 536-544

Baicker, K., Taubman, S. L., Allen, H. L., Bernstein, M., Gruber, J. H., Newhouse, J. P., Schneider, E.C., Wright, B.J., Zaslavsky, A.M., and Finkelstein, A. N. (2013). The Oregon Experiment — Effects of Medicaid on Clinical Outcomes. *New England Journal of Medicine, 368*(18), 1713-1722.

Barbaresco, S., Courtemanche, C.J., and Qi, Y. (2015) 'Impacts of the affordable care act dependent coverage provision on health-related outcomes of young adults,' *Journal of Health Economics*, 40, pp. 54–68.

Barcellos, S.H & Jacobson, M. (2015) Effect of Medicare on Medical expenditures risk and financial strain. *American Economic Journal: Economic Policy. Vol.7 N.* o4 41-70

Basu, A., Yin, W., & Alexander, G. C. (2010). Impact of Medicare Part D on Medicare-Medicaid Dual-Eligible Beneficiaries Prescription Utilization and Expenditures. *Health Services Research*, *45*(1), 133–151.

Belotti, F., Deb, P., Manning, W. G., & Norton, E. C. (2015). Twopm: Two-Part Models. *The Stata Journal: Promoting Communications on Statistics and Stata*, *15*(1), 3–20.

Berkowitz, S. A., Seligman, H. K., & Choudhry, N. K. (2014). Treat or Eat: Food Insecurity, Cost-related Medication Underuse, and Unmet Needs. *The American Journal of Medicine, 127(4).*

Booth, A. L., & Nolen, P. (2012). Gender Differences in Risk Behaviour: Does Nurture Matter? *The Economic Journal*, *122*(558).

BRFSS Combined Landline Telephone and Cellular Telephone Survey Multiple-Version Questionnaire Use of Data, 2011-2014.

BRFSS Landline Telephone Survey Multiple-Version Questionnaire Use of Data. 2011-2014

BRFSS Module Data for Analysis 2009-2015

BRFSS Modules Used by Category, 2009-2015.

BRFSS Use of Multiple-Version Questionnaire Data. 2009-2010.

Calonico, S., Cattaneo, M. D., Farrell, M. H., & Titiunik, R. (2017). Rdrobust: Software for Regression-discontinuity Designs. *The Stata Journal: Promoting Communications on Statistics and Stata*, *17*(2), 372–404.

Card, D., Dobkin, C., & Maestas, N. (2008). The Impact of Nearly Universal Insurance Coverage on Health Care Utilization: Evidence from Medicare. *American Economic Review*, *98*(5), 2242–2258.

Card, D., Dobkin, C., & Maestas, N. (2009). Does Medicare Save Lives?*. *Quarterly Journal of Economics*, *124*(2), 597–636.

Centers for Disease Control and Prevention (2013a). Diabetes—United States, 2006 and 2010. In: CDC health disparities and inequalities report—United States. MMWR 2013;62 (Suppl; November 22, 2013). Available at: http://www.cdc.gov/MMWr/preview/mmwrhtml/su6203a17.htm

Centers for Disease Control and Prevention (2013b). Prevalence of hypertension and controlled hypertension—United States, 2007–2010. MMWR 2013:62;144–148. In: CDC. CDC health disparities and inequalities report—United States. MMWR 2013, 62(Suppl; November 22, 2013). Available at: https://www.cdc.gov/mmwr/preview/mmwrhtml/su6203a24.htm

Centers for Disease Control and Prevention. (2014). National Diabetes Statistics Report: Estimates of Diabetes and Its Burden in the United States, 2014. Atlanta, GA: US Department of Health and Human Services. Available from: http://www.cdc.gov/diabetes/data/statistics/2014StatisticsReport.html.

Centers for Disease Control and Prevention. High Blood Pressure Fact. Retrieved from: http://www.cdc.gov/bloodpressure/facts.htm

Center for Medicare and Medicaid Services (2012). Chronic conditions among Medicare Beneficiaries. Available at: https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Chronic-Conditions/Downloads/2012Chartbook.pdf

Chatterji, P., Liu, X., & Yorük, B. K. (2018). The Effects of the 2010 Affordable Care Act Dependent Care Provision on Family Structure and Public Program Participation among Young Adults. CESifo Working Paper Series 7254, CESifo Group Munich.

Clemens, J., & Gottlieb, J. D. (2017). In the Shadow of a Giant: Medicare's Influence on Private Physician Payments. *Journal of Political Economy*, *125*(1), 1–39.

Cubanski, J. C. F., Koma, W., Damico, A., & Neuman, T. (2018, November 20). How Many Seniors Live in Poverty? Retrieved from https://www.kff.org/medicare/issue-brief/how-many-seniors-live-in-poverty/

Cubanski, J., Neuman, T., and Freed, M., 2019, The facts on Medicare spending and Financing, August Issue Brief, Henry J. Kaiser Family Foundation, San Francisco, CA.

Currie, J. and Gruber, J. (1996). Saving babies: The efficacy and cost of recent changes in the Medicaid eligibility of pregnant women', *Journal of Political Economy*, 104(6), pp. 1263–1296.

Currie, J., Gruber, J., & Fischer, M. (1995). Physician Payments and Infant Mortality: Evidence from Medicaid Fee Policy. *Am Econ. Rev*. 85 (2), 106–111

Deb, P., Norton, C (2018). Modeling Health Care Expenditure and Use. *Annual Review of Public Health. 39*:489–505

Decker, S. and Rapaport, C. (2002). Medicare and disparities in women's health, *NBER Working Paper 8761*.

Dillender, M. (2015). The effect of health insurance on workers' compensation filing: Evidence from the affordable care acts age-based threshold for dependent coverage. *Journal of Health Economics*, *43*, 204–228.

Duggan, M., & Morton, F. S. (2010). The Effect of Medicare Part D on Pharmaceutical Prices and Utilization. *American Economic Review*, *100*(1), 590–607.

Dunn, A. and Shapiro, A., (2017) Does Medicare Part D save lives? *American Journal of Health Economics.*

Engelhardt, G.V., and Gruber, J. (2011). Medicare Part D and the Financial Protection of the Elderly. *American Economic Journal: Economic Policy, 3(4):* 77-102.

Ettner, S. L. (1997). Adverse selection and the purchase of Medigap insurance by the elderly. *Journal of Health Economics*, *16*(5), 543–562.

Finkelstein, A., S. Taubman, B. Wright, M. Bernstein, J. Gruber, J. P. Newhouse, H. Allen, K. Baicker, and the Oregon Health Study Group (2012). The Oregon health insurance experiment: Evidence from the first year. *Quarterly Journal of Economics 127 (3),* 1057–1106.

Finkelstein, A.N. and McKnight, R., 2008, What did Medicare do? The initial impact of Medicare on mortality and out of pocket medical spending, *Journal of Public Economics, 92*, 1644-1668.

Finkelstein, A.N., 2007, The aggregate effect of health insurance: Evidence from the introduction of the Medicare, *Quarterly Journal of Economics, 122*, 1-37.

Freeman, J.D., Kadiyala, S., Bell, J.F. and Martin, D.P. (2008) 'The causal effect of health insurance on utilization and outcomes in adults: a systematic review of US studies', *Medical Care*, 46(10), pp. 1023–1032.

Gross, T., 2010, Using insurance before you lose it: Health care consumption at the end of coverage, Unpublished Manuscript.

Grossman, M. (1972). On the Concept of Health Capital and the Demand for Health. *Journal of Political Economy, 80*(2), 223-255.

Gundersen, C., & Ziliak, J. P. (2015). Food Insecurity and Health Outcomes. *Health Affairs*, *34*(11), 1830–1839. doi: 10.1377/hlthaff.2015.0645

Hahn, J., Todd, P., & Klaauw, W. (2001). Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design. *Econometrica*, *69*(1), 201–209.

Heflin, C. M., Siefert, K., & Williams, D. R. (2005). Food insufficiency and womens mental health: Findings from a 3-year panel of welfare recipients. *Social Science & Medicine*, *61*(9), 1971–1982.

Himmelstein, G. (2019). Effect of the Affordable Care Act's Medicaid Expansions on Food Security, 2010–2016. *American Journal of Public Health*, *109*(9), 1243–1248.

Hu, L., Kaestner, R., Mazumder, B., Miller, S. and Wong, A., 2016. Effect of Patient Affordable Care Act Medicaid expansions on Financial Well-being. National Bureau of Economic Research Working Paper No 22170, April 2016.

Huh, J. (2017). Medicaid and Provider Supply. Available at SSRN: https://ssrn.com/abstract=2853882 or http://dx.doi.org/10.2139/ssrn.2853882

Huh, J., Rief, J. (2017). Did Medicare Part D reduce Mortality? Journal of Health Economics. 53:17-37

Imbens, G. and T. Lemieux, 2008, Regression discontinuity designs: A guide to practice, *Journal of Econometrics, 142*, 615-635.

Kaestner, R. & Khan, N. (2010). Medicare part D and its effect on the use of prescription drugs, use of other health care service and health of the elderly. National Bureau of Economic Research Working Paper 16011, 2010

Kaestner, R., Bowen, G., Anuj, G. and Caitlyn, F. (2015) Effects of ACA Medicaid expansions on Health Insurance Coverage and Labor Supply. National Bureau of Economic Research Working Paper 21836, 2015

Kaestner, R., Schiman, C., & Alexander, G. C. (2017). Effects of Prescription Drug Insurance on Hospitalization and Mortality: Evidence from Medicare Part D. *Journal of Risk and Insurance*, *86*(3), 595–628.

Kaiser Family Foundation (2004). Health Insurance Coverage of the Near Elderly. Available at: https://www.kff.org/uninsured/report/health-insurance-coverage-of-the-near-elderly/

Kaiser Family Foundation. (2007). Massachusetts health care reform Plan: An update. The Henry J. Kaiser Family Foundation.

Kaiser Family Foundation. (2008). Medicare 2008 Benefits Table. The Henry J. Kaiser Family Foundation. Retrieved Jan, 2018, from https://www.kff.org/medicare/report/medicare-2008-benefits-table/

Kaiser Family Foundation. (2012). The role of Medicaid for people with diabetes. The Henry J. Kaiser Family Foundation. Available at: https://kaiserfamilyfoundation.files.wordpress.com/2013/01/8383_d.pdf

Kaiser Family Foundation. (2013). Uninsured rates for the Nonelderly by federal poverty level. The Henry J. Kaiser Family Foundation.

Kaiser Family Foundation. (2014). Health Care on a Budget: The Financial Burden of Health Spending by Medicare Households. The Henry J. Kaiser Family Foundation.

Kaiser Family Foundation. (2015). Medicare’s Income-Related Premiums: A Data Note. The Henry J. Kaiser Family Foundation.

Kaiser Family Foundation. (2016a). Medicaid income eligibility limits for other non-disabled adults, 2011-2016. The Henry J. Kaiser Family Foundation.

Kaiser Family Foundation. (2016b). Status of state action on the Medicaid expansions decision (2016). The Henry J. Kaiser Family Foundation.

Kaiser Family Foundation. (2017). The Medicare Part D prescription drug benefit. The Henry J. Kaiser Family Foundation.

Ketcham, J., & Simon, K. (2008). Medicare Part D s Effects on Elderly Drug Costs and Utilization. NBER working paper 14326.

Kolstad, J.T. and Kowalski, A.E. (2012). The Impact of Health Care Reform on Hospital and Preventive Care: Evidence from Massachusetts. *Journal of Public Economics*, 96, 909-929.

Lahiri, K., & Xing, G. (2003). Modeling Medicare-Eligible Veterans' Demand for Outpatient Services: A Two-Stage Approach. *Health Services and Outcomes Research Methodology*, *4*(4), 221–240.

Lee, D.S. and Lemieux, T., 2010, Regression discontinuity designs in economics*, Journal of Economic Literature, 48,* 281-355.

Leung, P., & Mas, A. (2016). Employment effects of the ACA Medicaid expansions National Bureau of Economic Research. Working Paper 22540, 2016.

Lichtenberg, F.R., 2002, The Effect of Medicare on Health Care Utilization and Outcomes. In: Garber, Alan M., editor. Frontiers in Health Policy Research. 5. MIT Press for the National Bureau of Economic Research; Cambridge and London: 2002.

Long, S. H., Marquis, M., & Rodgers, J. (1998). Do people shift their use of health services over time to take advantage of insurance? *Journal of Health Economics*, *17*(1), 105–115.

Lumsdaine, R., Stock, J., & Wise, D. (1995). Why are Retirement Rates So High at Age 65?NBER Chapters, in: Advances in the Economics of Aging, 61-81.

Mazumder, B., Miller, S. (2015). The Effects of the Massachusetts Health Reform on Household Financial Distress. Federal Reserve Bank of Chicago 2015.

McCullagh, P., and Nelder, J.A. (1989). Generalized Linear Models. 2nd ed. London: Chapman & Hall/CRC.

Mcwilliams, J. M., Zaslavsky, A. M., Meara, E., & Ayanian, J. Z. (2004). Health Insurance Coverage And Mortality Among The Near-Elderly. *Health Affairs*, *23*(4), 223–233.

Mcwilliams, J. M. (2003). Impact of Medicare Coverage on Basic Clinical Services for Previously Uninsured Adults. *Jama*, *290*(6), 757.

Mcwilliams, J. M., Meara, E., Zaslavsky, A. M., & Ayanian, J. Z. (2007). Use of Health Services by Previously Uninsured Medicare Beneficiaries. *New England Journal of Medicine*, *357*(2), 143–153.

Medicaid. (n.d.). Retrieved February 12, 2018, from https://www.medicare.gov/your-medicare-costs/help-paying-costs/medicaid/medicaid.html

Miller, S. (2011). The Effect of Insurance on Outpatient Emergency Room Visits: An Analysis of the 2006 Massachusetts Health Reform. *Journal of Public Economics*, 96, 893-908.

Moran, M. (2018). The Affordable Care Act's Medicaid Expansion and Food Insecurity rates. Available at: https://digitalcommons.usm.maine.edu/cgi/viewcontent.cgi?article=1137&context=muskie_capstones

Moulton, J. G., Diebold, J. C., & Scott, J. C. (2016). The Impact of Medicare Part D on Self-Employment. Research on Aging,39(1), 64-85.

Na, R. and Slusky, D. (2016). Does the ACAAs Medicaid Expansion Improve Health? *SSRN Electronic Journal SSRN Journal*.

Paez, K. A., Zhao, L., & Hwang, W. (2009). Rising Out-Of-Pocket Spending For Chronic Conditions: A Ten-Year Trend. *Health Affairs*, 28(1), 15-25

Piette, J. D., Heisler, M., & Wagner, T. H. (2004). Problems Paying Out-of-Pocket Medication Costs Among Older Adults With Diabetes. *Diabetes Care*, 27(2), 384-391. doi:10.2337/diacare.27.2.384

Porter, J., 2003, Estimation in the regression discontinuity model, Unpublished Manuscript, Harvard University, Department of Economics.

Powell, M., & Ansic, D. (1997). Gender differences in risk behaviour in financial decision-making: An experimental analysis. *Journal of Economic Psychology*, *18*(6), 605–628..

Preventing Chronic Disease | Defining and Measuring Chronic Conditions: Imperatives for Research, Policy, Program, and Practice - CDC. (2013, April 25). Retrieved from https://www.cdc.gov/pcd/issues/2013/12_0239.htm

Preventing Chronic Disease | Multiple Chronic Conditions Among US Adults: A 2012 Update - CDC. (n.d.). Retrieved from https://www.cdc.gov/pcd/issues/2014/13_0389.htm

Puhani, P. A. (2012). The treatment effect, the cross difference, and the interaction term in nonlinear "difference-in-differences" models. *Economics Letters*, *115*(1), 85–87. doi: 10.1016/j.econlet.2011.11.025

Sambamoorthi, U., Tan, X., & Deb, A. (2015). Multiple chronic conditions and healthcare costs among adults. *Expert Review of Pharmacoeconomics & Outcomes Research,15(5),* 823-832.

Schmidt, L., Shore-Sheppard, L. and Watson, T. (2015). The Effect of Safety-Net Programs on Food Insecurity. *Journal of Human Resources, 51(3)*, pp.589-614.

Schur, C.L., Doty, M.M., Berk, M.L. (2004) Lack of prescription coverage among the under 65: a symptom of underinsurance. Issue Brief (Common Fund). ;716:1–8.

Seligman, H. K., Bindman, A. B., Vittinghoff, E., Kanaya, A. M., & Kushel, M. B. (2007). Food insecurity is associated with diabetes mellitus: Results from the National Health Examination and Nutrition Examination Survey (NHANES) 1999-2002. *Journal of General Internal Medicine*, 22(7), 18-23.

Seligman, H. K., Laraia, B. A., & Kushel, M. B. (2010). Food insecurity is associated with chronic disease among low-income NHANES participants. *The Journal of Nutrition, 140(2)*, 304-310

Simon, K., Soni, A & Cawley, J. (2016). The impact of health insurance on preventive care and health behaviors: Evidence from 2014 ACA Medicaid expansions. *National Bureau of Economic Research Working Paper No 22265*, May 2016.

Sommers, B. D., Blendon, R. J., Orav, E. J., & Epstein, A. M. (2016). Changes in Utilization and Health Among Low-Income Adults After Medicaid expansions or Expanded Private Insurance. *JAMA Internal Medicine, 176*(10), 1501.

Sonchak, L. (2015) ‘Medicaid reimbursement, prenatal care and infant health’, *Journal of Health Economics*, 44, pp. 10–24.

Straud, Amy (2012, January) Older Americans and Credit Card Debt. Retrieved from: https://www.aarp.org/content/dam/aarp/research/public_policy_institute/security/2013/older-americans-and-credit-card-debt-AARP-ppi-sec.pdf

Stuff, J. E., Casey, P. H., Szeto, K. L., Gossett, J. M., Robbins, J. M., Simpson, P. M., Connell, C., & Bogle, M. L. (2004). Household food insecurity is associated with adult health status. *The Journal of Nutrition, 134(9),* 2330-2335.

U.S. Department of Health & Human Services (USDHHS), Office of Assistant secretary for planning and evaluation, ASPE, 2009-2015. Poverty Guidelines.

U.S. Department of Health and Human Services, Office of Disease Prevention and Health Promotion. Healthy People 2020. Washington, DC. November 10, 2016. Available from: https://www.healthypeople.gov/2020/topics-objectives.

USDA Food and Nutrition Service, SNAP. (2017). Available at: https://www.fns.usda.gov/snap/eligibility, Accessed 2/17

Weinfield, N. S., Mills, G., Borger, C., Gearing, M., Macaluso, T., Montaquila, J., & Zedlewski, S. (2014, August). Hunger in America 2014: National report. Retrieved from http://help.feedingamerica.org/HungerInAmerica/hunger-in-america-2014-full-report.pdf

Wherry, L., & Miller, S. (2016). Early coverage, access, utilization, and health effects associated with the Affordable Care Act Medicaid expansions: A quasi-experimental study. *Annals of Internal Medicine.*

Yörük, B. K., & Xu, L. (2018). Impact of the ACA’s Dependent Coverage Mandate on Health Insurance and Labor Market Outcomes Among Young Adults: Evidence from Regression Discontinuity Design. *Eastern Economic Journal*, *45*(1), 58–86.

Xu, L. and B.K. Yoruk. 2019, Impact of ACA dependent coverage mandate on health insurance and labor market outcomes among young adults: Evidence from regression discontinuity design, *Eastern Economic Journal, 45*, 58-86. 20

Yörük, B. K. (2018). Health insurance coverage and health care utilization: Evidence from the Affordable Care Act's dependent coverage mandate. *Forum for Health Economics and Policy*, *21*(2).