Did Medicare Part D Reduce Mortality?

Jason Huh and Julian Reif*

[Final version]

Abstract

We investigate the implementation of Medicare Part D and estimate that this prescription drug benefit program reduced elderly mortality by 2.2 percent annually. This was driven primarily by a reduction in cardiovascular mortality, the leading cause of death for the elderly. There was no effect on deaths due to cancer, a condition whose drug treatments are covered under Medicare Part B. We validate these results by demonstrating that the changes in drug utilization following the implementation of Medicare Part D match the mortality patterns we observe. We calculate that the value of the mortality reduction is equal to $5 billion per year.

1 Introduction

A major reason to provide public health insurance is its potential to increase an individual's life expectancy and improve her quality of life. This is supported by basic economic theory, which suggests that a reduction in the price of medical care should increase an individual's stock of health (Grossman 1972). Indeed, improving people's health was a primary motivation behind the enactment of social insurance programs such as Medicare, Medicaid, and the Affordable Care Act.

Although it is well documented that these social insurance programs increase health care utilization, many studies indicate that they provide, at best, only limited

*University of Illinois at Urbana-Champaign. We thank Jeff Clemens, Christina Marsh Dalton, Tatyana Deryugina, Bob Kaestner, Darius Lakdawalla, Anup Malani, Nolan Miller, and participants at the Chicago Booth Junior Health Economics Summit, the Midwest Health Economics Conference, the National Tax Association meeting, the Southeastern Health Economics Study Group, the UIUC Applied Economics Workshop, and the Urbana IGPA seminar series for helpful comments.

health benefits for adults.[1] If true, these programs may primarily increase the use of ineffective medical care. Although there is evidence that these programs still deliver significant insurance value to beneficiaries (Engelhardt and Gruber 2011; Finkelstein and McKnight 2008), the lack of major health benefits limits their cost-effectiveness.

We investigate the effect of Medicare Part D on elderly mortality. This prescription drug insurance program currently serves 39 million Medicare beneficiaries and spends $70 billion ($1,800 per beneficiary) per year (Medicare Board of Trustees 2014). Prescription drugs represent an increasingly valuable source of health care, with over ninety percent of the elderly consuming prescription drugs at least once per month (NCHS 2014). The introduction of Part D is an excellent natural experiment for detecting the effects of prescription drug insurance on health because it drastically increased coverage rates for the elderly. Between 2004 and 2007, about one-fourth of the elderly population gained prescription drug insurance (Kaestner and Khan 2012).

Our primary empirical specification compares trend differences in mortality between the young-elderly who have been eligible for Medicare Part D for at least one year (age 66) and the near-elderly who are not yet eligible (age 64), right around the implementation of Medicare Part D.[2] We employ detailed cause-of-death mortality records for the entire U.S. population, which allows us to measure mortality, a relatively rare event, very precisely. We estimate that Medicare Part D reduced annual mortality by 2.2 percent (0.036 percentage points) among the elderly in its initial years. This effect is driven primarily by a 4.4 percent reduction in cardiovascular mortality. We find no effect of Medicare Part D on deaths due to cancer, a condition whose drug treatments are covered under Medicare Part B. The effects are largest for men and for non-whites. We show in the main text and in an extensive appendix that our results are robust to using a variety of different specifications and are not driven by differential pre-existing trends in mortality between the control and treatment groups. Placebo exercises confirm that the mortality rate of individuals just under the age of 65, who are generally ineligible for Medicare, was unaffected by Medicare Part D.

We find mortality effects beginning as early as 2005, one year prior to the full implementation of Part D. We attribute this to Medicare Part D's 2004-2005 Pre-

[1] Baicker et al. (2013), Finkelstein and McKnight (2008), and Kaestner, Long, and Alexander (2014) find no or very limited effects of health insurance on health. Two notable exceptions are Card, Dobkin, and Maestas (2009) and Sommers, Long, and Baicker (2014).

[2] Our results are robust to using different age ranges for the treatment and control groups.

scription Drug Discount Card and Transitional Assistance Programs, which delivered $1.5 billion in subsidies to 1.9 million uninsured low-income elderly and granted large drug discounts to an additional 4.7 million elderly. We support this interpretation by providing evidence that elderly drug utilization increased during 2004-2005 among the individuals most likely to qualify for these programs.

Our empirical design yields intent-to-treat estimates of gaining drug insurance eligibility on mortality. If we attribute our estimated mortality effect entirely to previously uninsured individuals who gained drug coverage during our sample period, then this implies that prescription drug insurance reduces annual mortality by 9.6 percent, or 0.16 percentage points. To put both this estimate and our intent-to-treat estimate in context, we compare them to other studies estimating the effect of health insurance on mortality. Our estimates are of course larger than those from studies that find no statistically significant effect of health insurance on adult mortality (Finkelstein and McKnight 2008; Kaestner, Long, and Alexander 2014), although they are within the bounds of their 95 percent confidence intervals. Our estimates are smaller in magnitude than those from other studies that do find a statistically significant effect (Card, Dobkin, and Maestas 2009; Sommers, Long, and Baicker 2014). This is sensible because these other studies examine health insurance programs that include hospital and outpatient benefits as well as, in some cases, prescription drug benefits.

We examine drug utilization data from the Medical Expenditure Panel Survey to validate our findings. Consistent with our mortality analysis, we estimate that utilization and expenditures among the young-elderly increased by 25 to 30 percent for drugs treating diseases linked to cardiovascular mortality, but did not change for cancer drugs, which are covered primarily by Medicare Part B. This increase was exhibited by nearly all demographic groups, and was 45 percent larger for non-whites than for whites. Importantly, we present evidence that drug utilization increased beginning in 2004 for the low-income individuals targeted by the 2004-2005 Prescription Drug Discount Card and Transitional Assistance Programs. Overall, the observed changes in drug utilization patterns during this time period are consistent with the changing patterns in mortality.

Finally, we calculate that the social value of the reduction in elderly mortality attributable to Medicare Part D is worth about $5 billion per year. Combining this result with prior studies evaluating its non-health benefits yields a total benefit of

about $20 billion per year. This total does not account for other potential benefits of the Part D program, such as a reduction in morbidity, but nevertheless still represents a sizeable fraction of its total expenditures.

Whether health insurance improves health is a longstanding question in health economics. Prior work showing that health insurance reduces adult mortality has been limited either to a specific population such as sick individuals admitted to hospital emergency departments (Card, Dobkin, and Maestas 2009) or to a specific geographic area like Massachusetts (Sommers, Long, and Baicker 2014). Our paper advances this literature by providing additional evidence, derived from a strong empirical design coupled with detailed administrative data, that the public provision of health insurance can have a significant nationwide impact on total mortality.

We also contribute to the growing literature on Medicare Part D. Prior studies have documented that Part D increased elderly drug insurance coverage and drug utilization (Engelhardt and Gruber 2011; Kaestner and Khan 2012). Little is known about the health benefits of this program, however. We provide the first evidence that the increase in drug utilization attributable to Medicare Part D saved lives.

The rest of our paper is organized as follows. Section 2 provides background information on related literature and the Medicare Part D drug insurance program. Section 3 describes our data and Section 4 presents our main mortality results. Section 5 presents an analysis of the effect of Part D on drug use. Section 6 provides a cost-benefit analysis and Section 7 concludes.

2 Background and previous studies

2.1 Medicare Part D and prescription drug insurance

Medicare Part D is a prescription drug benefit program for seniors that was enacted as part of the Medicare Modernization Act (MMA) of 2003. The MMA also established the Prescription Drug Discount Card and Transitional Assistance Programs to provide relief from the high costs of prescription drugs to Medicare beneficiaries prior to the full implementation of Medicare Part D. These two programs began in June 2004 and remained in operation until 2006.[3]

[3]These two temporary programs are considered part of Medicare Part D (Medicare Board of Trustees 2004), but in this paper we will often mention them separately from the later (and larger) implementation of Part D because it is common in the literature to use January 1, 2006 as the

All Medicare beneficiaries, except for those with pre-existing Medicaid drug coverage, were eligible for the Prescription Drug Discount Card Program. The cards were offered by approved sponsors, usually established pharmacy benefit managers, who used their large membership numbers to negotiate discounted prices with drug manufacturers. The sponsors were allowed to charge an annual enrollment fee of up to $30 to cardholders. The discounts were substantial: the Centers for Medicare & Medicaid Services estimates that these cards delivered discounts of 12 to 21 percent for brand name drugs, and 45 to 75 percent for generic drugs (Hassol 2006). Between May 2004 and August 2005, the Drug Discount Card Program enrolled 6.6 million Medicare beneficiaries (16 percent of the Medicare population). Enrollment occurred quickly and the program was popular: more than half of all enrollees had entered the program by November 2004, and a 2005 survey of over 10,000 card members found that 69 percent reported using their discount cards "every time".[4]

The Transitional Assistance Program provided subsidies of up to $1,200 to low-income individuals who lacked access to prescription drug coverage when they signed up for drug discount cards.[5] These subsidies were administered in a manner similar to a debit card, with the amounts applied as credits to the drug discount card. During 2004-2005, 1.9 million qualifying individuals received a total of $1.5 billion in subsidies (Medicare Board of Trustees 2014). Drug discount card members, especially those receiving subsidies, were more likely to be non-white than beneficiaries not enrolled in these programs (Hassol 2006).

The rest of Medicare Part D began on January 1, 2006. Anybody eligible for traditional Medicare is eligible for Medicare Part D. This includes all individuals over the age of 65 who have worked for ten or more years in covered employment. Enrollment in Part D is voluntary, although individuals who delay enrollment must pay a small penalty that rises with the length of delay. Low-income individuals who qualify for both Medicaid and Medicare ("dual eligibles") are automatically enrolled into Part D. The program signed up 28 million members in 2006, its first year, and

"official" start date of Medicare Part D.

[4]Respondents receiving transitional assistance (subsidies) were even more likely (78 percent) to use their cards "every time" (Hassol 2006). The main reason for not using the card was that the respondents had no prescriptions to fill.

[5]The income threshold for obtaining access to the subsidy was set at 135% of the federal poverty line. The MMA specifically excludes low-income individuals with access to other sources of drug coverage from the subsidies. See http://www.ssa.gov/OP_Home/ssact/title18/1860D-31.htm for details.

grew to 39 million members by 2013.[6]

Medicare beneficiaries can obtain prescription drug coverage under Part D by joining a standalone Medicare Prescription Drug Plan, which offers only prescription drug benefits, or through Medicare Advantage, a managed care alternative to traditional government Medicare that uses private firms to provide insurance. Alternatively, beneficiaries can receive coverage through their employer, so long as it is sufficiently generous.

Beneficiaries select from among a number of different Part D plans. Although the plans may differ with respect to premiums, deductibles, and copays, each must be actuarially equivalent to, or more generous than, the standard benefit established by Congress. In 2006, the program's first year, this standard benefit design included a monthly premium of $32.20, a $250 deductible, and a coinsurance rate that begins at 25%, rises to 100% after an initial benefit limit (the "donut hole"), and then falls to 5% once the beneficiary has incurred $3,600 in out-of-pocket expenditures (Medicare Board of Trustees 2014). Low-income individuals are eligible for subsidies that defray some of these costs.

Medicare Part D expenditures totaled $47 billion in its first year. Expenditures were $70 billion in 2013 and are expected to increase to more than $170 billion annually by 2023 (Medicare Board of Trustees 2014). For comparison, the gross costs of the Affordable Care Act's coverage provisions are estimated to be $38 billion in 2014 and to rise to $227 billion by 2023 (Congressional Budget Office 2014).

About two-thirds of Medicare beneficiaries already had access to some form of prescription drug insurance prior to 2006. Kaestner and Khan (2012) estimate that Medicare Part D increased this coverage rate to about 90 percent. The majority of this increase occurred among individuals who were relatively poor and low educated.

Engelhardt and Gruber (2011) and Lichtenberg and Sun (2007) show that Medicare Part D also significantly crowded out other sources of insurance coverage. This means that Medicare Part D could have an impact on utilization and health not only through a reduction in the number of the uninsured, but also through a change in the composition of prescription drug coverage.

[6]Medicare's total enrollment, which includes members who elected not to sign up for Part D, was 52 million in 2013.

2.2 Prior studies

Our paper is related to two strands of literature. The first examines the effect of health insurance on health. The second examines the effect of the Medicare Part D prescription drug insurance program on utilization and spending.

2.2.1 Effect of health insurance on health

In their comprehensive review of the literature, Levy and Meltzer (2004) conclude that health insurance strongly benefits the health of vulnerable populations such as infants, but caution that the benefits for other populations may be quite modest. For example, the RAND health insurance experiment finds that increasing the generosity of health insurance improved the health status of persons with high blood pressure, but had no significant effect on the health status of the average patient (Brook et al. 1983). Lurie et al. (1984) find that the termination of MediCal benefits increased blood pressure among a group of low-income patients at the UCLA hospital. Bhattacharya, Goldman, and Sood (2003) estimate that health insurance improves the health status of HIV positive patients. It is worth noting that each of these health improvements are for illnesses that can be treated with prescription drugs.

Several studies have examined the effect of Medicare on mortality. Lichtenberg (2002) employs death probability data to estimate the effect of Medicare on mortality and finds that Medicare increases the survival rate of the elderly who are older than 65. In more recent work, Finkelstein and McKnight (2008) examine the effect of the 1965 introduction of Medicare on elderly mortality. They employ two different empirical designs, one that exploits variation in age-eligibility (similar to this paper) and another that exploits geographic variation in pre-existing insurance coverage. In neither case do they detect any significant effects on mortality.

Card, Dobkin, and Maestas (2009) also examine Medicare, but focus their analysis on elderly patients admitted to emergency departments with non-deferrable conditions. They estimate the effect of Medicare on mortality using the Medicare eligibility age in a regression discontinuity design. They find that Medicare reduced annual mortality by 4.3 percent in their patient population.

Sommers, Long, and Baicker (2014) investigate the effect of the 2006 Massachusetts health care reform, which expanded health care insurance to non-elderly adults, on mortality. They compare mortality trends in Massachusetts counties to mortality

trends in a control set of counties with similar demographics and economic conditions and estimate that the reform decreased total mortality by 2.9 percent.

The best available recent evidence comes from the Oregon Health Insurance Experiment, a randomized controlled trial of Medicaid in 2008 (Baicker et al. 2013). The researchers find a significant effect of insurance coverage on the use of preventive services, but no effect on the prevalence of hypertension, high cholesterol levels, and several other basic indicators of health. Although the empirical design of this study is excellent, its sample size of approximately 12,000 limits its ability to detect changes in health outcomes that are rare in the short run, such as mortality.

2.2.2 Effects of Medicare Part D

The majority of studies examining Medicare Part D have focused on its effects on drug utilization and out-of-pocket spending. Lichtenberg and Sun (2007) examine prescription drug data from Walgreens during the time period September 2004 through December 2006. They employ a difference-in-differences research design that compares the elderly to the non-elderly before and after the implementation of Medicare Part D, and conclude that the introduction of Medicare Part D was associated with a 13 percent increase in elderly prescription drug use and an 18 percent reduction in out-of-pocket drug spending.

Schneeweiss et al. (2009) analyze data on prescription drug purchases at three pharmacy chains that operated in multiple states between January 2005 and December 2006. Using segmented linear regression models, they estimate that the introduction of Medicare Part D increased drug use by 3 to 37 percent and decreased out-of-pocket spending by 37 to 58 percent.

Kaestner and Khan (2012) employ data from the Medicare Current Beneficiary Survey (MCBS), which contains detailed information on expenditures and drug use. They estimate that the introduction of Medicare Part D increased prescription drug use among the previously uninsured elderly by 30 percent and drug expenditures by 40 percent, and that this effect was largest for low-income minority groups.

Engelhardt and Gruber (2011) estimate that Medicare Part D resulted in a 75 percent crowd-out of other prescription drug insurance coverage. Despite this effect, they estimate that Medicare Part D caused a sizeable reduction in out-of-pocket spending, comparable to the deadweight loss of financing the program.

Increases in drug utilization are beneficial only to the extent that they improve

health (net of spending). However, surprisingly little is known about the effects of Medicare Part D on health outcomes.[7] One exception is a contemporaneous study by Kaestner, Long, and Alexander (2014), who examine Medicare enrollment data and estimate that Medicare Part D did not have a statistically significant effect on mortality.[8] There are two main differences between their study and ours. First, the treatment group in our analysis consists of all 66-year-olds. Kaestner et al.'s treatment group, by contrast, includes a larger age range (66-84), but also excludes all Medicare Advantage enrollees, dual eligibles, individuals with end-stage renal disease, the disabled, and non-whites. Thus their estimated treatment effect applies to a population that is, on average, older, richer, and more white than the population we study. This last difference is important because, as we show later, a large portion of our estimated effect is attributable to non-whites.

Second, the two studies employ different empirical designs. We compare changes in mortality among 66-year-olds to changes in mortality among 64-year-olds. By contrast, Kaestner, Long, and Alexander (2014) identify their effect by exploiting geographic and socioeconomic variation in pre-existing prescription drug coverage rates for the elderly (aged 66 and older) prior to 2006, the year of Medicare Part D's implementation. In other words, they compare changes in elderly mortality in groups with low pre-existing drug coverage rates to groups with high pre-existing coverage rates.

3 Data

We obtain confidential mortality data from the National Vital Statistics System of the National Center for Health Statistics for the years 2001-2008. These data provide demographic state of residence information for the universe of deaths that occurred in the United States. Table 1, which follows the same basic classification scheme used in Ruhm (2013), displays causes of death for the elderly population during the time period 2001-2008. The single largest category is cardiovascular disease, the main cause of death in 40 percent of all elderly deaths. The second leading cause is cancer,

[7]Prior to Part D, many beneficiaries gained drug coverage through Medicare Advantage programs. Gowrisankaran, Town, and Barrette (2011) present evidence that drug coverage reduces mortality rates for those enrolled in Medicare HMO's.

[8]We note, however, that our estimates are within the 95 percent confidence intervals of their estimates and thus are not ruled out by their analysis.

responsible for 22 percent of elderly deaths. The remaining 38 percent of deaths are due to other diseases or accidents. Our primary estimation sample, which includes only 64- and 66-year-old decedents, consists of 518,514 deaths that occurred between 2001 and 2008.

We obtain corresponding intercensal population estimates from the Surveillance, Epidemiology, and End Results (SEER) Program of the National Cancer Institute. These allow us to convert our data on number of deaths to a death rate, which is more suitable for analysis.

Finally, we obtain data on prescription drug use and expenditures from the prescription drug component of the Medical Expenditure Panel Survey (MEPS). The MEPS is a nationally representative survey of U.S. households, and its measures of prescription drug spending have been shown to closely match administrative measures from the National Health Expenditure Accounts (Bernard et al. 2012). Each survey has a two-year overlapping panel design, with each panel consisting of five rounds of interviews that take place over two full calendar years. We use the Full-Year Consolidated Data files in our analysis. These data consist of variables measured at the end of each calendar year, with each individual appearing in the data twice. The overlapping panel design means that, for any given year, our sample includes individuals in their first year of the panel and individuals in their second year of the panel.

For each drug they consume, MEPS respondents report an associated medical condition.[9] Each self-reported medical condition is then translated into ICD-9 codes (a common classification standard) by professional medical coders. Importantly for our analysis, these same medical codes are used to classify causes of death in the mortality data. Table 2 shows the average drug use and drug expenditures, by drug insurance status, among the young-elderly population for different medical conditions in the years prior to the implementation of Medicare Part D. Unsurprisingly, individuals who lack drug insurance consume fewer drugs and spend less on them. The largest categories in terms of either utilization or expenditures are treatments for heart disease, diabetes, lipid metabolism disorders, and digestive disorders. Appendix A lists the three most common drugs prescribed in each of these categories along with their primary uses. We also note in Table 2 that although lipid metabolism disorders

[9]Respondents can report up to three medical conditions for each drug, but in the vast majority (95 percent) of cases they reported only one. For the few cases when more than one condition was reported, we divide the associated drug use and expenditure data evenly across each condition.

and diabetes are categorized as "other diseases," individuals who suffer from these illnesses are very likely to die from cardiovascular disease.[10]

Table 2 reports that cancer prescription drug consumption was significantly lower than other types of prescription drug consumption during this time period. This is because most cancer drugs are administered in a physician's office and thus are covered by Medicare Part B rather than Part D. One notable exception is oral chemotherapy drugs. These drugs have become an important component of many cancer treatments, but were typically not covered by traditional Medicare until the advent of Part D (Davidoff et al. 2013; Weingart et al. 2008). Thus, it is possible that consumption of cancer drugs would increase following the implementation of Part D.

4 Effect of Medicare Part D on mortality

We pursue a difference-in-differences approach that compares the change in state-level mortality rates among the young-elderly to the corresponding change among the near-elderly, before and after the implementation of Medicare Part D.[11] A key feature of our dataset–which includes the universe of deaths–is a large sample size that allows us to employ narrow age bands in our analysis. The small difference in age between our control and treatment groups means they are likely to exhibit similar trends in mortality over time.

Our primary specification includes 66-year-olds in the treatment group and 64-year-olds in the control group. Our main identifying assumption is that, conditional on the included controls, any trend break in mortality between these two age groups is attributable to the Medicare Part D program.

We exclude 65-year-olds from the main analysis because of their short exposure to Medicare Part D, which limits the ability of the program to improve their health. For example, someone who dies one week after turning 65 probably did not have enough time to benefit from a new prescription to lower her cholesterol. On average,

[10]Diabetes greatly increases the risk of heart disease and stroke (Haffner et al. 1998). Lipid metabolism disorders such as elevated cholesterol levels substantially increase the risk of heart disease (Lewington et al. 2007).

[11]We follow Finkelstein and McKnight (2008) and aggregate to the state level, which allows us to control for state-level factors that may be important determinants of mortality, but one could alternatively estimate our difference-in-differences model at a different level of aggregation. As a robustness check, we confirmed that our results are not substantively affected if we aggregate to the national level rather than the state level.

a 65-year-old decedent in our dataset has only been exposed to the benefits of Part D for six months. By contrast, 66-year-olds have on average been exposed to the benefits of Medicare Part D for more than one year. This is enough time for many important drugs such as statins to exhibit beneficial effects (Cannon et al. 2004). For completeness, we report results for a specification that employs 65-year-olds as the treatment group instead of 66-year-olds in the appendix.

The young-elderly are significantly more likely than the near-elderly to be retired and to have access to Medicare's hospital and outpatient benefits. This raises the concern that results from this analysis may be driven by large shocks such as recessions or national policy changes that affect the young-elderly and the near-elderly differentially. We therefore restrict our analysis to the years 2001-2008. This provides four years of data following the implementation of the Medicare prescription drug programs, but avoids potential confounding effects from the Great Recession (McInerney and Mellor 2012). In the appendix, we report results from specifications that employ time windows of differing lengths.

4.1 Event study framework

We first employ an event study framework that allows for heterogeneous effects over time in both the pre- and post-periods. This specification is less statistically powerful than the more parametric regression we employ later, but it will allow us to evaluate whether the parallel trends assumption we maintain throughout this paper is reasonable. Our estimating equation is:

$$\ln(DEATHS_{ast}) = \beta_1 ELDERLY_a + \beta_2 \ln(POP_{ast}) + \mathbf{X_{st}}\gamma + \sum_{\tau=2001, \tau\neq 2004}^{2008} \lambda_\tau (ELDERLY_a * \mathbf{1}[\tau = t]) + \alpha_s + \delta_t + \epsilon_{ast} \quad (1)$$

The outcome variable is the log of the count of deaths in age group a, state s, and year t. There are two age groups: 66-year-olds and 64-year-olds. The indicator variable $ELDERLY_a$ is equal to 1 if the age group is 66-year-olds and 0 otherwise. The variable $\ln(POP_{ast})$ is the log of the state- and age-group-specific population in year t. This model includes a full set of state (α_s) and year (δ_t) fixed effects. The state-level control variables $\mathbf{X_{st}}$ were obtained from the Bureau of Economic Analysis and include per capita income, employment level, per capita government medical spending

(excluding Medicare spending), and private health care spending.[12] The coefficients of interest in this event study analysis are the λ_τ's on the interaction between the elderly indicator variable and the indicator function $\mathbf{1}[\tau = t]$. All estimates are weighted by the square-root of the relevant population.

We cluster standard errors at the state level to allow for heteroskedasticity and arbitrary serial correlation within states over time.[13] We also estimate a large series of placebo regressions (which should not produce statistically significant estimates) in order to confirm that our approach to inference does not understate standard errors.

We expect (but do not require) any potential effects of Medicare Part D to begin in 2005 because of the widespread availability and use of the drug discount cards and subsidies provided by the Medicare Drug Discount Card and Transitional Assistance Programs, which were launched in mid-2004. Recall that the Transitional Assistance Program spent $1.5 billion on prescription drug subsidies for low-income elderly who could prove that they lacked drug coverage. Vulnerable populations such as this one are more likely than the general adult population to demonstrate health improvements following an increase in their health benefits (Levy and Meltzer 2004).

Figure 1a plots estimates of λ_τ from equation (1) when we employ deaths from all causes as the dependent variable. Each point estimate reports the change in young-elderly mortality relative to the change in near-elderly mortality. Results are normalized to be relative to the baseline year, 2004. We observe an initial decline in young-elderly mortality in 2005 followed by another in 2006. The effect then remains visible through 2008. Figures 1b, 1c, and 1d display estimates of λ_τ when equation (1) is estimated separately for each of the three main cause-of-death subcategories: cardiovascular, cancer, and other diseases. Cardiovascular deaths among the young-elderly decrease dramatically beginning in 2005 and then remain constant through 2008. Other disease mortality also decreases among the young-elderly beginning in 2005, although more gradually than for cardiovascular mortality. When we estimate our model using cancer deaths, however, we do not see any lasting effects in the post-period for the young-elderly.

None of the plots in Figure 1 exhibits differential trends in mortality between

[12] These data are available at http://www.bea.gov/regional/downloadzip.cfm.

[13] This is consistent with the prior literature (Finkelstein and McKnight 2008). We have also estimated specifications that cluster standard errors at the age $\times$ year level and find that this increases the statistical significance of our results. To be conservative, we cluster at the state level in the main text.

the young- and near-elderly prior to 2004, which provides support for our identifying assumption. Moreover, the estimated effects of the Part D program are visible beginning in 2005–especially for cardiovascular mortality–suggesting that the 2004-2005 Drug Discount and Transitional Assistance Programs successfully increased the use of effective drug treatments among the uninsured elderly population.

Next, we examine the cardiovascular mortality results in more detail by estimating that model separately by gender and race. Those results are shown in Figures 2 and 3. The estimated effects are largest for males and non-whites. The latter is consistent with prior research finding that much of the increase in drug utilization caused by Medicare Part D occurred among low-income and minority individuals (Kaestner and Khan 2012).

Obtaining prescription drugs requires access to medical professionals. This means the effect of Medicare Part D may vary across states with different levels of physician availability. Indeed, Clayton (2014) finds that the effectiveness of early Medicaid prescription drug coverage expansions is much greater for states with a relatively high supply of physicians than for those with a relatively low supply. We explore the applicability of this finding to our setting by estimating our model separately for states with a high (above median) or low (below median) number of physicians per capita using data from the Area Health Resource File. Figure 4 shows that–consistent with Clayton (2014)–the estimated effect is larger for states with more physicians per capita.

We do not expect to see any effects of Medicare Part D on deaths due to external causes because, as shown in Table 2, there is almost no drug consumption associated with these deaths. We thus do not present results for this subcategory of deaths in the main text. However, we make estimates for this category available in the appendix as part of a falsification exercise.

4.2 Regression framework

We now impose additional structure on the regression model (1) by requiring the λ_τ coefficients to be constant in the pre- and post-periods, which will generate more precise estimates. An examination of Figure 1 suggests this is a reasonable assumption.

Our new estimating equation is:

$$\ln(DEATHS_{ast}) = \beta_1 ELDERLY_a + \beta_2 \ln(POP_{ast}) + \mathbf{X_{st}}\gamma + \lambda(ELDERLY_a * POST05_t) + \alpha_s + \delta_t + \epsilon_{ast} \quad (2)$$

The variables are defined the same way as in equation (1). The parameter of interest is λ, the coefficient on the interaction term $ELDERLY_a * POST05_t$, where $POST05_t$ is an indicator equal to 1 during 2005-2008 and 0 otherwise.

Results for the full sample of decedents are reported in the first two columns of Table 3. The second column, which includes all control variables, estimates that the annual death rate for 66-year-olds fell by 2.2 percent, relative to 64-year-olds, in the initial years 2005-2008 following the implementation of Medicare Part D. This is driven primarily by cardiovascular mortality, which declined by 4.4 percent. These correspond to absolute reductions of 0.036 and 0.023 percentage points, respectively.[14] The estimated effects for cancer and other diseases are not statistically significant, although we cannot rule out the possibility of modestly sized effects for these two categories.[15]

Columns (3)-(6) show how these estimates vary by gender and race. All subgroups except for females experienced a significant decline in young-elderly cardiovascular mortality. All subgroups except for females also experienced a significant decline in all-cause mortality. The magnitudes are greatest for males and for non-whites. No subgroup experienced a significant decline in young-elderly cancer mortality.

Table 4 shows that our results also vary by physician density. Column (1) replicates our main result from Table 3. Columns (2) and (3) show that the estimated effects for all deaths, and cardiovascular deaths in particular, are larger for states with a high (above-median) number of physicians per capita than for states with a low (below-median) number.

Appendix B examines the robustness of our results by estimating several alternative specifications. These include employing death rates instead of the log of death counts as the dependent variable; employing 65-year-olds instead of 66-year-olds as the treatment group; employing younger ages for the control group and/or older ages

[14]The total death rate and cardiovascular death rate for 66-year-olds between 2001 and 2004 are 1.629 percent and 0.521 percent annually, respectively.

[15]The 95 percent confidence intervals for cancer and other diseases are [-2.6, 2.1] and [-5.2, 0.7], respectively.

for the treatment group; increasing the number of years in the sample; and decreasing the number of years in the sample. Our main results hold up across all these different specifications.

Finally, Appendix B also reports results for two different sets of placebo exercises. The first set estimates our main specification but employs different pairwise combinations of ages drawn from the under-65 population, the majority of whom are ineligible for Medicare Part D, as the treatment and control groups. The second uses our main specification to estimate the effect of Medicare Part D on deaths due to external causes, for which there is nearly zero associated prescription drug consumption. In neither case do we find significant effects.

4.3 Discussion

Our main specification estimates that annual mortality for 66-year-olds decreased by 2.2 percent relative to 64-year-olds in the initial years following the implementation of Medicare Part D. This is driven primarily by a decrease of 4.4 percent in cardiovascular mortality. One way to gauge the size of these effects is to compare them to overall trends during this time period. Between 2001-2004 and 2005-2008, the total and cardiovascular mortality rates for 66-year-olds fell by 8.32 and 17.1 percent, respectively. Our estimates therefore explain about 25 percent of both these reductions. By way of comparison, Cutler, McClellan, and Newhouse (1999) estimate that nearly 30 percent of the decline in 30-day mortality due to heart attacks between 1975 and 1995 can be attributed to pharmaceuticals.

Comparing to other studies of health insurance also provides a useful gauge. Our estimate is of course larger than estimates from other studies that find no effect of health insurance on adult mortality, although we note that our estimate is within the bounds of their 95 percent confidence intervals (Finkelstein and McKnight 2008; Kaestner, Long, and Alexander 2014). It is smaller, however, than what many other studies have found. Card, Dobkin, and Maestas (2009) estimate that Medicare reduced annual mortality by 4.3 percent for young-elderly California patients admitted to emergency departments with non-deferrable conditions.[16] Sommers, Long, and Baicker (2014) estimate that the Massachusetts 2006 health care reform reduced non-elderly adult mortality by 2.9 percent, and Sommers, Baicker, and Epstein (2012)

[16]Card, Dobkin, and Maestas (2009) estimate that Medicare reduced annual mortality by 1 percentage point. Annual mortality for their sample was 23 percent.

estimate that state Medicaid expansions that occurred between 2000 and 2005 reduced non-elderly adult mortality by 6.1 percent. It is not surprising that these other studies find larger effects than we do. These insurance expansions cover hospital and outpatient care, which may be more likely to save lives than prescription drugs. The Massachusetts and Medicaid expansions also included drug insurance benefits. Furthermore, Card, Dobkin, and Maestas (2009) examine a relatively sick patient population with a significantly higher mortality rate than the average mortality rate of our treatment group.

Our empirical design yields intent-to-treat estimates that represent a lower bound on the effect of prescription drug insurance on mortality. If one is willing to assume that our estimated effect is attributable entirely to previously uninsured individuals who gained drug coverage, then we can calculate the effect of drug insurance, rather than just drug insurance eligibility, on mortality. This is not a trivial assumption, because the treatment group in our analysis includes previously insured individuals who switched plans as a result of Part D, which may also have contributed to our estimated effect of Part D on mortality. Nevertheless, this calculation yields a parameter of interest that can be compared to other studies. Dividing our main result by the estimated 23 percent of the young-elderly population who gained prescription drug coverage for the first time as a result of Part D (Kaestner and Khan 2012) yields an estimated treatment-on-the-treated effect of 9.6 percent. This is several times smaller than the corresponding treatment-on-the-treated effect estimates for the comparison studies mentioned above. For example, Medicare reduced the uninsured rate among the young-elderly population studied in Card, Dobkin, and Maestas (2009) by 8 percentage points, and the Massachusetts health reform reduced that state's non-elderly adult uninsured rate by 6.8 percentage points (Sommers, Long, and Baicker 2014). These imply treatment-on-the-treated effects of 54 and 43 percent, respectively.

Another alternative gauge is medical studies of drug treatments, although this comparison is not straightforward because the increase in drug utilization caused by Medicare Part D was not limited to a single drug. This caveat notwithstanding, studies of statins–a common cardiovascular treatment in our sample–indicate that they can work quickly, with effects apparent as early as 30 days after the start of treatment (Cannon et al. 2004). The magnitude of the estimated effects of statins on mortality is significant: Aronow et al. (2001) estimate that they reduce 6-month mortality by over 30 percent for individuals with stable coronary disease.

5 Effect of Medicare Part D on utilization

What is the channel for the Medicare Part D mortality effects we found in the previous section? One likely explanation is that the reduction in the consumer price of drugs encouraged greater utilization among the newly insured, which then improved health.[17] In this section we use the 2001-2008 Medical Expenditure Panel Surveys (MEPS) to examine how the increased utilization caused by Part D varied by type of drug and by socioeconomic status. We expect the increase to be largest for cardiovascular drugs, and for individuals whose incomes were low enough that they were unlikely to have had pre-existing private prescription drug coverage, but not so low that they might be eligible for drug coverage through Medicaid.

We again employ a difference-in-differences model to estimate changes in drug use between the young-elderly (ages 66-75) and the near-elderly (ages 55-64) following the implementation of Medicare Part D. We omit age 65 from the sample to ensure consistency with our previous mortality analysis, although this does not matter for our results. We use 10-year age bands in this analysis rather than one-year age bands because the small sample size of the MEPS reduces statistical power, especially when we estimate the model for different types of drugs.

We begin by estimating the following equation:

$$DRUGS_{it} = \beta_1 ELDERLY_i + \lambda(ELDERLY_i * POST05_t) + \mathbf{X_{it}}\gamma + \delta_t + \epsilon_{it} \quad (3)$$

The indicator variable $ELDERLY_i$ takes on a value of 1 if the individual belongs to the young-elderly group (ages 66-75) and 0 otherwise. We include year fixed effects to allow for arbitrary national trends in drug consumption. We also include an individual-level set of controls, $\mathbf{X_{it}}$, which includes marital status, race, educational attainment, gender, census region, and household income groups.[18] The parameter of interest is λ, the coefficient on the interaction $ELDERLY_i * POST05_t$, where $POST05_t$ is an indicator for the post-period 2005-2008. We employ the MEPS-

[17] Medicare Part D also resulted in a positive income effect for the elderly, which may have improved their health. If 64-year-olds are forward-looking, however, they will anticipate this future income effect and adjust their behavior accordingly. Thus, it is unlikely that the relative difference in mortality trends between 66- and 64-year-olds is explainable solely by income effects.

[18] Marital status: never married, married, divorced/separated, or widowed. Race: white or non-white. Educational attainment: no high school degree, high school degree, some college, or college degree. Household income group: see Table 6 for definitions. Census region: Northeast, Midwest, South, or West.

provided sampling weights in order to generate nationally representative estimates. We follow Engelhardt and Gruber (2011) and cluster standard errors by household $\times$ age group. State identifiers are unavailable in the public version of the MEPS.

The dependent variable, $DRUGS_{it}$, is either drug use (measured as number of prescriptions filled) or drug expenditures by individual i in year t. Drug use is our preferred outcome of interest because it is an unambiguous measure of health care utilization. Although drug use and expenditures are related, the latter is confounded with price changes. For example, Medicare's Drug Discount Card Program reduced the prices faced by consumers and thus likely increased drug use. Because these price reductions were the result of negotiating discounts with drug manufacturers (i.e., they are not subsidies paid by Medicare), the sign of the effect on total expenditures is ambiguous and depends on the price elasticity of demand for pharmaceutical drugs.[19]

We report results by drug type in Table 5. The bottom row indicates that the implementation of Medicare Part D increased total per capita drug use by 3.08 prescription fills per year and increased total per capita expenditures by $244 for the young-elderly, relative to the near-elderly. These correspond to increases of 17 and 20 percent, respectively, when compared to their pre-2005 levels for the uninsured.

The other rows of Table 5 show how these increases are distributed across different types of drugs. Similar to Zimmer (2014), we observe a significant increase in the utilization of drugs used to treat ischemic and hypertensive heart disease, diabetes, and lipid metabolism disorders, each of which is linked to increased risk of cardiovascular death. Table 5 reports relative increases of 26, 26, and 31 percent for these three categories, respectively, when compared to pre-2005 baseline levels. The corresponding estimates for drug expenditures for these categories are similar to the estimates for utilization.

Importantly, we observe no statistically significant increases in the utilization of, or expenditures for, cancer drugs and its subcategories. As discussed earlier, most cancer drugs were already covered by Medicare Part B, with the important exception of oral chemotherapy drugs. While the positive point estimates for total cancer drug use and expenditures suggest that utilization of these drugs may have increased, it was not widespread enough for us to detect it statistically.

[19]There is not a consensus on whether demand for pharmaceutical drugs is inelastic. For example, Lichtenberg and Sun (2007) estimate an elasticity of -0.72, but Lakdawalla and Philipson (2012) estimate an elasticity between -1.1 and -1.25.

5.1 Results by subgroup

Table 6 reports descriptive statistics for the young-elderly of differing income levels in 2003, the year in which the Medicare Part D legislation was enacted. Prescription drug insurance coverage rates range from 59 percent for individuals with incomes between 100% and 125% of the Federal Poverty Level (FPL) to 80 percent for individuals with incomes above 400% of the FPL. The drug insurance coverage rate for individuals in the lowest income group (<100% FPL) is actually *higher* than it is for those with slightly higher incomes. This can be attributed to Medicaid, which provided prescription drug coverage to its beneficiaries during this time period.[20] The fraction of very low-income (<100% FPL) individuals who report being enrolled in Medicaid is about double the number in the second-lowest income group (100% FPL $\leq$ Income $<$ 125% FPL). This difference is significant and may actually understate the true magnitude, since the MEPS undercounts national Medicaid enrollment figures by more than 10 percent (Bernard et al. 2012; Nelson 2003).

We investigate how this increase in utilization varies over time and across the five different income groups displayed in Table 6 by estimating an event-study regression that allows for heterogeneous treatment effects:

$$DRUGS_{igt} = \beta_1 ELDERLY_i + \mathbf{X_{igt}}\gamma + \sum_{g=1}^{5} \sum_{\tau=2001, \tau \neq 2004}^{2008} \lambda_{g\tau}(GROUP_g * ELDERLY_i * \mathbf{1}[\tau = t]) + \delta_t + \epsilon_{igt} \quad (4)$$

The dependent variable is drug use by individual i in income group g at time t. The constant effects of income on drug use are captured in the control vector $\mathbf{X_{igt}}$. Figures 5 and 6 plot estimates of $\lambda_{g\tau}$ from equation (4) for total drug use and cardiovascular drug use, respectively. The increase in both total and cardiovascular drug utilization is largest for individuals with incomes between 100% and 125% FPL, the group with the lowest rate of pre-existing prescription drug coverage, although the estimated effects are not statistically significant. We note that individuals in this group were also the ones most likely to qualify for subsidies from the 2004-2005 Transitional Assistance Program, which required that individuals demonstrate both a lack of drug

[20] In fact, at the time there were concerns that Medicare Part D would actually have a *negative* effect on drug utilization for these dual eligibles because of increased cost-sharing and because of the complexities involved in switching to a different prescription drug coverage program (Basu, Yin, and Alexander 2010; Domino and Farley 2010).

insurance coverage and an income below 135% FPL. Indeed, Figures 5 and 6 show an increase in utilization for these individuals beginning already in 2004, although we caution that these estimates are not statistically significant. Nevertheless, this suggests that Medicare Part D's 2004-2005 interim programs were successful in their goal of providing relief from the costs of prescription drugs to low-income Medicare beneficiaries who lacked prescription drug coverage.

Next, we require the treatment effect to be constant in the pre- and post-periods in order to generate more precise estimates, as we did in the mortality analysis. We also examine heterogeneity by gender and race. Let there be $g = 1...G$ groups that might exhibit heterogeneous treatment effects. Then our estimating equation becomes:

$$DRUGS_{igt} = \beta_1 ELDERLY_i + \mathbf{X_{igt}}\gamma + \sum_{g=1}^{G} \lambda_g (GROUP_g * ELDERLY_i * POST05_t) + \delta_t + \epsilon_{igt} \quad (5)$$

Column (1) of Table 7 reports how the estimated treatment effect varies across different income groups. Everybody except those in the lowest income category experienced a statistically significant increase in drug use. Individuals with incomes between 100% and 125% FPL, who had the lowest rate of pre-existing drug insurance coverage, experienced the largest increase: relative to the near-elderly, their prescription drug use increased by 8.35 fills per year. Columns (2) and (3) report results from similar regressions that examine heterogeneity by gender and race rather than income. Males and females exhibit similar increases in utilization, while the increase for non-whites is 45 percent larger than the increase for whites. Although the racial difference is large, we do not have enough power to conclude that the coefficients in column (3) are statistically different from each other.

5.2 Discussion

Consistent with prior studies, we estimate that Medicare Part D significantly increased drug utilization. This is not the only possible mechanism for improving health. For example, consumers might switch to more effective medications rather than just increasing consumption. Nevertheless, we find that these changes in drug usage are consistent with our prior mortality findings. The utilization of cardiovascular drugs, but not cancer drugs, greatly increased, and these increases were larger

in magnitude for non-whites than for whites. Moreover, this increase in utilization appears to have begun as early as 2004 for those individuals who were most likely to qualify for the Drug Discount Card and Transitional Assistance Programs.

One exception is drug utilization patterns for males and females, which look similar following the implementation of Medicare Part D despite our finding that males experienced a larger subsequent drop in mortality. There are several possible explanations for this discrepancy. First, the MEPS sample we employ is relatively small, which causes the estimates to be imprecise. For example, we cannot reject the hypothesis that male drug utilization increased by twice as much as female drug utilization did. Second, we do not have enough power to detect differential changes in subcategories of drug consumption. That is, it is possible that males, but not females, switched from non-cardiovascular to cardiovascular drugs following the implementation of Part D. Finally, the discrepancy might be attributable to heterogeneous treatment effects of prescription drugs. Existing studies examining sex-based differences among cardiovascular treatments conclude that they benefit males more than females (Mosca et al. 2011; Rathore, Wang, and Krumholz 2002). A limitation of our analysis is that we cannot distinguish between these competing hypotheses.

6 Social value of the estimated mortality reduction

We calculate the value of the mortality reduction associated with Medicare Part D in its initial years by multiplying the number of life-years saved by $100,000, a common estimate of the value of a statistical life-year (Cutler 2004). Readers who prefer a different value may adjust accordingly, since our estimated benefit is linear in this value.

We previously estimated that Medicare Part D led to an annual mortality reduction of 2.2 percent during its initial years. Converting this estimate into life-years saved requires making assumptions about two important factors not fully addressed in our empirical analysis: the size of the affected population and the magnitude of the longevity increase.

The treatment group in our mortality analysis includes only 66-year-olds. Using a narrow age band increases the plausibility of our main identifying assumption, but also means that, strictly speaking, our estimates only apply to 66-year-olds. It is not clear a priori whether the effect of Part D on mortality should be larger or smaller

for individuals over the age of 66, although in the appendix we present evidence suggesting that the effect may be slightly larger for older age groups. For the purposes of this exercise, we assume that the effect of Part D is the same for all individuals aged 66 or older. Obviously our calculated benefit would be larger (smaller) if the true mortality reduction for the older elderly is larger (smaller) than it is for 66-year-olds.

Applying our main estimate of a 2.2 percent mortality reduction to the elderly population yields the number of lives saved by Medicare Part D. It is not straightforward to convert this to the number of *life-years* saved. The individuals whose lives were saved by the introduction of Medicare Part D likely had lower life expectancies than a typical member of the elderly population. Failing to account for this lower life expectancy will bias estimates of the social cost, as discussed in Deryugina et al. (2016). As a benchmark, Cutler (2004) estimates that the historical reduction in cardiovascular mortality increased longevity by about four years. Because the bulk of our estimated mortality decline is due to a reduction in cardiovascular mortality, we adopt his estimate for our analysis.

Applying all these assumptions to our empirical estimate yields an estimated initial health benefit of about \$16 billion.[21] In order to be conservative, we assume that in later years the benefit accrues only to new beneficiaries, which implies a subsequent annual benefit of about \$1 billion.[22] Together these two estimates imply an average benefit of \$5 $(= (16 + 3)/4)$ billion per year for the four years that make up the post period in our empirical analysis. We note that this amount does not account for other potential health benefits of the Medicare Part D program, such as a reduction in morbidity, and thus should be viewed as a lower bound on the program's total health benefits.

Our estimated value of \$5 billion lies in-between estimates of other, non-health benefits that have been attributed to the Medicare Part D program. Engelhardt and Gruber (2011) present evidence that Medicare Part D reduced financial risk by reducing out-of-pocket costs for beneficiaries and compute that the certainty equivalent of this risk reduction is equal to \$14 billion annually. Kaestner, Long, and Alexander (2014) estimate that Medicare Part D reduced annual hospital expenditures by \$1.5 billion. Combining these two estimates together with ours yields a total annual

[21] Prior the implementation of Medicare Part D, there were about 36 million elderly and the annual elderly mortality rate was about 5 percent. \$16 billion = 36 million $\times 0.05 \times 0.022 \times 4 \times \$100,000$.

[22] There were about 2.1 million 65-year-olds alive in 2004. \$1 billion = 2.1 million $\times 0.05 \times 0.022 \times 4 \times \$100,000$.

benefit of $20.5 billion.

One can also compare our estimated benefit to the estimated social costs of Medicare Part D. Prior work has pointed to the deadweight loss of raising funds as the primary social cost of this program (Engelhardt and Gruber 2011). The literature on this topic estimates that the marginal cost of raising public funds in the United States is about $0.30 per dollar of revenue raised (Jorgenson and Yun 2002). This implies that the deadweight loss associated with Medicare Part D was $14 billion per year, or nearly three times larger than our estimated mortality benefit.

7 Conclusion

The effect of health insurance on health is a fundamental question for policymakers. We investigate the effect of Medicare Part D on mortality, the ultimate indicator of health. This program provides coverage for prescription drugs–an increasingly important component of medical treatment–to tens of millions of elderly Americans. We estimate that it reduced annual mortality by 2.2 percent in its initial years. Further analysis shows that this was due primarily to a reduction in cardiovascular mortality. A secondary analysis confirms that Medicare Part D increased the use of drug treatments for cardiovascular disease and that the changes in drug utilization over time and across different socioeconomic groups are broadly consistent with the mortality patterns we observe. Under reasonable assumptions, we calculate that the annual value of the health gains from reduced mortality is equal to $5 billion.

Detecting changes in mortality is difficult because deaths are a rare occurrence in most datasets. We overcome this obstacle by employing the universe of death records to take advantage of quasi-random variation in the age-eligibility for Medicare. Importantly, our results do not appear to be driven by differential pre-existing trends in mortality between our treatment and control groups, and placebo exercises confirm that Medicare Part D did not have any significant effects on individuals just under the age of 65.

Our results confirm the basic theoretical prediction that reducing the price of medical care should improve health. This paper focuses on mortality because it is easily measured, but quality of life, another important health outcome, is also likely to improve as a result of gaining access to drug insurance. That remains an area for future research.

8 Tables and figures

Table 1: Causes of death for individuals aged 65 and over, 2001-2008

Cause of Death	Average Deaths Per Year	Percent of Total
Cardiovascular	*713,795*	*40.01%*
Heart Disease	555,453	31.13%
Heart Failure	53,461	3.00%
Ischemic and Hypertension	413,135	23.16%
Other Heart	88,858	4.98%
Cerebrovascular (Stroke)	128,476	7.20%
Peripheral Vascular	6,430	0.36%
Other CVD	23,435	1.31%
Cancer	*389,159*	*21.81%*
Digestive	89,143	5.00%
Lung	114,713	6.43%
Breast	23,917	1.34%
Genital	42,699	2.39%
Lymph	40,414	2.27%
Bladder	11,010	0.62%
Thyroid	1,038	0.06%
Other Cancer	66,226	3.71%
Other Diseases	*636,999*	*35.70%*
Diabetes	53,410	2.99%
Alzheimer's	67,194	3.77%
Chronic Lower Respiratory	109,987	6.16%
Kidney	36,249	2.03%
Renal Failure	34,898	1.96%
Other Kidney	1,352	0.08%
Upper Respiratory	363	0.02%
Respiratory Failure	3,120	0.17%
Lipid Metabolism	5,181	0.29%
Digestive System	54,856	3.07%
Parkinson's	18,197	1.02%
Pneumonia	52,099	2.92%
Other	236,343	13.25%
External Causes	*44,196*	*2.48%*
Transport Accidents	7,742	0.43%
Non-transport Accidents	29,879	1.67%
Falls	15,449	0.87%
Drowning/Submersion	453	0.03%
Smoke/Fires/Flame	1,091	0.06%
Poison/Noxious Substance	967	0.05%
Other Accidents	11,920	0.67%
Suicide	5,408	0.30%
Homicide	840	0.05%
Other External Causes	328	0.02%
Total	1,784,149	100.00%

Notes: This table shows the average number of deaths per year for different causes of death in the 2001-2008 National Vital Statistics dataset.

Table 2: Prescription drug utilization and expenditures by the young-elderly, 2001-2004

	Number of Drugs		Expenditures		Cardio
Medical Condition	**Insured**	**Uninsured**	**Insured**	**Uninsured**	**Death Risk**
Cardiovascular	7.31	4.81	$411	$264	x
Heart Disease	7.02	4.65	$391	$251	x
Heart Failure	0.28	0.23	$12	$11	x
Ischemic and Hypertension	5.22	3.67	$295	$200	x
Other Heart	1.52	0.74	$84	$40	x
Cerebrovascular (Stroke)	0.15	0.10	$10	$8	x
Peripheral Vascular	0.00	0.00	$0	$0	x
Other CVD	0.14	0.06	$10	$5	x
Cancer	0.19	0.12	$21	$9	
Digestive	0.02	0.01	$3	$1	
Lung	0.01	0.03	$1	$1	
Breast	0.07	0.02	$10	$3	
Genital	0.04	0.02	$3	$2	
Lymph	0.01	0.00	$0	$0	
Bladder	0.00	0.00	$0	$0	
Thyroid	0.00	0.00	$0	$0	
Other Cancer	0.04	0.03	$3	$2	
Other Diseases	18.32	11.81	$1,340	$861	
Diabetes	2.37	1.53	$168	$108	x
Alzheimer's	0.03	0.05	$4	$7	
Chronic Lower Respiratory	0.99	0.49	$73	$33	
Kidney	0.10	0.04	$6	$2	
Renal Failure	0.03	0.02	$2	$1	
Other Kidney	0.06	0.02	$4	$1	
Upper Respiratory	0.71	0.31	$48	$18	
Respiratory Failure	0.05	0.05	$4	$2	
Lipid Metabolism	1.79	1.14	$202	$130	x
Digestive System	1.27	0.78	$134	$108	
Parkinson's	0.10	0.06	$10	$5	
Pneumonia	0.04	0.02	$2	$1	
Other	10.89	7.33	$690	$447	
External Causes	0.09	0.07	$5	$3	
Transport Accidents	0.07	0.06	$4	$3	
Non-transport Accidents	0.02	0.01	$1	$0	
Falls	0.00	0.00	$0	$0	
Drowning/Submersion	0.00	0.00	$0	$0	
Smoke/Fires/Flame	0.01	0.00	$0	$0	
Poison/Noxious Substance	0.01	0.00	$0	$0	
Other Accidents	0.00	0.00	$0	$0	
Suicide	0.00	0.00	$0	$0	
Homicide	0.00	0.00	$0	$0	
Other External Causes	0.00	0.00	$0	$0	
Unspecified	1.68	1.05	$100	$56	
Total	27.58	17.85	$1,877	$1,193	

Notes: This table displays the annual average per capita utilization and expenditures for prescription drugs for respondents aged 66-75 in the 2001-2004 Medical Expenditure Panel Survey (MEPS). The fraction of respondents reporting zero prescriptions is 9.7 percent. Expenditures include payments made by respondents and insurers. Estimates are calculated using the MEPS-provided survey weights and are computed separately for uninsured and insured respondents, where "uninsured" means the individual lacks prescription drug insurance. The last column indicates whether the medical condition associated with the respondents' prescriptions is linked to increased risk of cardiovascular death.

Table 3: Effect of Medicare Part D on mortality at age 66

	Coefficient on Post05*Elderly					
	Full sample		Gender		Race	
			Male	Female	White	Non-white
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Any Cause of Death	-0.021 *	-0.022 **	-0.035 **	-0.009	-0.019 *	-0.036 *
	(0.008)	(0.008)	(0.009)	(0.011)	(0.008)	(0.016)
Cardiovascular	-0.044 **	-0.044 **	-0.057 **	-0.030	-0.041 **	-0.051 *
	(0.013)	(0.013)	(0.016)	(0.017)	(0.014)	(0.022)
Cancer	-0.002	-0.002	-0.006	0.000	0.005	-0.038
	(0.011)	(0.012)	(0.016)	(0.016)	(0.011)	(0.030)
Other	-0.019	-0.022	-0.039 *	-0.003	-0.029	-0.003
	(0.015)	(0.015)	(0.019)	(0.019)	(0.015)	(0.027)
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes

Notes: This table shows estimates of the coefficient on the interaction term between the elderly indicator and the post-2005 indicator from equation (2) using data from the 2001-2008 National Vital Statistics. The dependent variable is the log of deaths for age group a in state s in year t. Each row and column corresponds to a separate regression for a specific cause of death used as an outcome variable in equation (2). The number of observations in each regression is equal to 816 (=8*2*51). Standard errors, given in parentheses, are clustered by state. All regressions are weighted by the square-root of population. * Significant at 5 percent. ** Significant at 1 percent.

Table 4: Effect of Medicare Part D on mortality at age 66, by physician density

	Coefficient on Post05*Elderly		
	Full sample	Physicians per capita	
		Above median	Below median
Dependent variable	(1)	(2)	(3)
Any Cause of Death	-0.022 **	-0.027 **	-0.021
	(0.008)	(0.009)	(0.016)
Cardiovascular	-0.044 **	-0.062 **	-0.016
	(0.013)	(0.015)	(0.025)
Cancer	-0.002	0.002	-0.017
	(0.012)	(0.015)	(0.022)
Other	-0.022	-0.025	-0.029
	(0.015)	(0.022)	(0.017)
State fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: This table shows estimates of the coefficient on the interaction term between the elderly indicator and the post-2005 indicator from equation (2) using data from the 2001-2008 National Vital Statistics. The physician data are obtained from the Area Health Resource File. The dependent variable is the log of deaths for age group a in state s in year t. Each row and column corresponds to a separate regression for a specific cause of death used as an outcome variable in equation (2). The number of observations in each regression is equal to 816 (=8*2*51) in column (1), 400 (=8*2*25) in column (2), and 416 (=8*2*26) in column (3). Standard errors, given in parentheses, are clustered by state. All regressions are weighted by the square-root of population. * Significant at 5 percent. ** Significant at 1 percent.

Table 5: Effect of Medicare Part D on young-elderly drug use and expenditures

	Coefficient on Post05*Elderly		Pre-2005 Mean (Uninsured)		Cardio
Medical Condition	**No. of Drugs**	**Expenditures**	**No. of Drugs**	**Expenditures**	**Death Risk**
Cardiovascular	0.81**	$ 31	4.81	$ 264	x
Heart Disease	0.82**	$ 32	4.65	$ 251	x
Heart Failure	0.00	$ -1	0.23	$ 11	x
Ischemic and Hypertension	0.96**	$ 45**	3.67	$ 200	x
Other Heart	-0.15	$ -12	0.74	$ 40	x
Cerebrovascular (Stroke)	-0.01	$ 0	0.10	$ 8	x
Peripheral Vascular	0.01	$ 0	0.00	$ 0	x
Other CVD	-0.01	$ -2	0.06	$ 5	x
Cancer	0.03	$ 34	0.12	$ 9	
Digestive	0.01	$ -1	0.01	$ 1	
Lung	-0.00	$ 1	0.03	$ 1	
Breast	-0.02	$ -4	0.02	$ 3	
Genital	-0.01	$ 5	0.02	$ 2	
Lymph	0.01	$ 13	0.00	$ 0	
Bladder	0.00	$ 0	0.00	$ 0	
Thyroid	0.01	$ 0	0.00	$ 0	
Other Cancer	0.03	$ 19	0.03	$ 2	
Other Diseases	1.94**	$ 166**	11.81	$ 861	
Diabetes	0.40*	$ 31	1.53	$ 108	x
Alzheimer's	-0.01	$ -1	0.05	$ 7	
Chronic Lower Respiratory	0.24	$ 36**	0.49	$ 33	
Kidney	-0.01	$ 6	0.04	$ 2	
Renal Failure	-0.01	$ 0	0.02	$ 1	
Other Kidney	-0.00	$ 6	0.02	$ 1	
Upper Respiratory	0.12	$ 10*	0.31	$ 18	
Respiratory Failure	-0.00	$ 2	0.05	$ 2	
Lipid Metabolism	0.35**	$ 34*	1.14	$ 130	x
Digestive System	0.14	$ 7	0.78	$ 108	
Parkinson's	-0.02	$ -1	0.06	$ 5	
Pneumonia	0.01	$ 1	0.02	$ 1	
Other	0.71	$ 42	7.33	$ 447	
External Causes	-0.01	$ 4	0.07	$ 3	
Transport Accidents	-0.02	$ -1	0.06	$ 3	
Non-transport Accidents	0.00	$ -1	0.01	$ 0	
Falls	0.00	$ 0	0.00	$ 0	
Drowning/Submersion	0.00	$ 0	0.00	$ 0	
Smoke/Fires/Flame	0.00	$ 0	0.00	$ 0	
Poison/Noxious Substance	0.00	$ 0	0.00	$ 0	
Other Accidents	0.00	$ 0	0.00	$ 0	
Suicide	0.00	$ 0	0.00	$ 0	
Homicide	0.00	$ 0	0.00	$ 0	
Other External Causes	0.00	$ 0	0.00	$ 0	
Unspecified	0.31	$ 11	1.05	$ 56	
Total	**3.08****	**$ 244****	**17.85**	**$ 1,193**	

Notes: This table presents estimates of λ, the coefficient on the interaction between the elderly indicator and the post-2005 indicator from equation (3), using data from the 2001-2008 Medical Expenditure Panel Survey. Each row and column is a separate regression where the dependent variable is either drug use or drug expenditure for a particular medical condition. The number of observations in each regression is equal to 39,329. The pre-2005 means come from Table 2. Standard errors, given in parentheses, are clustered by household $\times$ age group. * Significant at 5 percent. ** Significant at 1 percent.

Table 6: Descriptive statistics for the young-elderly, 2003 MEPS

	Fraction on Medicaid	Fraction non-white	Fraction male	Has drug insurance	Number of observations
Income < 100% FPL	0.35	0.29	0.34	0.70	277
100% FPL <= Income < 125% FPL	0.18	0.23	0.39	0.59	136
125% FPL <= Income < 200% FPL	0.13	0.19	0.41	0.69	348
200% FPL <= Income < 400% FPL	0.04	0.09	0.44	0.69	590
Income >= 400% FPL	0.02	0.09	0.50	0.80	549

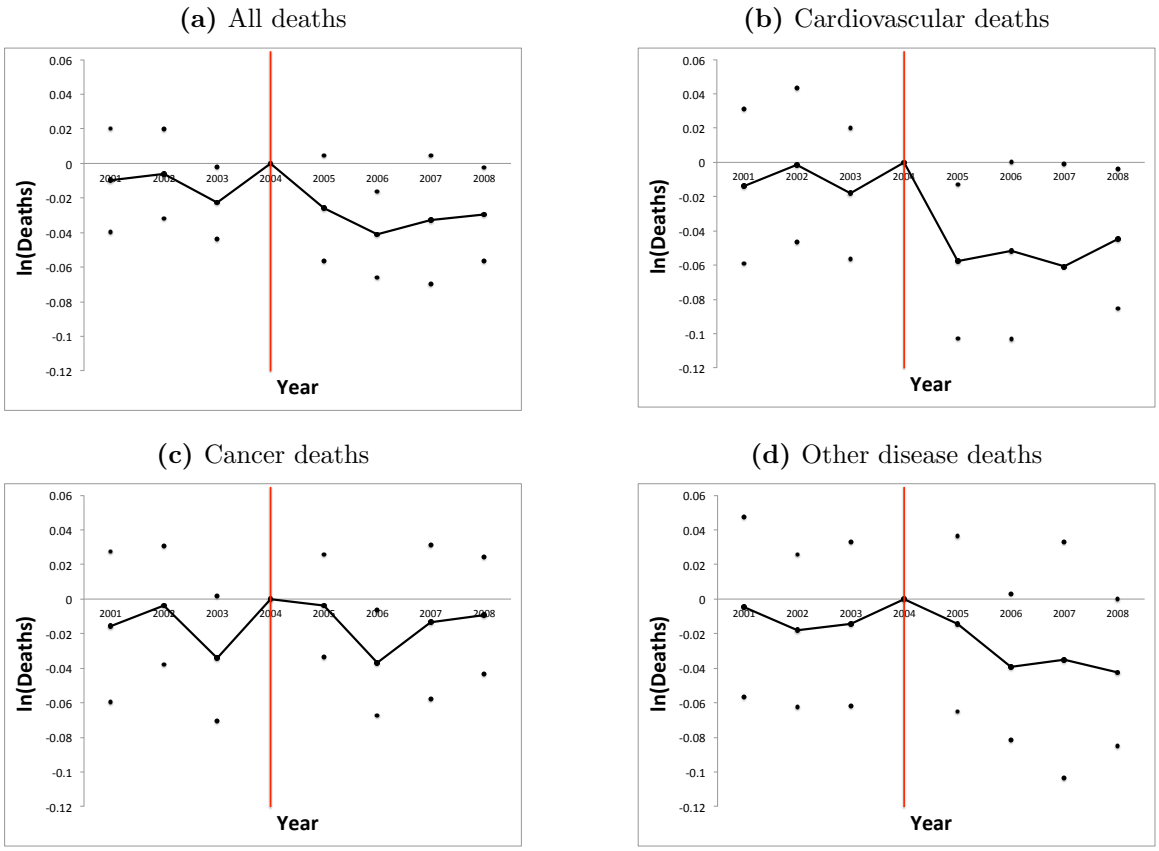
Notes: This table displays weighted means for the young-elderly (aged 66-75) by income group, using data from the 2003 Medical Expenditure Panel Survey. The total number of observations is equal to 1,900.

Table 7: Effect of Medicare Part D on total drug use among the young-elderly

	Coefficient on Post05*Elderly*Group		
Group	**(1)**	**(2)**	**(3)**
Income < 100% FPL	1.62		
	(1.67)		
100% FPL <= Income < 125% FPL	8.35 **		
	(2.67)		
125% FPL <= Income < 200% FPL	3.51 *		
	(1.53)		
200% FPL <= Income < 400% FPL	2.68 *		
	(1.20)		
Income >= 400% FPL	2.71 **		
	(0.95)		
Male		3.15 **	
		(0.93)	
Female		3.01 **	
		(0.96)	
White			2.88 **
			(0.85)
Non-white			4.19 **
			(1.33)
Region fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Number of observations	39,329	39,329	39,329

Notes: This table provides estimates of λ_g from equation (5), using data from the 2001-2008 Medical Expenditure Panel Surveys. The dependent variable is drug use (prescription fills per year). The pre-2005 means of the dependent variable for the insured and the uninsured are 27.58 and 17.85, respectively. Standard errors, given in parentheses, are clustered by household $\times$ age group. * Significant at 5 percent. ** Significant at 1 percent.

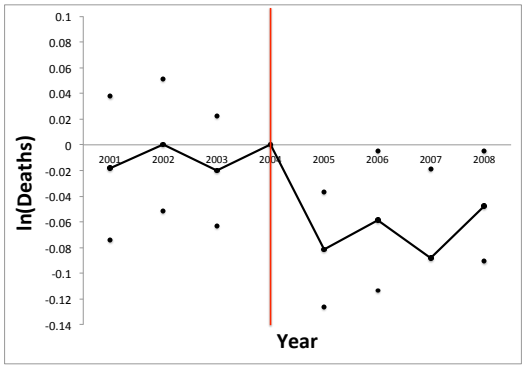
Figure 1: Event-study plot of the effect of Medicare Part D on mortality at age 66



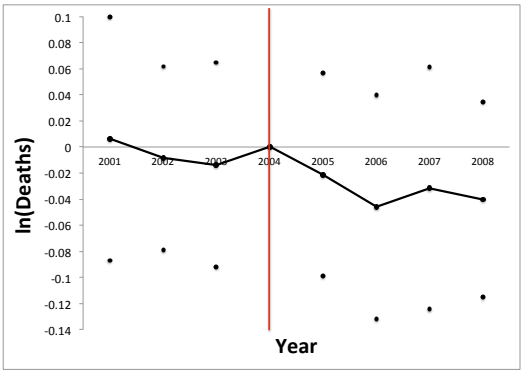
Notes: Panels (a)-(d) show estimates of the coefficient on the interaction term between the elderly indicator variable and the indicator function from equation (1) using data from the National Vital Statistics. The dependent variable is the log of deaths for age a in state s in year t. Control variables include log of population, an indicator variable for age group, state fixed effects, year fixed effects, and time-varying state-level control variables. Dots display 95% confidence intervals. Standard errors are clustered by state. All regressions are weighted by the square-root of population. The vertical line indicates 2004, the year in which the Medicare Drug Discount and Transitional Assistance Programs began.

Figure 2: Event-study plot of the effect of Medicare Part D on cardiovascular mortality at age 66, by gender

(a) Male cardiovascular deaths



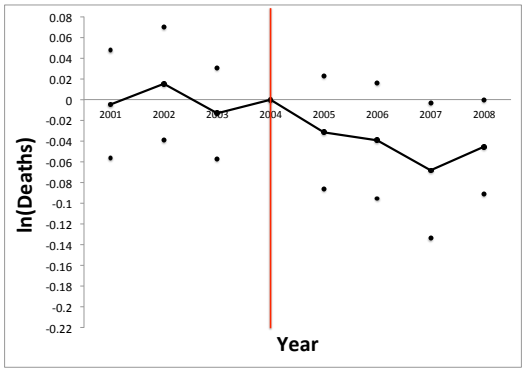
(b) Female cardiovascular deaths



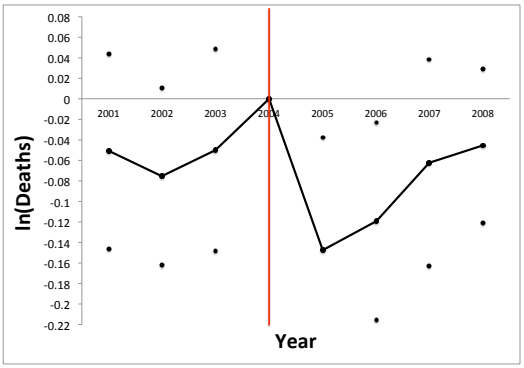
Notes: Panels (a) and (b) show estimates of the coefficient on the interaction term between the elderly indicator variable and the indicator function from equation (1) using data from the National Vital Statistics. The dependent variable is the log of deaths for age a in state s in year t. Control variables include log of population, an indicator variable for age group, state fixed effects, year fixed effects, and time-varying state-level control variables. Dots display 95% confidence intervals. Standard errors are clustered by state. All regressions are weighted by the square-root of population. The vertical line indicates 2004, the year in which the Medicare Drug Discount and Transitional Assistance Programs began.

Figure 3: Event-study plot of the effect of Medicare Part D on cardiovascular mortality at age 66, by race

(a) White cardiovascular deaths



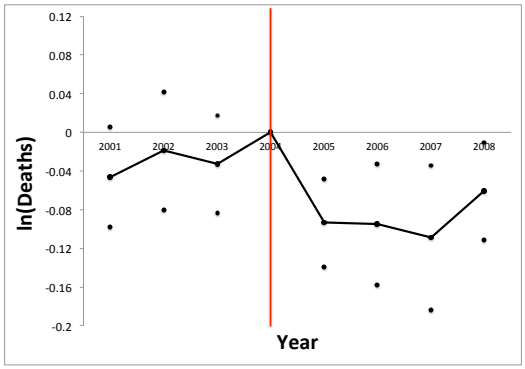
(b) Non-white cardiovascular deaths



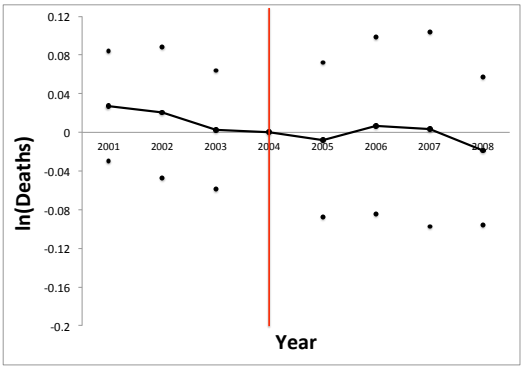
Notes: Panels (a) and (b) show estimates of the coefficient on the interaction term between the elderly indicator variable and the indicator function from equation (1) using data from the National Vital Statistics. The dependent variable is the log of deaths for age a in state s in year t. Control variables include log of population, an indicator variable for age group, state fixed effects, year fixed effects, and time-varying state-level control variables. Dots display 95% confidence intervals. Standard errors are clustered by state. All regressions are weighted by the square-root of population. The vertical line indicates 2004, the year in which the Medicare Drug Discount and Transitional Assistance Programs began.

Figure 4: Event-study plot of the effect of Medicare Part D on cardiovascular mortality at age 66, by physician density

(a) States with high physicians per capita



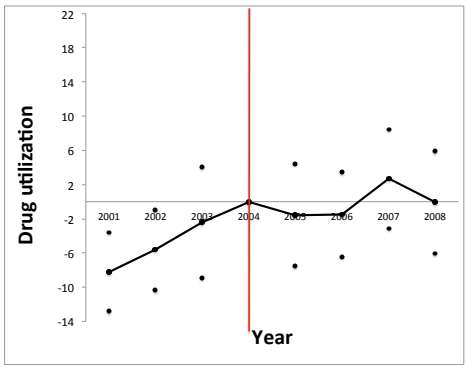
(b) States with low physicians per capita



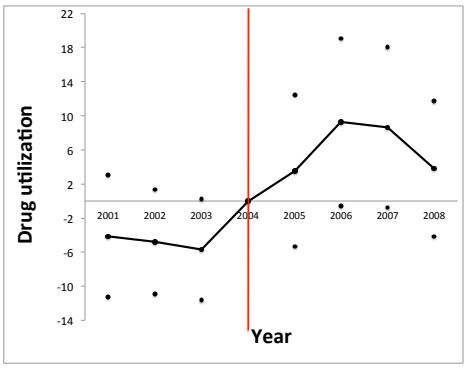
Notes: Panels (a) and (b) show estimates of the coefficient on the interaction term between the elderly indicator variable and the indicator function from equation (1) using data from the National Vital Statistics for states with above- and below-median physicians per capita, respectively. The physician data are obtained from the Area Health Resource File. The dependent variable is the log of deaths for age a in state s in year t. Control variables include log of population, an indicator variable for age group, state fixed effects, year fixed effects, and time-varying state-level control variables. Dots display 95% confidence intervals. Standard errors are clustered by state. All regressions are weighted by the square-root of population. The vertical line indicates 2004, the year in which the Medicare Drug Discount and Transitional Assistance Programs began.

Figure 5: Event-study plot of the effect of Medicare Part D on total drug use, by income

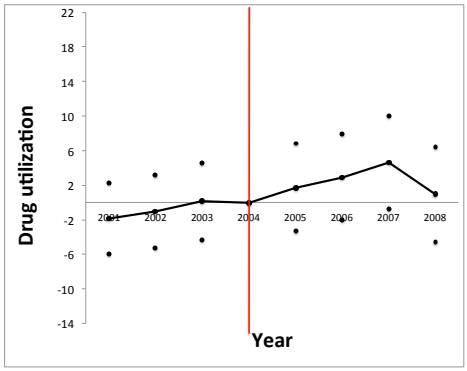
(a) Income < 100% FPL



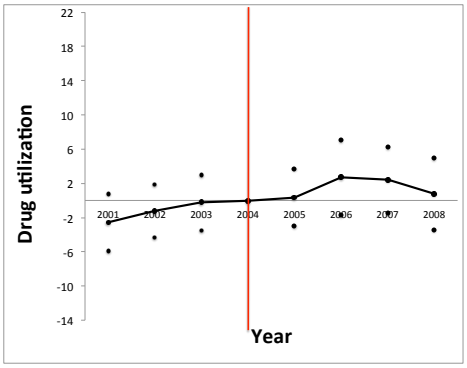
(b) 100% FPL ≤ Income < 125% FPL



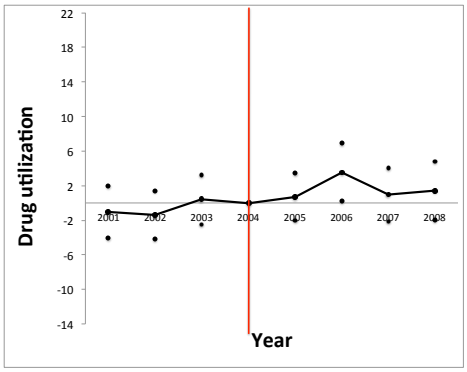
(c) 125% FPL ≤ Income < 200% FPL



(d) 200% FPL ≤ Income < 400% FPL



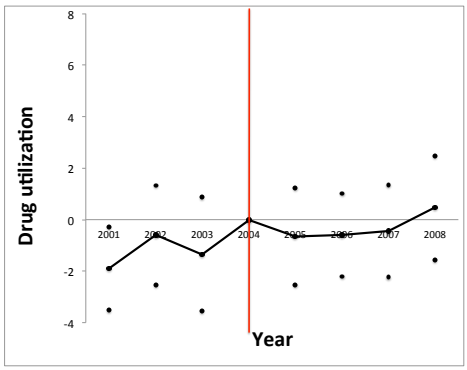
(e) Income ≥ 400% FPL



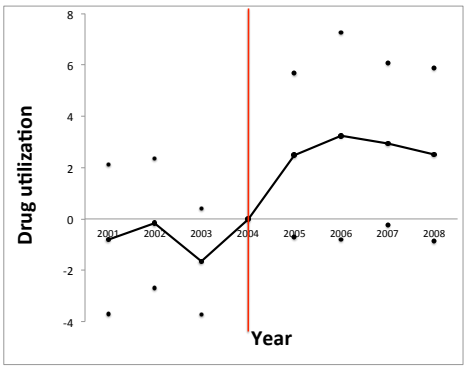
Notes: Panels (a)-(e) show estimates of the coefficient on the interaction term between the individual's income group, the elderly indicator variable, and the indicator function from equation (4) using data from the 2001-2008 Medical Expenditure Panel Surveys. The dependent variable is total drug use. Dots display 95% confidence intervals. Standard errors are clustered by household × age group. The regression employs the MEPS survey weights. The vertical line indicates 2004, the year in which the Medicare Drug Discount and Transitional Assistance Programs began.

Figure 6: Event-study plot of the effect of Medicare Part D on cardiovascular drug use, by income

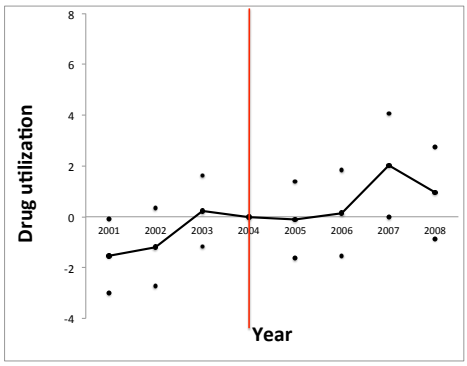
(a) Income < 100% FPL



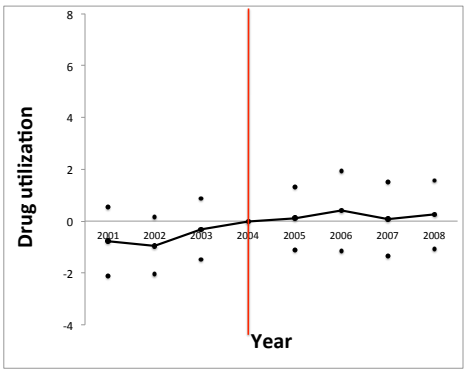
(b) 100% FPL ≤ Income < 125% FPL



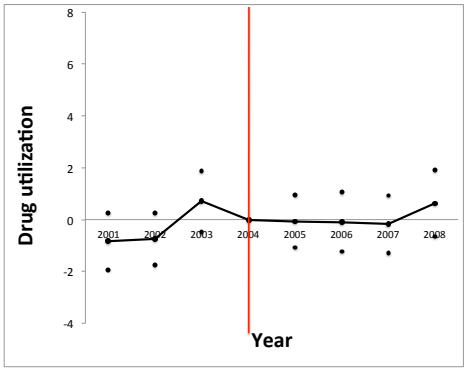
(c) 125% FPL ≤ Income < 200% FPL



(d) 200% FPL ≤ Income < 400% FPL



(e) Income ≥ 400% FPL



Notes: Panels (a)-(e) show estimates of the coefficient on the interaction term between the individual's income group, the elderly indicator variable, and the indicator function from equation (4) using data from the 2001-2008 Medical Expenditure Panel Surveys. The dependent variable is cardiovascular drug use. Dots display 95% confidence intervals. Standard errors are clustered by household × age group. The regression employs the MEPS survey weights. The vertical line indicates 2004, the year in which the Medicare Drug Discount and Transitional Assistance Programs began.

References

Aronow, H. D., E. J. Topol, M. T. Roe, P. L. Houghtaling, K. E. Wolski, A. M. Lincoff, R. A. Harrington, R. M. Califf, E. M. Ohman, N. S. Kleiman, et al. (2001). Effect of lipid-lowering therapy on early mortality after acute coronary syndromes: an observational study. *Lancet 357*(9262), 1063–1068.

Baicker, K., S. L. Taubman, H. L. Allen, M. Bernstein, J. H. Gruber, J. P. Newhouse, E. C. Schneider, B. J. Wright, A. M. Zaslavsky, and A. N. Finkelstein (2013). The oregon experiment—effects of medicaid on clinical outcomes. *New England Journal of Medicine 368*(18), 1713–1722.

Basu, A., W. Yin, and G. C. Alexander (2010). Impact of medicare part d on medicare–medicaid dual-eligible beneficiaries' prescription utilization and expenditures. *Health Services Research 45*(1), 133–151.

Bernard, D., C. Cowan, T. Selden, L. Cai, A. Catlin, and S. Heffler (2012). Reconciling medical expenditure estimates from the meps and nhea, 2007. *Medicare & Medicaid Research Review 2*(4).

Bhattacharya, J., D. Goldman, and N. Sood (2003). The link between public and private insurance and hiv-related mortality. *Journal of Health Economics 22*(6), 1105–1122.

Brook, R. H., J. E. Ware Jr, W. H. Rogers, E. B. Keeler, A. R. Davies, C. A. Donald, G. A. Goldberg, K. N. Lohr, P. C. Masthay, and J. P. Newhouse (1983). Does free care improve adults' health? results from a randomized controlled trial. *New England Journal of Medicine 309*(23), 1426–1434.

Cannon, C. P., E. Braunwald, C. H. McCabe, D. J. Rader, J. L. Rouleau, R. Belder, S. V. Joyal, K. A. Hill, M. A. Pfeffer, and A. M. Skene (2004). Intensive versus moderate lipid lowering with statins after acute coronary syndromes. *New England Journal of Medicine 350*(15), 1495–1504.

Card, D., C. Dobkin, and N. Maestas (2009). Does medicare save lives? *Quarterly Journal of Economics 124*(2), 597–636.

Clayton, D. (2014). The effect of prescription drug coverage on mortality: Evidence from medicaid implementation. *Working Paper*.

Congressional Budget Office (2014). Updated estimates of the effects of the insurance coverage provisions of the affordable care act.

Cutler, D., M. McClellan, and J. Newhouse (1999). The costs and benefits of intensive treatment for cardiovascular disease. *Measuring the Prices of Medical Treatments*, 34.

Cutler, D. M. (2004). *Your money or your life: Strong medicine for America's health care system*. Oxford University Press.

Davidoff, A. J., T. Shaffer, M. Z. Erten, J. S. Shoemaker, I. H. Zuckerman, N. Pandya, B. C. Stuart, L. G. Bryant-Comstock, and R. Shenolikar (2013). Use and spending on antineoplastic therapy for medicare beneficiaries with cancer. *Medical Care 51*(4), 351–360.

Deryugina, T., G. Heutel, N. H. Miller, D. Molitor, and J. Reif (2016). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *Working Paper*.

Domino, M. and J. Farley (2010). Did medicare part d improve access to medications? *Psychiatric Services 61*, 118–120.

Engelhardt, G. V. and J. Gruber (2011). Medicare part d and the financial protection of the elderly. *American Economic Journal: Economic Policy 3*(4), 77–102.

Finkelstein, A. and R. McKnight (2008). What did medicare do? the initial impact of medicare on mortality and out of pocket medical spending. *Journal of Public Economics 92*(7), 1644–1668.

Gowrisankaran, G., R. Town, and E. Barrette (2011). Managed care, drug benefits and mortality: An analysis of the elderly. *BE Journal of Economic Analysis & Policy 11*(2).

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy 80*(2), 223.

Haffner, S. M., S. Lehto, T. Rönnemaa, K. Pyörälä, and M. Laakso (1998). Mortality from coronary heart disease in subjects with type 2 diabetes and in nondiabetic subjects with and without prior myocardial infarction. *New England Journal of Medicine 339*(4), 229–234.

Hassol, A., S. Jureidini, T. Doksum, and L. Hadden (2006). Evaluation of the medicare-approved prescription drug discount card and transitional assistance program. *Final Report to the Centers for Medicare & Medicaid Services*.

Jorgenson, D. W. and K.-Y. Yun (2002). *Investment, Volume 3: Lifting the Burden: Tax Reform, the Cost of Capital, and US Economic Growth*, Volume 3. MIT Press Books.

Kaestner, R. and N. Khan (2012). Medicare part d and its effect on the use of prescription drugs and use of other health care services of the elderly. *Journal of Policy Analysis and Management 31*(2), 253–279.

Kaestner, R., C. Long, and G. C. Alexander (2014). Effects of prescription drug insurance on hospitalization and mortality: Evidence from medicare part d. *Working Paper*.

Lakdawalla, D. and T. Philipson (2012). Does intellectual property restrict output? an analysis of pharmaceutical markets. *Journal of Law and Economics 55*(1), 151–187.

Levy, H. and D. Meltzer (2004). What do we really know about whether health insurance affects health. *Health Policy and the Uninsured*, 179–204.

Lewington, S., G. Whitlock, R. Clarke, P. Sherliker, J. Emberson, J. Halsey, N. Qizilbash, R. Peto, and R. Collins (2007). Blood cholesterol and vascular mortality by age, sex, and blood pressure: a meta-analysis of individual data from 61 prospective studies with 55,000 vascular deaths. *Lancet 370*(1829), 1839.

Lichtenberg, F. R. (2002). The effects of medicare on health care utilization and outcomes. *Frontiers in Health Policy Research 5*(3).

Lichtenberg, F. R. and S. X. Sun (2007). The impact of medicare part d on prescription drug use by the elderly. *Health Affairs 26*(6), 1735–1744.

Lurie, N., N. B. Ward, M. F. Shapiro, and R. H. Brook (1984). Termination from medi-cal—does it affect health? *New England Journal of Medicine 311*(7), 480–484.

McInerney, M. and J. M. Mellor (2012). Recessions and seniors' health, health behaviors, and healthcare use: analysis of the medicare current beneficiary survey. *Journal of Health Economics 31*(5), 744–751.

Medicare Board of Trustees (2004). 2004 annual report of the boards of trustees of the federal hospital insurance and federal supplementary medical insurance trust funds.

Medicare Board of Trustees (2014). 2014 annual report of the boards of trustees of the federal hospital insurance and federal supplementary medical insurance trust funds.

Mosca, L., E. Barrett-Connor, and N. K. Wenger (2011). Sex/gender differences in cardiovascular disease prevention what a difference a decade makes. *Circulation 124*(19), 2145–2154.

National Center for Health Statistics (2014). Health, united states, 2013: With special feature on prescription drugs.

Nelson, L. (2003). How many people lack health insurance and for how long? Congress of the US, Congressional Budget Office.

Rathore, S. S., Y. Wang, and H. M. Krumholz (2002). Sex-based differences in the effect of digoxin for the treatment of heart failure. *New England Journal of Medicine 347*(18), 1403–1411.

Ruhm, C. J. (2013). Recessions, healthy no more? *NBER Working Paper*.

Schneeweiss, S., A. R. Patrick, A. Pedan, L. Varasteh, R. Levin, N. Liu, and W. H. Shrank (2009). The effect of medicare part d coverage on drug use and cost sharing among seniors without prior drug benefits. *Health Affairs 28*(2), w305–w316.

Sommers, B. D., K. Baicker, and A. M. Epstein (2012). Mortality and access to care among adults after state medicaid expansions. *New England Journal of Medicine 367*(11), 1025–1034.

Sommers, B. D., S. K. Long, and K. Baicker (2014). Changes in mortality after massachusetts health care reform: A quasi-experimental study. *Annals of Internal Medicine 160*(9), 585–593.

Weingart, S., E. Brown, P. Bach, K. Eng, S. Johnson, T. Kuzel, T. Langbaum, R. Leedy, R. Muller, L. Newcomer, et al. (2008). Nccn task force report: Oral chemotherapy. *Journal of the National Comprehensive Cancer Network: JNCCN 6*, S1–14.

Zimmer, D. M. (2014). The effect of medicare part d on prescription drug composition and demand. *Working Paper*.

A Data Appendix

The four most drug-intensive diseases, as defined by Table 2, are heart disease, digestive system diseases, diabetes, and lipid metabolism disorders. Table 8 displays the three most commonly prescribed medications in the Medical Expenditure Panel Survey for these four diseases. The last column shows what fraction of the total drug use for a specific disease corresponds to a particular drug. For example, Atorvastatin accounts for 34 percent of all drug prescriptions for lipid metabolism disorders.

Table 8: Top three drug treatments for common medical conditions

Drug name	Primary medical use	Fraction of category
Heart disease		
METOPROLOL	Hypertension, chest pain, heart attack	8.3%
LISINOPRIL	Hypertension, heart failure, heart attack, kidney disease	7.3%
ATENOLOL	Hypertension, heart pain, heart attack	6.4%
Digestive diseases		
OMEPRAZOLE	Indigestion, stomach ulcers, acid reflux	15.9%
LANSOPRAZOLE	Stomach ulcers, acid reflux	13.7%
ESOMEPRAZOLE	Indigestion, stomach ulcers, acid reflux	12.0%
Diabetes		
METFORMIN	Type 2 diabetes	16.7%
GLIPIZIDE	Type 2 diabetes	9.0%
GLYBURIDE	Type 2 diabetes	8.9%
Lipid metabolism disorders		
ATORVASTATIN	High cholesterol, cardiovascular disease prevention	33.9%
SIMVASTATIN	High cholesterol, cardiovascular disease prevention	21.8%
LOVASTATIN	High cholesterol, cardiovascular disease prevention	6.1%

Notes: This table lists the three most commonly prescribed drugs for four different diseases frequently treated with prescription medication using data from the 2001-2008 Medical Expenditure Panel Survey. The last column reports what fraction of total prescriptions for the disease category is represented by a particular drug.

B Robustness checks

Table 9 presents results when we use the per capita mortality rate as the outcome variable instead of the log of deaths. Column (1) of the table estimates that Medicare Part D reduced mortality among 66-year-olds relative to 64-year-olds by 30.07 per 100,000, and cardiovascular mortality by 22.23 per 100,000. These correspond to reductions of 1.8 percent and 4.3 percent, respectively, which is very similar to the estimates of 2.2 and 4.4 percent that are presented in the main text. Columns (2)-(5) show analogous results when we estimate this model separately by gender and race. Again, the results are very similar to those presented in the main text.

Table 10 displays estimates when we employ 65-year-olds as the treatment group instead of 66-year-olds. Because 65-year-olds have been exposed to Medicare Part D for only six months on average, we expect them to be less affected by Medicare Part D. We continue to find a statistically significant effect for cardiovascular and total mortality in the full sample, although the point estimates are attenuated, as expected. Estimates are again larger for males and non-whites, although the latter are statistically insignificant due to the attenuation and the large standard errors.

Table 11 displays estimates using all pairwise combinations of control and treatment from the 61-69 age range. We do not include these estimates in the main text because the differences in age between treatment and control are larger than our primary specification (2=66-64), which potentially compromises our main identifying assumption. Nevertheless, we report these estimates here to show that there is nothing unique about our particular treatment and control groups. Moreover, the estimates in Table 11 suggest that the treatment effect may be larger for older Medicare beneficiaries.

As a placebo exercise, we estimate our main specification using different combinations of ages drawn from the under-65 population. The results for all-cause and cardiovascular mortality are reported in Tables 12 and 13. Across all sixty of these regressions, we find only four (marginally) significant effects.

A second placebo exercise employs deaths due to external causes as the dependent variable. We estimate an event-study regression and plot the results in Figure 7. As expected, there does not appear to be any effect for this category of deaths.[23]

[23]We also estimated a regression model that constrains the treatment effect to be constant during 2005-2008. It confirms that the estimated treatment effect for external causes is statistically insignificant.

Next, we expand our pre- and post-period by four years each. This makes use of the most recent data available from the National Vital Statistics System. This larger sample size increases precision, but risks introducing bias because this specification may capture other events that might differentially affect 64- and 66-year-olds. Figure 8 displays event-study plots for this expanded time period. The plots suggest that there may have been short-term differential changes in mortality during the late 1990's and again around 2009. The former may be due to the Balanced Budget Act of 1997, which cut Medicare spending, and the latter may be due to the Great Recession.[24] However, Table 14 shows that our main difference-in-differences results are not substantively affected when we include these additional years in our estimation sample.

Finally, Table 15 displays estimates when we limit our sample to the years 2002-2007. This smaller sample size reduces precision, but may also reduce bias, for the same reasons mentioned previously. In any case, both Table 14 and Table 15 report a statistically significant decline in the relative mortality of the young-elderly for all causes and for cardiovascular diseases in particular. We never find a significant effect for cancer mortality, either in the full sample or for subgroups, in either specification. Additional specifications (not reported) that include or exclude differing numbers of years yield similar results.

[24] Although elderly mortality has historically been procyclical, McInerney and Mellor (2012) show that it becomes countercyclial beginning in 1994, which is consistent with our estimates.

Table 9: Effect of Medicare Part D on mortality at age 66, using death rates as an alternative outcome variable

	Coefficient on Post05*Elderly				
	Full sample	Gender		Race	
		Male	Female	White	Non-white
Dependent variable	(1)	(2)	(3)	(4)	(5)
Any Cause of Death	-30.07 **	-53.27 **	-11.73	-27.03 *	-55.23 *
	(10.79)	(17.25)	(11.03)	(11.00)	(27.19)
Cardiovascular	-22.23 **	-31.75 **	-14.89 **	-20.19 **	-39.41 *
	(6.32)	(11.63)	(4.44)	(6.05)	(14.74)
Cancer	-0.30	-3.88	2.06	2.27	-14.95
	(5.56)	(9.59)	(6.41)	(5.61)	(15.60)
Other	-4.05	-9.11	0.16	-6.19	5.93
	(4.87)	(7.77)	(6.05)	(4.93)	(14.40)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: This table shows estimates of the coefficient on the interaction term between the elderly indicator and the post-2005 indicator from equation (2) using data from the 2001-2008 National Vital Statistics. The dependent variable is the death rate per 100,000 population for age group a in state s in year t. The average total death rate and cardiovascular death rate for 66-year-olds between 2001 and 2004 are 1,629 and 521 per 100,000, respectively. Each row and column corresponds to a separate regression for a specific cause of death used as an outcome variable in equation (2). The number of observations in each regression is equal to 816 (=8*2*51). Standard errors, given in parentheses, are clustered by state. All regressions are weighted by the square-root of population. * Significant at 5 percent. ** Significant at 1 percent.

Table 10: Effect of Medicare Part D on mortality at age 65

	Coefficient on Post05*Elderly				
	Full sample	Gender		Race	
		Male	Female	White	Non-white
Dependent variable	(1)	(2)	(3)	(4)	(5)
Any Cause of Death	-0.017 *	-0.025 **	-0.005	-0.016 *	-0.017
	(0.007)	(0.008)	(0.012)	(0.007)	(0.015)
Cardiovascular	-0.026 *	-0.040 **	0.001	-0.023 *	-0.025
	(0.010)	(0.011)	(0.017)	(0.011)	(0.020)
Cancer	0.001	0.005	-0.004	0.002	-0.014
	(0.009)	(0.013)	(0.019)	(0.010)	(0.026)
Other	-0.020	-0.034 *	-0.003	-0.023 *	-0.004
	(0.012)	(0.016)	(0.018)	(0.011)	(0.024)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: This table shows estimates of the coefficient on the interaction term between the elderly indicator and the post-2005 indicator from equation (2) using data from the 2001-2008 National Vital Statistics. It employs 65-year-olds as the treatment group instead of 66-year-olds (the primary specification in the main text). The dependent variable is the log of deaths for age group a in state s in year t. Each row and column corresponds to a separate regression for a specific cause of death used as an outcome variable in equation (2). The number of observations in each regression is equal to 816 (=8*2*51). Standard errors, given in parentheses, are clustered by state. All regressions are weighted by the square-root of population. * Significant at 5 percent. ** Significant at 1 percent.

Table 11: Effect of Part D on mortality, using different ages for treatment and control

	Coefficient on Post05*Elderly			
Age	**Any Cause**	**Cardiovascular**	**Cancer**	**Other**
Control X Treatment	**(1)**	**(2)**	**(3)**	**(4)**
64 X 69	-0.040 **	-0.065 **	-0.002	-0.053 **
	(0.006)	(0.011)	(0.013)	(0.013)
63 X 69	-0.046 **	-0.076 **	-0.013	-0.048 **
	(0.010)	(0.014)	(0.013)	(0.016)
62 X 69	-0.034 *	-0.082 **	0.017	-0.041 *
	(0.013)	(0.013)	(0.017)	(0.018)
61 X 69	-0.030 **	-0.056 **	0.011	-0.038 *
	(0.010)	(0.013)	(0.012)	(0.017)
64 X 68	-0.053 **	-0.081 **	-0.021	-0.056 **
	(0.006)	(0.010)	(0.011)	(0.012)
63 X 68	-0.055 **	-0.089 **	-0.022	-0.053 **
	(0.009)	(0.013)	(0.014)	(0.019)
62 X 68	-0.049 **	-0.098 **	0.000	-0.051 **
	(0.008)	(0.010)	(0.011)	(0.015)
61 X 68	-0.037 **	-0.065 **	0.004	-0.043 *
	(0.008)	(0.010)	(0.010)	(0.019)
64 X 67	-0.042 **	-0.067 **	-0.022 *	-0.041 **
	(0.006)	(0.010)	(0.010)	(0.011)
63 X 67	-0.048 **	-0.081 **	-0.031 *	-0.037 *
	(0.008)	(0.013)	(0.012)	(0.014)
62 X 67	-0.038 **	-0.086 **	-0.005	-0.030
	(0.009)	(0.013)	(0.011)	(0.015)
61 X 67	-0.034 **	-0.060 **	-0.005	-0.032 *
	(0.008)	(0.013)	(0.008)	(0.016)
64 X 66	-0.022 **	-0.044 **	-0.002	-0.022
	(0.008)	(0.013)	(0.012)	(0.015)
63 X 66	-0.016 *	-0.044 **	0.004	-0.010
	(0.007)	(0.014)	(0.011)	(0.015)
62 X 66	-0.011	-0.053 **	0.023	-0.006
	(0.006)	(0.014)	(0.012)	(0.013)
61 X 66	-0.011	-0.037 *	0.019 *	-0.009
	(0.006)	(0.014)	(0.009)	(0.015)
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: This table shows estimates of the coefficient on the interaction term between the elderly indicator and the post-2005 indicator from equation (2) using data from the 2001-2008 National Vital Statistics. The dependent variable is the log of deaths for age group a in state s in year t. Each row and column corresponds to a separate regression for a specific cause of death used as an outcome variable in equation (2) and a specific pair of ages used for the control and treatment groups. The number of observations in each regression is equal to 816 (=8*2*51). Standard errors, given in parentheses, are clustered by state. All regressions are weighted by the square-root of population. * Significant at 5 percent. ** Significant at 1 percent.

Table 12: Placebo exercise: effect of Medicare Part D on all-cause mortality

	Coefficient on Post05*Elderly				
	Full sample	Gender		Race	
Age		Male	Female	White	Non-white
Control X Treatment	(1)	(2)	(3)	(4)	(5)
63 X 64	0.002	0.008	-0.006	0.002	-0.004
	(0.007)	(0.008)	(0.010)	(0.008)	(0.015)
62 X 64	0.009	0.019 *	-0.003	0.006	0.020
	(0.006)	(0.008)	(0.009)	(0.006)	(0.020)
61 X 64	0.012	0.020 *	0.003	0.011	0.017
	(0.007)	(0.009)	(0.009)	(0.007)	(0.016)
62 X 63	0.008	0.011	0.004	0.006	0.021
	(0.004)	(0.007)	(0.007)	(0.005)	(0.015)
61 X 63	0.009	0.010	0.008	0.008	0.021
	(0.005)	(0.007)	(0.010)	(0.006)	(0.012)
61 X 62	0.003	0.002	0.007	0.004	0.001
	(0.006)	(0.008)	(0.009)	(0.006)	(0.016)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: This table shows results of the placebo exercises using data from the 2001-2008 National Vital Statistics. Instead of employing age 64 as the control group and age 66 as the treatment group, it employs different combinations of ages from the under-65 population, which was not affected by the implementation of Medicare Part D. The dependent variable is the log of all-cause deaths for age group a in state s in year t. Each row and column corresponds to a separate regression in equation (2). The number of observations in each regression is equal to 816 (=8*2*51). Standard errors, given in parentheses, are clustered by state. All regressions are weighted by the square-root of population. * Significant at 5 percent. ** Significant at 1 percent.

Table 13: Placebo exercise: effect of Medicare Part D on cardiovascular mortality

	Coefficient on Post05*Elderly				
	Full sample	Gender		Race	
Age		Male	Female	White	Non-white
Control X Treatment	(1)	(2)	(3)	(4)	(5)
63 X 64	-0.007	0.009	-0.033	-0.015	0.012
	(0.013)	(0.013)	(0.021)	(0.015)	(0.023)
62 X 64	-0.014	-0.004	-0.030	-0.020	-0.001
	(0.012)	(0.014)	(0.019)	(0.013)	(0.030)
61 X 64	0.004	0.023 *	-0.029	0.000	0.017
	(0.010)	(0.011)	(0.016)	(0.010)	(0.028)
62 X 63	-0.008	-0.013	0.002	-0.005	-0.017
	(0.010)	(0.015)	(0.019)	(0.011)	(0.023)
61 X 63	0.007	0.010	0.000	0.010	0.001
	(0.010)	(0.013)	(0.020)	(0.012)	(0.024)
61 X 62	0.019	0.028 *	0.001	0.019	0.021
	(0.010)	(0.012)	(0.019)	(0.010)	(0.025)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: This table shows results of the placebo exercises using data from the 2001-2008 National Vital Statistics. Instead of employing age 64 as the control group and age 66 as the treatment group, it employs different combinations of ages from the under-65 population, which was not affected by the implementation of Medicare Part D. The dependent variable is the log of cardiovascular deaths for age group a in state s in year t. Each row and column corresponds to a separate regression in equation (2). The number of observations in each regression is equal to 816 (=8*2*51). Standard errors, given in parentheses, are clustered by state. All regressions are weighted by the square-root of population. * Significant at 5 percent. ** Significant at 1 percent.

Table 14: Effect of Medicare Part D on mortality at age 66, using data from 1997-2012

	Coefficient on Post05*Elderly				
	Full sample	Gender		Race	
		Male	Female	White	Non-white
Dependent variable	(1)	(2)	(3)	(4)	(5)
Any Cause of Death	-0.017 **	-0.024 **	-0.012	-0.019 **	-0.017
	(0.006)	(0.008)	(0.007)	(0.006)	(0.012)
Cardiovascular	-0.028 **	-0.031 **	-0.029 *	-0.031 **	-0.020
	(0.008)	(0.011)	(0.013)	(0.009)	(0.015)
Cancer	-0.004	-0.009	0.000	-0.001	-0.020
	(0.005)	(0.010)	(0.010)	(0.006)	(0.020)
Other	-0.023 *	-0.030 *	-0.016	-0.032 **	0.002
	(0.011)	(0.014)	(0.014)	(0.012)	(0.019)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

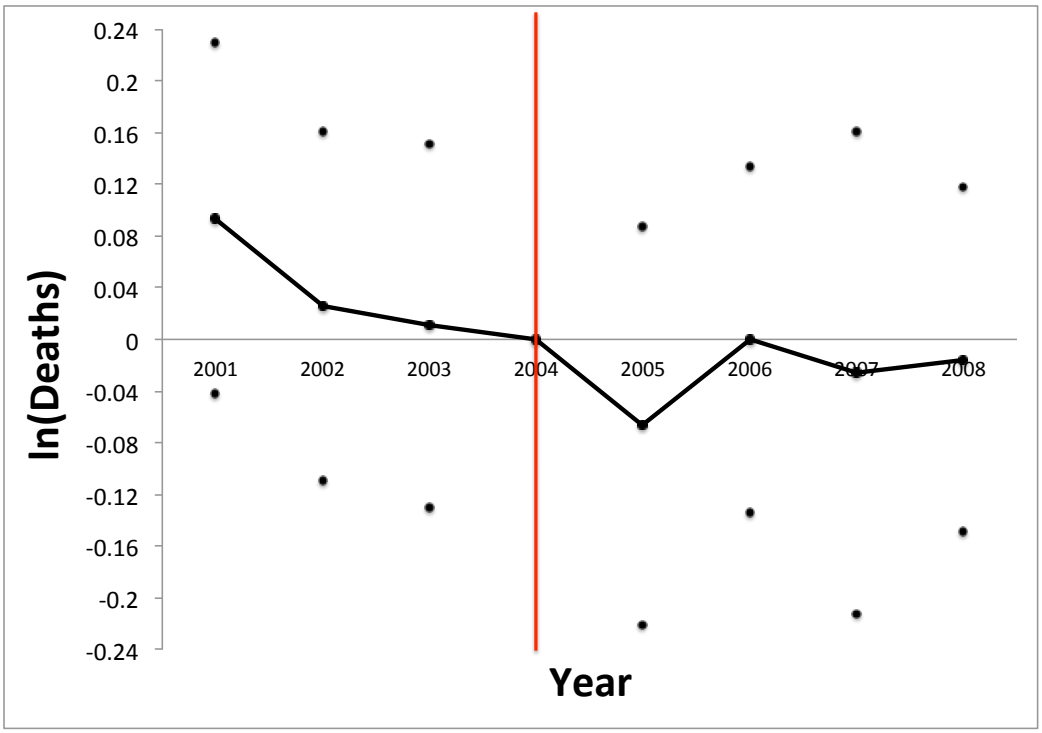
Notes: This table shows estimates of the coefficient on the interaction term between the elderly indicator and the post-2005 indicator from equation (2) using data from the 1997-2012 National Vital Statistics. The dependent variable is the log of deaths for age group a in state s in year t. Each row and column corresponds to a separate regression for a specific cause of death used as an outcome variable in equation (2). The number of observations in each regression is equal to 816 (=8*2*51). Standard errors, given in parentheses, are clustered by state. All regressions are weighted by the square-root of population. * Significant at 5 percent. ** Significant at 1 percent.

Table 15: Effect of Medicare Part D on mortality at age 66, using data from 2002-2007

	Coefficient on Post05*Elderly				
	Full sample	Gender		Race	
		Male	Female	White	Non-white
Dependent variable	(1)	(2)	(3)	(4)	(5)
Any Cause of Death	-0.023 *	-0.035 **	-0.010	-0.016	-0.040 *
	(0.009)	(0.010)	(0.013)	(0.009)	(0.019)
Cardiovascular	-0.049 **	-0.065 **	-0.028	-0.041 *	-0.068 *
	(0.017)	(0.021)	(0.022)	(0.018)	(0.027)
Cancer	-0.003	0.001	-0.010	0.004	-0.036
	(0.011)	(0.016)	(0.018)	(0.011)	(0.036)
Other	-0.017	-0.038	0.009	-0.019	-0.001
	(0.019)	(0.021)	(0.026)	(0.018)	(0.034)
State fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

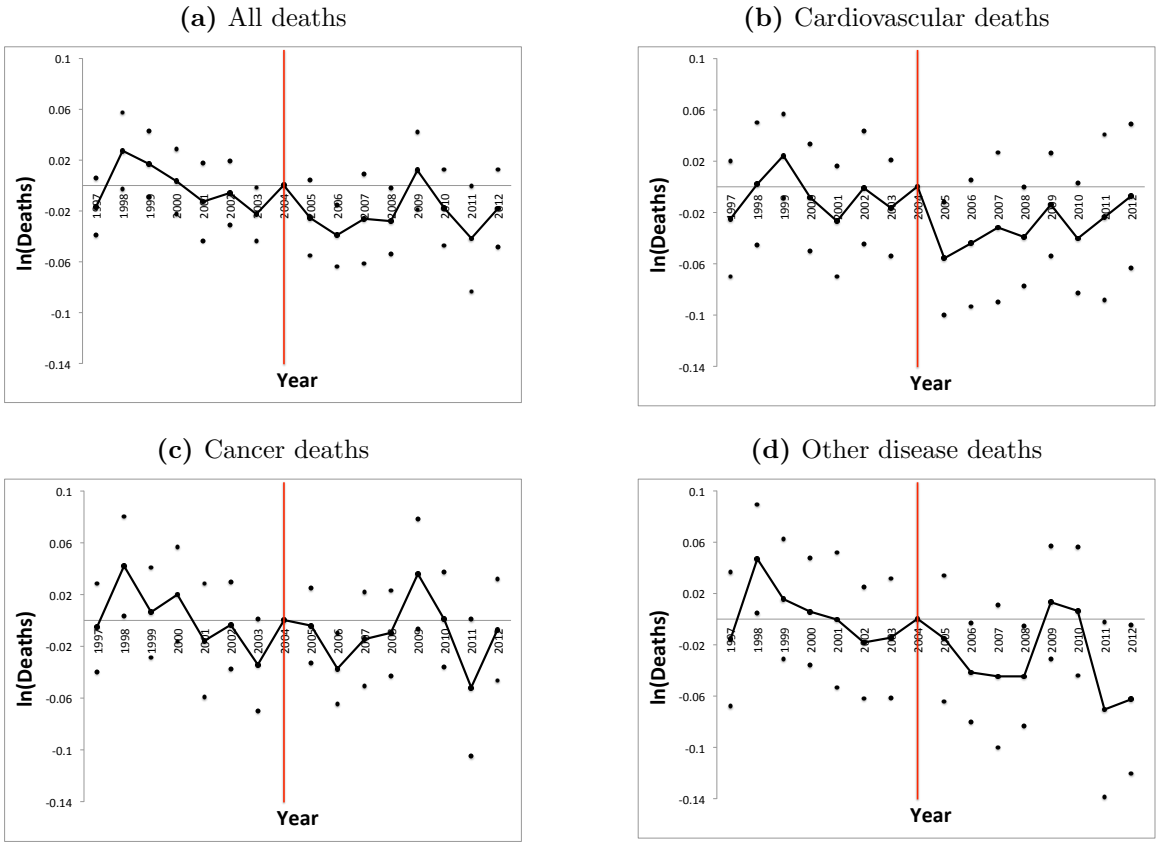
Notes: This table shows estimates of the coefficient on the interaction term between the elderly indicator and the post-2005 indicator from equation (2) using data from the 2002-2007 National Vital Statistics. The dependent variable is the log of deaths for age group a in state s in year t. Each row and column corresponds to a separate regression for a specific cause of death used as an outcome variable in equation (2). The number of observations in each regression is equal to 816 (=8*2*51). Standard errors, given in parentheses, are clustered by state. All regressions are weighted by the square-root of population. * Significant at 5 percent. ** Significant at 1 percent.

Figure 7: Placebo exercise: event-study plot of the effect of Medicare Part D on mortality at age 66, for deaths due to external causes



Notes: Figure shows estimates of the coefficient on the interaction term between the elderly indicator variable and the indicator function from equation (1) using data from the 2001-2008 National Vital Statistics. The dependent variable is the log of deaths due to external causes for age a in state s in year t. Other controls include log of population, an indicator variable for age group, state fixed effects, year fixed effects, and time-varying state-level control variables. Dots display 95% confidence intervals. Standard errors, given in parentheses, are clustered by state. Regression is weighted by the square-root of population. The vertical line indicates 2004, the year in which the Medicare Drug Discount and Transitional Assistance Programs began.

Figure 8: Event-study plot of the effect of Medicare Part D on mortality at age 66, using data from 1997-2012



Notes: Panels (a)-(d) show estimates of the coefficient on the interaction term between the elderly indicator variable and the indicator function from equation (1) using data from the 1997-2012 National Vital Statistics. The dependent variable is the log of deaths for age a in state s in year t. Control variables include log of population, an indicator variable for age group, state fixed effects, year fixed effects, and time-varying state-level control variables. Dots display 95% confidence intervals. Standard errors are clustered by state. All regressions are weighted by the square-root of population. The vertical line indicates 2004, the year in which the Medicare Drug Discount and Transitional Assistance Programs began.