Health Insurance, Price Changes, and the Demand for Pain Relief Drugs: *Evidence from Medicare Part D*[*]

Aparna Soni[†]

September 25, 2018

Abstract

Overdose deaths from prescription opioids are on the rise, and policymakers seek solutions to curb opioid misuse. Recent proposals call for price-based solutions, such as opioid taxes and removal of opioids from insurance formularies. However, there is limited evidence on how opioid consumption responds to price stimuli. This study addresses that gap by estimating the effects of prices on the utilization of opioids as well as other prescription painkillers. I use nationally representative individual-level data on prescription drug purchases to exploit the introduction of Medicare Part D in 2006 as an exogenous change in out-of-pocket drug prices. I find that new users have a relatively high price elasticity of demand for prescription opioids, and that consumers treat over-the-counter painkillers as substitutes for prescription painkillers. My results suggest that increasing out-of-pocket prices of opioids, through formulary design or taxes, may be effective in reducing new opioid use.

Keywords: Health insurance, Pain relief, Opioids, Medicare Part D, Elasticity

JEL Codes: I11, I12, I13

[*] I am grateful to my dissertation committee, Kosali Simon, Jeffrey Prince, Haizhen Lin, and Daniel Sacks, for their continued guidance and support. I also thank Abby Alpert, Colleen Carey, Christopher Carpenter, John Cawley, Laura Dague, Kurt Lavetti, David Molitor, Anita Mukherjee, Christopher Ruhm, David Slusky, and seminar participants at Indiana University and the 2018 Conference of the American Society of Health Economists.

Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

[†] Department of Business Economics and Public Policy, Indiana University. E-mail: apsoni@indiana.edu

1 Introduction

Prescription opioid utilization has nearly doubled over the past 15 years, even as use of non-opioid and over-the-counter (OTC) painkillers fell.[1] Although the medical purpose of opioids is to treat pain, these drugs are frequently misused due to their addictive properties. Prescription opioid misuse has devastating public health consequences, including increased overdose deaths, emergency department utilization, drug diversion, and crime (Council of Economic Advisers, 2017). Opioid overdose deaths now exceed 42,000 per year, and prescription opioids are responsible for between 34 and 77 percent of these deaths.[2] Moreover, prescription opioids often serve as a bridge to illicit heroin and fentanyl; studies have found that 80 percent of heroin users reported using prescription opioids prior to heroin (Jones, 2013), and heroin dealers specifically target areas with higher rates of opioid prescribing (Quinones, 2015). Thus, curbing prescription opioid use and initiation is a top public health priority.[3] Recent proposals call for price-based policies to reduce opioid consumption. The goal of this paper is to predict potential implications of these policies by estimating the price elasticity of demand for prescription opioids and identifying the effects of price changes on opioid initiation.

Policymakers can influence consumers' out-of-pocket (OOP) opioid prices through two main levers. First, state governments can implement opioid taxes, which may be passed down to consumers in the form of higher list prices.[4] So far, 15 states have introduced bills that – if passed – would levy taxes or fees on prescription painkillers (Potter & Mulvihill, 2018).[5] Second, public insurers can revise their formularies to reduce coverage of the drugs, thereby

[1] See Figure 1 and Figure 2.

[2] The Center for Disease Control and Prevention's (CDC) mortality data does not distinguish deaths from pharmaceutical fentanyl and illegally produced fentanyl, so the prescriptions deaths displayed in Panel A of Appendix Figure A- 2 may include deaths from both types of fentanyl. Panel B of Appendix Figure A- 2 uses an alternative way to classify deaths: the "semisynthetic and natural opioids" and the "heroin" bars refer unambiguously to prescription and illicit opioids, respectively. The "synthetic opioids" bar consists of deaths from both prescription and illicit fentanyl.

[3] See Appendix A1 for additional details on the opioid crisis and policy efforts to curb opioid abuse.

[4] In general, prescription drugs are exempt from sales tax in all states, except Illinois (where they are taxed at 1 percent at the state level but exempt from local sales tax) and Louisiana – where they are tax-exempt at the state level, but local areas can opt to tax. In contrast, over-the-counter (OTC) drugs are subject to sales tax in all states except Connecticut, Maryland, Minnesota, New Jersey, New York, Pennsylvania, Texas, Vermont, Virginia, and Washington DC. In Illinois, OTC drugs are taxed at a lower rate than other goods.

[5] In 2018, Kentucky voted on an opioid tax which would have levied a 25-cent on drug distributors for each dose sent to the state. Although the bill eventually failed to pass in the state Senate, the House did vote in favor of the tax, which suggests that there was considerable legislative support for the measure.

increasing the portion of drug spending borne by consumers. For example, as of 2019, all Medicare Part D plans will reduce coverage of opioids for acute pain for opioid-naïve patients to 7 days. The current average length of a prescription is otherwise 22 days. Over 50 percent of opioid spending is from public sources (Appendix Figure A- 1), so formulary changes in Medicare and Medicaid will likely have substantial effects. Even private insurance companies are taking steps to reduce inappropriate opioid utilization: several large insurers now impose similar 7-day limits for opioid-naïve patients, and the insurance giant Cigna ended coverage of Oxycontin in 2018.

These policies share the common goal of reducing equilibrium quantity of prescription opioids by increasing consumers' OOP prices. However, the effects of these policies depend on the price elasticity of demand for opioids. In spite of the prominence of pain relief drugs, little is known about patients' price sensitivity and the extent to which individuals substitute between addictive and less addictive painkillers. While an extensive literature documents a negative price elasticity of demand for prescription drugs in general (Coulson & Stuart, 1995; Duggan & Scott Morton, 2010; Gaynor, Li, & Vogt, 2007; Joyce, Escarce, Solomon, & Goldman, 2002; Ketcham & Simon, 2008; Lichtenberg & Sun, 2007; Yin et al., 2008),[6] these earlier findings may not apply to opioids because the impact of prices on drug utilization depends on the therapeutic class of drug (Gatwood et al., 2014; Goldman et al., 2004). Because opioids are addictive, it is plausible that opioid demand is less price elastic and that price elasticities are heterogeneous across new and existing users (Becker & Murphy, 1988).

The empirical challenge to obtaining unbiased elasticity estimates is to identify exogenous variation in drug prices. I accomplish this by exploiting shocks to OOP prices produced by the introduction of Medicare Part D in 2006.[7] My analysis distinguishes between opioids, which have a high risk for addiction, and non-opioid prescription painkillers (primarily NSAIDs), which carry relatively lower risks. I find that while the demand for non-opioid painkillers is not responsive to price changes, the price elasticity for prescription opioids is -0.9. This implies that consumers are more sensitive to the price of opioids than they are to other

[6] Appendix A2 provides a detailed review of the literature on price elasticities for prescription drugs.

[7] For example, the OOP price of an opioid prescription for an elderly person fell from an average of $17 before Part D to $8 after Part D. For near-elderly individuals, in contrast, the OOP price changed from $15 to $11 over the same time period (author's calculations based on MEPS 2000-09).

prescription drugs; previous studies that exploit Part D find price elasticity estimates of all prescription drugs ranging from -0.2 to -0.5 (Duggan & Scott Morton, 2010; Ketcham & Simon, 2008; Liu et al., 2011; Yin et al., 2008).[8] By providing some of the first evidence of the impact of OOP prices on consumers' demand for prescription opioids and other pain relief drugs, this paper contributes to the growing literature on price elasticities of prescription drugs.

Individuals may not be homogeneous with respect to price sensitivity, so I separately study subpopulations of interest, such as new opioid users, people with joint and back pain, cancer patients, and those with a history of drug poisoning. Policymakers wish to reduce the flow of new initiates because opioid-naïve patients who are prescribed opioids for acute pain relief are at high risk for developing new, persistent opioid abuse (Lee et al., 2017; Shah, Hayes, & Martin, 2017). I find that the post-Part D change in opioid utilization came primarily from new users who did not use opioids prior to 2006. On the other hand, there was no detectable effect of OOP prices for existing users. This finding contributes to the broader literature on how prices of addictive goods, such as cigarettes and alcohol, affect initiation (DeCicca, Kenkel, & Mathios, 2008; Saffer & Chaloupka, 1999). It is also important from a welfare perspective to understand potential responses among people with different types of medical conditions because public health experts view cancer and surgery as "legitimate" reasons to use opioids, whereas the use of opioids to manage joint and back pain is more controversial. If, for example, I find that cancer patients are the most price-sensitive group, then an opioid tax may be welfare-reducing.

Although there is some existing work on the demand for prescription opioids, little is known about the effects of prices on opioid initiation and heterogeneous consumption responses among people with different medical conditions. One previous paper uses Part D data to study the impact of entering the donut hole on the utilization of 150 different types of drugs; the authors estimate a small price elasticity of -0.04 for opioids (Einav, Finkelstein, & Polyakova, 2018). However, the study sample is limited to people who have spent up to the donut hole, i.e. those who are sicker and therefore more likely to be existing opioid users. In the Appendix of a working paper that studies the impact of Part D on drug diversion, the authors present evidence that Part D increased the number of opioid prescriptions by 28 percent and reduced OOP prices

[8] In Appendix Table A- 4, I confirm the price elasticity of demand of all prescription drugs using a similar empirical approach as the approach used in the main analysis of this paper. I obtain an elasticity of -0.45, which is similar to that obtained in previous studies.

by 48 percent (implying a price elasticity of -0.6). However, this study does not address new versus existing users or other subpopulations of interest. The current paper makes important contributions by estimating how opioid-naïve people and existing users respond differently to price changes in opioids; I show that disregarding this distinction underestimates the full effect of price changes. I also identify price elasticities separately for people with different medical conditions, and show that price increases do not differentially affect cancer patients (who have uncontroversial "legitimate" reasons for opioid use) and that those with back and joint pain (controversial justification for opioid use) are more likely to respond to price changes. Section 7 offers additional discussion of my results in light of the existing literature.

1.1 Substitution between Prescription and Over-the-Counter Painkillers

The second contribution of this paper is to estimate cross-price elasticities of demand between prescription painkillers and OTC painkillers. These estimates are important from a policy perspective because promoting substitution toward other effective but less addictive treatments for pain has been proposed as a way to address the opioid crisis (Centers for Disease Control and Prevention, 2016). OTC painkillers are substantially less addictive, are less costly for the government, and have fewer negative spillover effects such as drug diversion. However, there are few studies that study potential substitution between prescription and OTC drugs, and what little evidence exists is primarily based on observational rather than experimental data (Leibowitz, 1989; O'Brien, 1989; Stuart & Grana, 1995). Moreover, none of these existing studies specifically analyzes painkillers.

Part D is an appropriate setting to study potential substitution between prescription and OTC drugs. The elderly are heavy users of both types of drugs (Qato, Wilder, Schumm, Gillet, & Alexander, 2016), and the implementation of the policy lends itself to quasi-experimental analysis, which reduces concern about selection bias. I use scanner data on households' grocery and drug purchases to study the effect of the prescription OOP price reduction associated with Part D on people's OTC painkiller purchases. I estimate a small but positive cross-price elasticity of demand for OTC painkillers (elasticity = 0.1), which implies that consumers view prescriptions and OTC painkillers as substitutes to some extent. My findings suggest that a

targeted subsidy for OTC painkillers may be an effective way to shift demand away from opioids.

The remainder of this paper proceeds as follow. Section 2 proposes a conceptual framework for predicting the effects of prices on the demand for addictive painkillers and their substitutes. Section 3 presents the Medical Expenditure Panel Survey and Nielsen Household Consumer Panel datasets utilized in this analysis. Section 4 describes the empirical methods and results for the impact of price changes on utilization of prescription painkillers. Section 5 presents results for new versus existing users. Section 6 provides cross-price elasticity estimates for OTC painkillers with respect to prescription painkiller prices, and Section 7 concludes.

2 Conceptual Framework

In this section, I develop a general theoretical framework to predict how changes in OOP prices of prescription painkillers will affect quantity demanded.[9] I assume that the demand for pain relief is a derived demand for health (Grossman, 1972). Individuals maximize lifetime utility (U) – which is a function of total consumption of all goods (Y), pain relief (P), and addictive capital (S) – subject to a lifetime budget constraint. Pain relief itself depends on consumption of addictive prescription painkillers (opioids, or O), non-addictive prescription painkillers (NSAIDs, or N), and non-addictive OTC painkillers (C). Quantity demanded of each of the three types of painkillers depends on individuals' incomes as well as the portion of the drug price they are responsible for paying (i.e. OOP prices). By increasing prescription drug coverage in the elderly population, Part D resulted in an exogenous decrease in the OOP price of prescription painkillers, but did not affect the price of OTC painkillers as these drugs are not covered by insurance companies. I assume that all three types of painkillers are positively associated with utility (i.e. $U_O > 0$, $U_N > 0$, and $U_C > 0$).

Proposition 1. *Assuming conventional downward sloping demand curves, a reduction in the price of prescription opioids (non-opioid prescription painkillers) should increase quantity*

[9] My data measures *utilization* of drugs, which may not be synonymous with demand. Utilization is based on patients' demand for the drug as well as physicians' willingness to write prescriptions. A reduction in OOP price can increase utilization in three ways: 1) encourage patients to seek prescriptions by increasing physician visits, 2) increase the number of prescriptions written by physicians, and 3) increase the number of prescriptions that are filled (compliance).

demanded of prescription opioids (non-opioid prescription painkillers), holding income and other prices constant.

However, opioids are addictive goods and may not obey the law of demand: it is plausible that physiological forces associated with dependence and addiction may compel a person to continue consuming a good, even if economic incentives change. My model accounts for opioids' addictive properties by including addictive capital in the individual's utility function. Addictive capital is measured by the stock of total past consumption of the addictive painkiller. I assume that addictive goods (O) have the three characteristics described below (Cawley & Ruhm, 2011).

1. Withdrawal: Consumption of the addictive goods reduces symptoms associated with withdrawal, so the marginal utility of current consumption is positive ($U_O > 0$).
2. Tolerance: Being addicted has overall harmful health consequences, so the stock of past consumption lowers utility ($U_S < 0$).
3. Reinforcement: The marginal utility of current consumption rises with the stock of past consumption ($U_{OS} > 0$).

Proposition 2. *For addictive painkillers, new users are more price-sensitive because they have not yet built up enough addictive capital to make future prices and consumption a significant consideration in their decision-making.*

A large literature on consumer behavior in other markets with addiction finds that while existing users of addictive goods are less sensitive to price changes, prices do affect the probability of initiation by new users. For example, one study finds that a 10 percent increase in the price of alcohol was found to decrease the probability that an individual currently drinks by 5.5 percent; the same study finds that the heaviest drinkers are least price sensitive (W.G. Manning, Blumberg, & Moulton, 1995). In the cigarette market also, studies show that price sensitivity varies by intensity of use. A meta-analysis shows that while the mean price elasticity of demand for cigarettes is -0.5, estimates vary widely ranging from -3.1 to 1.4 (Gallet & List, 2003). Specifically, higher cigarette prices can lead to large decreases in the probability of initiation by non-smokers (Gilleskie & Strumpf, 2005). The literature also finds that excise taxes on cigarettes can significantly deter smoking among adolescents, who have had less time to become addicted to the good as compared to older adults (Chaloupka & Wechsler, 1997; Gruber,

2001; Gruber & Zinman, 2000; Lewit, Coate, & Grossman, 1981). This inverse relationship between intensity of use and price elasticity exists in the market illicit drugs also. In the cocaine market, for example, the price elasticity of demand is -1.0 for the general population, but only -0.3 for those who are current users (Chaloupka, Grossman, & Tauras, 1999).

Proposition 3. *Existing users may also respond to price changes of the addictive good if they behave as rational addicts.*

The Theory of Rational Addiction proposes that consumers are sophisticated and account for tolerance and reinforcement when deciding current consumption (Becker & Murphy, 1988). Reinforcement implies that consumption of the addictive good today will positively affect the individual's marginal utility of consuming the addictive good tomorrow. This means that a price change in the addictive good may compel forward-looking addicts to change their consumption habits.

Proposition 4. *If OTC and prescription painkillers are substitutes, the quantity demanded of OTC painkillers falls when the price of prescription painkillers falls.*

The individual in my model maximizes pain relief by choosing an optimal mix of O, N, and C. The optimal mix depends on their relative prices and their relative productivities. Previous medical studies suggest that prescription and OTC painkillers are therapeutic substitutes for certain medical conditions (Chang, Bijur, Esses, Barnaby, & Baer, 2017). If consumers view prescription and OTC painkillers as economic substitutes, we should expect to see a reduction in C after Part D reduces the prices consumers face of O and N.

3 Data

This study uses two main data sources: the household component of the Medical Expenditure Panel Survey (MEPS, years 2000 to 2009) and the Nielsen Household Consumer Panel (NHCP, years 2004 to 2009).[10] The MEPS is a nationally representative survey that

[10] In selecting the appropriate time period for this analysis, I note that including additional years of post-2006 data would increase the sample size but may also bias the results by introducing other notable events that should have differentially affected the elderly and near-elderly. For example, the Affordable Care Act of 2010 increased overall health insurance access for the near-elderly group but not for the elderly group (Frean, Gruber, &

provides detailed information on individuals' medical expenditures, pharmaceutical utilization, and health outcomes (Agency for Healthcare Research and Quality, 2015). The MEPS is conducted annually, and the survey follows a panel design, featuring five rounds of interviews covering two full years. The original sample size is approximately 35,000 individuals per year; my analytical sample consists of 50,579 individuals aged 55 to 74 across the years 2000 to 2009. My analysis uses the MEPS full-year Consolidated Data File, which contains respondents' socio-demographic and economic characteristics; the MEPS Prescribed Medicines file, which contains all the prescription drugs purchased by respondents;[11] and the MEPS Medical Conditions File, which describes all medical conditions and treatment attempts.

The MEPS is uniquely suited for this study as it contains detailed information on prescription medication use in the years relevant for this study. Purchases of prescription drugs are reported by individual respondents and then verified by the prescribing pharmacy.[12] The MEPS provides comprehensive information on medication characteristics, including the drug name, form, strength, quantity purchased, and National Drug Code. Other datasets, such as the National Health Interview Survey and Behavioral Risk Factors Surveillance System, have the advantage of larger samples but do not contain prescription data. The Part D claims data does not have information on individuals before 2006. The MEPS has been used in past studies to study the effects of Part D on drug utilization (Alpert, 2016; Engelhardt & Gruber, 2011; Powell, Pacula, & Taylor, 2017). However, the MEPS has limitations, such as relatively small sample sizes. Also, any individual panel only contains two years of observations, which limits the ability to estimate long term effects of the policy change. Table 1 provides descriptive statistics of the MEPS sample.

Because the MEPS provides data only for prescription drugs and not for OTC drugs, I use the NHCP to obtain information on purchases of the latter (Nielsen, 2015). The NHCP contains detailed information on grocery and drugstore purchases of a panel of 40,000 to 60,000

Sommers, 2016). The Oxycontin reformulation and removal of Darvocet (e.g. Propoxyphene) also occurred in 2010 and significantly changed the landscape of the opioids market. I therefore limit my period of analysis to pre-2010 years.

[11] The Prescribed Medicines file consists of only outpatient prescription drug purchases and excludes prescription drug administered in hospitals, clinics, or physician's offices.

[12] The data has been verified by the prescribing pharmacy only for those who consented to release their pharmacy records. For those who did not consent, expenditures are based on self-reported expenditures that have been adjusted for outliers and imputations from the pharmacy data.

households. My analytical sample consists of 335,060 household-year observations across the years 2004 to 2009. Variables include household demographics, geographic identifiers (to the zip code level), and product characteristics (to the UPC code level). I use the NHCP to acquire data on households' OTC drug costs and utilization. Table 2 provides descriptive statistics of the NHCP sample.

The two main outcomes of interest in this paper are quantity purchased of a drug class and OOP price. I first calculate the percent change in OOP prices caused by Part D and the percent change in quantity purchased of the drug class caused by Part D. Then using the following elasticity formula, I obtain the estimated price elasticity of demand for the drug class.

$$\varepsilon = \frac{Percent\ Change\ in\ Quantity}{Percent\ Change\ in\ Price}$$

Equation 1

In my main analysis, I measure quantity as the units of days supplied of the drug for each person-year observation; days supplied can range from 0 to 365. Although MEPS provides information on the quantity of drugs purchased, the unit varies depending on the type of drug. Painkiller prescriptions come in different forms, including immediate release tablets, extended release tablets, liquid solutions injections, and patches. The reported MEPS quantity may be in number of bottles, number of pills, number of ounces, number of patches, etc. To obtain a consistent unit, I convert all purchases to "number of days supplied" of the drug. For example, for a strong oxycodone, a 28-pill bottle might mean a 28-day supply, but for a mild NSAID, a 28-pill bottle might mean only a 7-day supply. A similar days supplied measure has been used in previous Part D studies (Ketcham & Simon, 2008; Lichtenberg & Sun, 2007; Yin et al., 2008). MEPS provides information on days supplied from the years 2010 onward, so for earlier years, I impute the number of days supplied of each drug using post-2010 data of the same drug.[13] I also conduct sensitivity analyses in which the quantity is measured as number of prescriptions, rather than "number of days supplied."

To measure price, I use the OOP price (adjusted by pharmaceutical PPI) as my key outcome variable since this is the price faced by the individual. MEPS provides information on

[13] See Appendix A3 for additional details on the imputation process.

the total price paid for each prescription, as well as the breakdown by source of payment. For the NHCP outcomes, I simply use the reported price as my outcome, since these drugs are all purchased over the counter so other payment sources do not exist.

I first estimate elasticities for all painkillers combined. However, painkillers vary widely in terms of both strength and potential for abuse. I therefore categorize the drugs into two classes, based on their risk for addiction and dependence:

1. Opioids: Pain relief drugs whose distribution is controlled by the US Drug Enforcement Administration (DEA) because they have potential for abuse and can lead to physical or psychological dependence. This class includes drugs such as codeine, fentanyl, hydrocodone, oxycodone, tramadol, and opioid combinations such as hydrocodone and acetaminophen.
2. Non-Opioid Painkillers: Pain relief drugs that must still be obtained via a prescription but are not controlled by the DEA because they have no known potential for abuse. These are mostly prescription-strength NSAIDs, such as Aspirin and Ibuprofen, and Acetaminophen.[14]

Table 3 provides additional details about the composition of each class.[15] In addition to analyzing these three broad classes of painkillers (all painkillers, opioids, and non-opioid painkillers), I separately assess the opioids category by:

1. High-dose vs. low-dose opioids: I define high-dose opioids as prescriptions that contain greater than 90 morphine milligram equivalents (MME) per day. In the MEPS, the mean (median) MME per day for an opioid prescription is 43 (30). I obtain information on MME from the CDC website (National Center for Injury Prevention and Control, 2017). I also examine total MME consumption as a continuous outcome variable.
2. Extended-release vs immediate-release opioids. Extended-release formulations, such as Oxycontin, are designed to release slowly into the bloodstream and have the advantage of being taken at less frequent intervals than their immediate-release counterparts.

In supplementary analysis, I also analyze changes in the consumption of the most commonly used opioids by the elderly during 2000-09: hydrocodone, propoxyphene, oxycodone, tramadol, codeine, morphine, fentanyl, and methadone. Such analysis is useful because even

[14] Although NSAIDs have no known potential for addiction, they are not without risk. Side-effects of prolonged NSAID use include liver damage and GI bleeding. Nevertheless, most studies find that opioids represent a substantially higher risk of death and adverse events than NSAIDs (Solomon, Rassen, & Glynn, 2010).

[15] Table 3 provides an abridged version of the painkiller classification. See Appendix Table A- 2 for the complete classification.

within the opioids class, different drugs may pose different public health risks. For example, the drugs most often involved in prescription opioid overdose deaths are oxycodone, hydrocodone, and methadone. The most frequently diverted drugs are oxycodone and hydrocodone.

4 Impact of Price Changes on Prescription Painkiller Utilization

4.1 Empirical Methods

The empirical objective of this study is to estimate the effect of OOP drug prices on utilization of prescription painkillers. A naïve approach to this question might examine the cross-sectional relationship between observed drug prices and purchases. However, even with a rich set of control variables, this approach would not identify the causal effect of price on utilization because of the likely presence of latent confounds; it is not possible to calculate an unbiased estimate unless we know whether price changes are due to a supply shock or a demand shock. A reasonable alternative method may be to use prescription drug coverage as an instrument for price, as there is substantial empirical evidence to show that obtaining drug insurance lowers the OOP price of drugs. However, simply comparing drug uninsured with drug insured individuals would not yield an unbiased causal estimate because of selection: people who are in worse health are more likely to enroll in generous insurance plans as well as consume more drugs; this would bias the estimate upwards.

In order to overcome this endogeneity, I propose a difference-in-differences (DD) estimation strategy that exploits the introduction of Medicare Part D[16] in January 2006 as an exogenous change in OOP drug prices for a treatment group of Medicare enrollees.[17] Part D provided publicly subsidized prescription drug coverage to Medicare eligibles and reduced the fraction of drug-uninsured elderly from 26 percent to 8 percent in its first year (Appendix Figure A- 3). Thus, the policy represented a sharp decrease in OOP drug prices for many people over the age of 65 who previously lacked drug coverage, while it was less likely to affect prices for

[16] See Appendix A4 for additional background on Medicare Part D.

[17] Other researchers have used the RAND Health Insurance Experiment (HIE) to estimate the price elasticity of demand for health care overall (Willard G Manning, Newhouse, Duan, Keeler, & Leibowitz, 1987). While the HIE is useful in identifying the effects of cost sharing for most medical services, plan design did not differ independently for drug coverage, making it difficult to isolate the impact of drug price changes. Moreover, the HIE data is from the 1980s, whereas prescription painkillers became more popular in the late 1990s; consumer preferences for painkillers were likely very different in the 1980s than in more recent years.

younger people who were ineligible for the policy.[18] In contrast to insurance plans that individuals select and fully pay for themselves, Part D plans were available at highly subsidized rates to all Medicare-eligible adults and are therefore less likely to correlate with other factors that affect the demand for drugs. Part D has been used extensively to study causal effects of prescription drug coverage (Basu, Yin, & Alexander, 2010; Duggan & Scott Morton, 2010, 2011; Engelhardt & Gruber, 2011; Ketcham & Simon, 2008; Lichtenberg & Sun, 2007; Yin et al., 2008).[19]

I estimate difference-in-differences (DD) models, comparing utilization among a treatment group that was affected by Part D (those aged 65 to 74, N=22,265) with those who were not affected (those aged 55 to 64 and not on Medicare, N=28,314),[20] before and after the introduction of the policy in January 2006. The use of the near-elderly control group helps separate Part D's effects from other secular factors that may have changed at the same time (e.g., drugs going off patent). Specifically, I treat the MEPS data as a series of repeated cross sections and estimate the following baseline model for each utilization outcome described in Section 3:

$$Y_i = \alpha + \beta(Treatment_i \times Post_i) + \gamma X_i + \sum \eta_j Age_i + \vartheta_i + \varepsilon_i$$

Equation 2

where Y_i represents the number of days supplied of a drug for individual i, $Treatment_i$ is an indicator equal to one if the individual belongs to the treatment group, $Post_i$ is an indicator equal to one for observations following January 2006, X_i is a vector of demographic control variables (sex, marital status, household income, educational attainment, race/ethnicity, and region), Age_i is a vector of age-fixed effects, ϑ_i is an indicator variable for each year, and ε_i is

[18] Although 74 percent of the elderly had prescription drug coverage even before 2006, this coverage was often less than adequate. We may expect drug utilization to increase even for those who had coverage before 2006 if Par D coverage was more generous than previous drug plans, e.g. offered lower cost-sharing, fewer restrictions such as prior authorization, or more medications covered in formularies.

[19] While Part D is an older policy, it is still a topic of discussion in the current literature because provides a valuable context for studying the causal effects of increased pharmaceutical access (Bradford & Bradford, 2016; Buchmueller & Carey, 2017; Carey, 2017; Dunn & Shapiro, 2017; Huh & Reif, 2016; Kaplan & Zhang, 2017; Powell et al., 2017). The purpose of the current analysis is not to evaluate the impact of Part D as a policy, but rather to understand more generally how utilization of prescription painkillers responds to prices; Part D merely serves an identification strategy.

[20] While this classification of treatment and control groups works in the MEPS, the NHCP is a household-level dataset, and households can consist of individuals of differing ages. Nevertheless, the NHCP provides detailed ages of each household member, so I define the treatment group as households with at least one member aged 65-74, and the control group as households with all members <65.

an idiosyncratic error term. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS. The DD coefficient of interest β represents the change in drug utilization for elderly individuals following the introduction of Part D, relative to the change for near-elderly individuals.

I use Equation 2 to estimate the effect of Part D on utilization outcomes, but not on OOP price outcomes. This is because OOP prices in MEPS are observed only for individuals who actually buy the drugs, and changes in observed OOP prices may be driven by three phenomena: 1) list prices of drugs decreased after Part D due to insurers' increased bargaining power (Duggan & Scott Morton, 2010); 2) expanded drug coverage reduced OOP price faced by consumers; and 3) consumers likely responded to increased drug coverage by substituting to more expensive drugs which would seemingly increase the average OOP prices observed in the data. Equation 2 would capture both the static effect of declining list and OOP prices (holding constant the pre-Part D mix of drugs), as well as the dynamic effect of elderly individuals shifting consumption to more expensive drugs in response to increased drug coverage. However, the denominator of Equation 1 should ideally represent only the static effect. I isolate the static effect by identifying the pre-Part D "basket" of painkillers purchased by the elderly and the near-elderly pre-Part D and using a different DD model to estimate Part D's effect on changes in OOP price for this fixed basket of drugs.

For this analysis, I create an NDC-treatment group-year dataset. I first calculate the number of days supplied of each NDC in the year 2003 separately for the treatment group and the control group (adjusting for MEPS survey weights).[21] Appendix Table A- 3 presents the composition of the 2003 basket of pain relief drugs for each group. I then calculate the average OOP price per day supplied for each NDC-treatment group-year observation (adjusting for MEPS survey weights). Next, I estimate the following equation:

$$Y_{dgt} = \alpha + \beta\left(Treatment_g \times Post_t\right) + \mu\left(Treatment_g\right) + \vartheta_t + \varepsilon_{dgt}$$

Equation 3

[21] Part D was signed into law at the end of 2003. The year 2003 is therefore unlikely to be biased by possible anticipation effects (Alpert, 2016).

where Y_{dgt} represents the out-of-pocket price per day supplied of NDC *d* purchased by treatment group *g* in the year *t* and other variables are defined as in Equation 2. Importantly, the regressions are weighted by the 2003 level of utilization. The DD coefficient of interest β represents the change in OOP price for elderly individuals following the introduction of Part D, compared to the change for near-elderly individuals. A similar approach was used for estimating drug elasticities in previous studies (Chandra, Gruber, & McKnight, 2010; Contoyannis, Hurley, Grootendorst, Jeon, & Tamblyn, 2005; Landsman, Yu, Liu, Teutsch, & Berger, 2005)

4.2 Caveats

There are four primary concerns with this identification strategy. First, Part D simultaneously changed seniors' OOP prices for all drugs. To the extent that consumers consider opioids and non-opioid painkillers substitutes, my elasticity estimates may be biased downward. (If there were to be a reduction in the OOP price of opioids only and no change in the OOP price of non-opioid painkillers, we would expect a larger utilization response than in the case where OOP prices of both classes reduced simultaneously. My elasticity estimates can therefore be interpreted as a lower bound.) This is a common issue in existing studies that estimate drug-specific elasticities, since policy-induced price variation is usually not drug-specific (Chandra et al., 2010; Einav et al., 2018; Goldman et al., 2004).

Second, Medicare Part D was signed into law in late 2003 but not implemented until January 2006. Elderly individuals in 2004-05 may have delayed drug purchases in anticipation of gaining Part D coverage in 2006 (Alpert, 2016). Alternatively, in post-Part D years, those who are near the age of 65 may delay drug purchases until they gain Part D coverage after age 65. This possibility, if it exists, would bias my estimates downward and may increase the likelihood of Type II error. I account for this possibility by estimating a set of DD models in which I split the "post" period into two time periods: 2004-05 and 2006-09. I also estimate specifications of Equation 2 that omit the years 2004 and 2005 from analysis and omit 63- and 64-year-olds from the sample.

Perhaps Part D influenced opioid purchases through non-price mechanisms, e.g. if the policy increased pharmaceutical advertising and detailing in a way that made elderly individuals

more likely to seek out opioids and instigated physicians to prescribe more opioids. While this is theoretically plausible, empirical studies have found limited evidence that Part D influenced advertising of opioids. An analysis of the effects of direct-to-consumer advertising found that although Part D increased pharmaceutical advertising, opioids are among the top 10 *non*-advertised drug classes for older adults (Alpert, Lakdawalla, & Sood, 2015). Moreover, the authors find little evidence that Part D caused changes in physician detailing.

Finally, my sample includes only those aged 55 to 74, so there may be concerns about extending my conclusions about price sensitivity to those outside this age group. In spite of these concerns about external validity, the elderly are an important group to study because they are the largest users of prescription opioids. The majority of prescription opioid growth over the past 15 years came from those aged 65 and older (100 percent increase in prescription opioid utilization over this time period) and those aged 45 to 64 (71 percent increase in utilization). Conversely, adults aged 18 to 44 and children younger than 18 saw only marginal changes in their prescription opioid utilization (Panel B of Figure 1). Moreover, Medicare is the largest payer of opioid pain relievers, covering 20 to 30 percent of opioid spending since 2006 (Zhou, Florence, & Dowell, 2015), another indication that it is important for federal policymakers to understand how this population responds to price stimuli.

4.3 Baseline Results

Table 4 displays both pre-2006 means for the treatment group and DD estimates from Equation 2 and Equation 3 for the impact of Part D on painkiller utilization (Columns 1-3) and OOP price (Columns 4-6). Column 5 displays the implied elasticity estimate (calculated using the results from the first six columns). The first row of Table 4 shows that Part D led to a 4.3 increase in the number of days supplied of all prescription painkillers ($p<0.10$), which represents an 11 percent increase compared to pre-2006 levels. Part D also led to a $0.51 decrease in the OOP price per day supplied of all prescription painkillers ($p<0.01$), which represents a 38 percent decline from pre-2006. The implied elasticity is therefore -0.29 (calculated by dividing 11 percent by -38 percent). This result suggests that the demand for prescription painkillers is downward sloping and slightly inelastic; a 10 percent decrease in price would lead to a 2.9 percent decrease in quantity demanded.

However, when I stratify the painkillers into opioids and non-opioids, I find that the elasticities vary widely. While there is no detectable effect of OOP prices on the demand for non-opioid painkillers, the demand for opioids is more elastic (ε=-0.89). Subsequent panels of Table 4 show that the majority of the increase in opioids purchases came from low-dose opioids and extended-release opioids. It is also interesting to note that Part D led to a large increase of 74 percent in the total MMEs consumed. Most of the increase in opioid utilization came from hydrocodone and morphine (Appendix Table A- 5).

4.4 Parallel Trends Tests

The key identifying assumption of the DD model is that in the absence of Part D, both groups would have trended similarly. One way to evaluate the plausibility of this assumption is to compare descriptive statistics from the two groups. Table 1 reports statistics for MEPS respondents in the treatment and control groups just prior to Part D's implementation. Individuals in the treatment group are significantly less likely to be married (plausibly because people in the treatment group are older and more likely to be widowed), less educated, and have lower household income (likely because more people in the treatment group are retired) than those in the control group. However, the treatment and control group do not differ substantially in gender composition, race/ethnicity, and region of residence.

More important than comparing descriptive statistics is to assess whether the two groups exhibit comparable pre-2006 trends in their OOP painkiller prices and utilization. Figure 4 presents the average OOP drug prices for each NDC over time, weighted by the 2003 level of utilization. Figure 4 shows that prior to the introduction of Part D, OOP prices for the treatment and control group followed similar trends. After 2006, both groups experienced declines in OOP prices, but the decline for the treatment group was much larger in magnitude than the reduction experienced by the control group. The fact that prices for the two age groups trended similarly before 2006 increases our confidence that they would have trended similarly after 2006, were it not for the introduction of Part D.

Similarly, Figure 5 presents the utilization for each class of painkillers over time, separately for the treatment and control group. Again, purchases of painkillers appear to trend fairly closely for the older and younger groups in the years before Part D. There was a sizeable

reduction in non-opioid painkiller utilization for both groups in 2004-05; this decrease can be attributed to the removal of certain widely used Cox-II inhibitors (e.g. Vioxx, Bextra, etc) from the market in late 2004 and early 2005. After the implementation of Part D in 2006, there was a large increase for the treatment group, while the control group's utilization remained constant or trended upward more gradually.

To formalize the relationship illustrated in Figure 4 and Figure 5, I estimate a specification of Equation 2 that replaces the $Treatment_i \times Post_i$ term with a series of interaction terms between the treatment group indicator and an indicator for each year. I omit the year 2005 as the reference year. Specifically, I estimate the following equation:

$$Y_i = \alpha + \sum \beta_j \left(Treatment_i \times Year_i\right) + \gamma X_i + \sum \eta_j Age_i + \vartheta_i + \varepsilon_i$$

Equation 4

where $Treatment_i \times Year_i$ represents the interaction between the treatment indicator and the year indicator for each year except 2005. All other variables are defined as in Equation 2. Table 5 presents the coefficient estimates of the β_j terms for the utilization and OOP price outcomes for all painkillers, opioids, and non-opioid painkillers. For all the main outcomes presented in Table 5, the pre-2006 β_j terms are statistically indistinguishable from 0. I also conduct an F test of whether the point estimates for all the pre-2006 β_j terms are jointly different from zero. For all outcomes, I cannot reject the null hypothesis at a p-value of 0.10. Appendix Table A- 6 presents results for the remaining outcomes. Of the 10 outcomes presented in Appendix Table A- 6, I reject the null hypothesis of parallel trends for only one outcome – utilization of extended-release opioids. Together, the evidence suggests that the near-elderly control group services as a reasonable comparison group for the utilization responses of the elderly treatment group.

Table 5 also shows that the larger utilization effects came in 2007 and later. This finding is consistent with previous studies that find substantial impacts of Part D on utilization only after the second half of 2006 (Yin et al., 2008). This is likely because enrollment of seniors into Part D was gradual during the first half of 2006; earlier Part D enrollees were sicker and less likely to respond immediately to price changes.

4.5 Heterogeneity Tests

In Table 6, I use respondents' reported conditions to assess the effects of Part D on prescription painkiller utilization for subpopulations that are of interest to policymakers. In the first panel, I stratify the sample into individuals who have cancer and those who do not. Opioids are widely accepted as legitimate pain treatment for cancer patients (Centers for Disease Control and Prevention, 2016). I find that the OOP price reductions associated with Part D led to a 45 percent increase in opioid utilization for people with cancer and 49 percent increase for those without cancer. Part D led to a 37 percent increase in opioid utilization for those with joint or back pain and had no detectable effect for those without joint or back pain. Finally, I stratify the sample by whether respondents had medical or non-medical substance poisoning. I find that those who had a poisoning event did not experience any significant change in painkiller utilization after Part D, whereas those who did not have a poisoning event increased opioid utilization by 52 percent when OOP prices dropped.

4.6 Sensitivity Analyses and Robustness Checks

Despite the parallel trend test regarding the comparability of individuals in the elderly and near-elderly groups, there may be lingering concerns about the parallel trends assumption. To provide additional confidence in the causal interpretation of β, I conduct falsification tests which estimate a series of models similar to Equation 2, but define $Treatment_g$ as different 10-year age groups whose eligibility for drug coverage was unaffected by Medicare Part D: non-disabled individuals aged 45-54, 35-44, 25-34, and 18-24. I expect to find no effect of Part D on prices and utilization for these "false" treatment groups relative to the control group of those aged 55-64. If I do find significant effects, it would imply that the model is biased due to violations in the parallel trends assumption. Failure to find significant effects will provide additional confidence in the approach. Results for these falsification tests are presented in Appendix Table A- 7. Of the 12 falsification tests, I reject the null hypothesis at a significance level of 0.10 for only one outcome – utilization of opioids for the false treatment group consisting of individuals aged 18-24. However, the coefficient is in the opposite direction as expected, i.e. utilization of opioids for those aged 18-24 decreased relative to the 55-64 group.

Appendix Table A- 8 displays results from a specification in which I split the post period into two periods to study potential anticipation effects from the announcement of Part D in late 2003. For all painkillers, there was a marginally significant increase in utilization even during 2004-05 ($p<0.10$). However, this rise was smaller in magnitude than the 2006-09 increase. For opioid painkillers, the increased utilization happened only in 2006-09; for non-opioid painkillers, there was no detectable effect in either time period. Results in the second and third column of Appendix Table A- 9 provide additional confidence in the finding that potential anticipatory effects do not bias my results. The second column displays results from a specification of Equation 2 that omits the years 2004 and 2005 from analysis, and the third column displays results from a specification that omits 63- and 64-year-olds from the sample. In both cases, the results are very similar to the baseline estimates.

Next, I expose Equation 2 to a number of sensitivity analyses. Appendix Table A- 9 presents these results. In the first column of Panel A, I omit the demographic control variables from the right hand side. In column 2, I omit the years 2004-05 from analysis. Column 3 omits respondents aged 63-64 from the control group. In the fourth column, I use an alternative definition of "treatment" in which I omit younger Medicare recipients (rather than include them in the treatment group). In column 5, I include a vector of interaction terms for the treatment group indicator with an indicator for each year on the right hand side. The sixth column includes a right-hand side variable that controls for the respondent's health status (measured by their total medical expenses in the year). In the seventh column, I include both treatment X year fixed effects and control for respondent's health status; this is to account for the fact that older individuals are in worse health than younger ones. Panel B presents results in which I include additional years of MEPS data in the analysis. All of these sensitivity analyses yield results that are remarkably similar to those presented in the baseline model.

In Appendix Table A- 10, I conduct another sensitivity analysis in which I change the units of my outcome to "number of prescriptions" of the drug rather than "number of days supplied." I do this because my original outcome variables involved an imputation to convert prescriptions into days supplied. Although the magnitudes of the estimates are expectedly different because of the different unit used, qualitatively the outcomes are very similar to the original specification.

My baseline analysis studies the aggregate effects of Part D on painkiller utilization. The DD estimate captures the direct effect experienced by those who were previously drug uninsured and gained prescription drug coverage through Part D, as well as substitution effects for those who switched from private drug insurance to Part D once the publicly subsidized option became available. While many studies in the Part D literature use this DD approach to study aggregate effects, it is important to note that 74 percent of the elderly had drug coverage even before the introduction of Part D. Thus, the DD estimate may underestimate the true effect of gaining new drug coverage. To provide suggestive evidence, I hone in on income groups that were particularly likely to gain new coverage to Part D and find that the largest effects on utilization came from middle-income individuals with household income between 125 and 400 percent of the poverty level (Appendix Table A- 11). This is consistent with previous studies that find that middle-income individuals were more likely to gain drug coverage after 2006, since low-income elderly people likely had drug coverage through Medicare and high-income people likely had coverage through employer insurance (Levy & Weir, 2009).

My sample includes people who are aged 55 to 74 (i.e. plus and minus 10 years from the age 65 cutoff). In Appendix Table A- 12, I assess whether my results are sensitive to the selection of age groups included. I do this by first estimating Equation 2 for a sample with only people aged 50 to 79 (with people below 65 defined as the control group and people 65 and over defined as the treatment group). I then restrict my sample to people aged 51 to 78, then 52 to 77, and so on until I reach people aged 60 to 69. For each sample, I obtain results that are remarkably similar to my original set of results that use people aged 55 to 74. This suggests that the results are not sensitive to the selection of age groups included in the sample.

5 Elasticity Estimates for New vs. Existing Users

The results discussed above provide evidence of a relationship between OOP prices and utilization of opioids. However, these multi-year estimates do not fully exploit the panel nature of the MEPS data. Panel 10 is the only panel of the MEPS that contains observations of the same individuals both before and after the introduction of Part D (years 2005 and 2006). These data allow for the use of individual fixed effects to control for time invariant differences across individuals that may influence their response to Part D. Moreover, this analysis using a single

panel of the MEPS allows me to assess whether price-sensitivity differs for new versus existing users. I define new users as those who did not purchase any drug in the relevant category in the year 2005 prior to the implementation of Part D. I define existing users as those who purchased a drug in the relevant category at least one time in the year 2005. I estimate the following fixed effects equation first for Panel 10 pooled, then stratified by new and existing users:

$$Y_{it} = \alpha + \beta(Treatment_i \times Post_t) + \sum \eta_j Age_{it} + \gamma_i + \vartheta_t + \varepsilon_{it}$$

Equation 5

where γ_i is an individual-level fixed effects, ϑ_t is an indicator variable for each interview round (each respondent is interviewed a total of 5 times during the two-year period), and all other variables are defined as in Equation 2. Standard errors are clustered at the individual level. The coefficient of interest, β, is the estimated impact of Part D within each individual. This estimate is driven by the change in drug utilization for an elderly MEPS respondent compared to the change for similar non-elderly respondents, before and after the implementation of Part D in 2006.

There are two key differences with this analysis, compared to that presented in Section 4. First, new users by definition are those that had a pre-2006 utilization of 0, so I cannot calculate percent changes or elasticities for the new users. Moreover, I cannot observe OOP prices for new users because the MEPS only provides prices for respondents who actually purchased the drug. To ensure that new and existing users both actually experienced OOP price declines after Part D, I estimate a specification of Equation 5 in which the outcome variable is the OOP price per *prescription* of *all drugs* (not just painkillers). The finding that new and existing users experienced similar OOP price declines for non-painkillers will increase confidence that they would have experienced similar OOP price declines for painkillers, had I been able to observe them.

Table 7 provides estimates from Panel 10. To compare to the baseline results presented in Table 4, pre-2006 means and coefficients should be multiplied by 2.5 (i.e. the number of rounds per year). For comparison purposes, the first panel reports estimates of Equation 2 using only Panel 10 data. The point estimates (multiplied by 2.5) are similar to earlier estimates in sign and magnitude. However, I find a large gap between new and existing users in their response to Part

D. The second panel reports shows that new users experienced a 17 percent reduction in OOP prices and increased their utilization of opioids by 1.79 days supplied per year and non-opioid painkillers by 2.48 painkillers per year. The third panel shows results for existing users. While existing users experienced a statistically significant 21 percent decline in OOP prices, there was no detectable change in their opioid or non-opioid painkiller utilization. These results suggest that it was only the new users who were responsive to Part D's price changes.

6 Cross-Price Elasticity Estimates for Over-the-Counter Painkillers with Respect to Prescription Painkiller Prices

Part D presents a useful opportunity to study the degree of substitutability between prescription and OTC painkillers. I first estimate the impact of Part D on utilization of OTC painkillers using the NHCP data and DD models described in Equation 2.[22] My outcome variable of interest is the household's total days supplied per year of OTC painkillers, such as Ibuprofen, Naproxen, and Aspirin. I also include household fixed effects on the right hand side to exploit the panel structure of the NHCP. To calculate cross-price elasticities of demand, I divide the estimated percent change of OTC quantity by the percent change of OOP prescription prices from Table 4.

Table 8 displays the estimated effects of Part D on quantity of OTC painkillers purchased and resulting cross-price elasticities of OTC painkillers with respect to the price of prescription painkillers. I find that Part D led to a 4.3 percent decline in days supplied of OTC painkillers. This implies a positive and statistically significant cross-price elasticity ($\varepsilon = 0.11$), which suggests that consumers view prescriptions and OTC painkillers as substitutes.

I estimate event study models (Appendix Table A- 16) and sensitivity analyses similar to those described in Section 4. In Appendix Table A- 17, I present results from sensitivity analyses in which I exclude the demographic control variables, estimate models without Nielsen survey

[22] I also confirm that Part D did not change prices of OTC drugs for elderly households relative to younger households. Because Part D plans do not cover OTC drugs, the estimated treatment effect of the policy on OTC drug price should theoretically be close to zero and statistically insignificant. Appendix Table A- 15 confirms that Part D led to no detectable change on OTC prices.

weights, omit household fixed effects, and use as my outcome variable an indicator variable for "any OTC purchase." The substantive results are mostly robust to these sensitivity analyses.

7 Discussion

My results help inform the designing of new opioid policies that act through price mechanisms. I find consistent evidence that opioid utilization responds to price stimuli, with a price elasticity of -0.9. Price changes affect the utilization of opioid-naïve individuals, but not of existing opioids users. Moreover, the results for cross-price effects provide evidence of substitution between prescription and OTC painkillers. These findings suggest that opioid-naïve people may be highly responsive to opioid prices and that they likely have substitutes that they are willing to use in place of opioids. Therefore, increasing the OOP price of opioids, through measures such as taxes and formulary design, may be effective in reducing the flow of new opioid use. For example, assuming a policy increases the OOP price of opioids by 10 percent, the per-person opioid consumption would decrease by 9 percent. (This could be understated if demand shifts to the left. Moreover, demand is typically more elastic at higher prices, so as policies increase OOP prices, elasticity may increase.[23]) However, price-based policies will not significantly change utilization among existing users, and so alternative policies are needed to reduce the stock of existing addicts.

In the context of the existing literature, my elasticity result for opioids appears relatively large. Other papers that exploit the introduction of Part D find elasticity estimates for prescription drugs overall ranging from -0.2 to -0.5 (Duggan & Scott Morton, 2010; Ketcham & Simon, 2008; Liu et al., 2011; Yin et al., 2008). Papers that exploit discontinuities in the cost-sharing structure of insurance plans as their empirical design, as opposed to the introduction of Part D, find elasticity estimates that are even more inelastic, ranging from -0.04 to -0.3 (Chandra et al., 2010; Coulson & Stuart, 1995; Einav et al., 2018; Hillman et al., 1999; Joyce et al., 2002). However, this discrepancy is likely because my analysis estimates the elasticity of a specific class of drugs, whereas much of the earlier literature estimates the elasticity for prescription

[23] Previous studies suggest that the form of the policy matters. Consumers underreact to price changes that are not salient (Chetty, Looney, & Kroft, 2009).

drugs overall. Studies show that the impact of prices on drug utilization depends on the therapeutic class of the drug (Goldman et al., 2004), so there is reason to believe that these earlier findings on prescription drugs overall may not apply to pain relief drugs.

Among the few existing studies that identify elasticities separately by drug class, one uses Part D data to study the impact of entering the donut hole on utilization of 150 different types of drugs; for opioids, the authors estimate an elasticity of only -0.04 (Einav et al., 2018). My elasticity estimate for opioids (-0.89) is very different from that of Einav et al. However, this is likely because my paper uses a different identification strategy and answers a different question. Einav et al. exploits within-year price variation around the donut hole, so the sample by definition is limited to people who have spent up to the donut hole (i.e. those who are sicker and therefore have likely used prescription painkillers in the past).[24] Behavioral responses are likely to differ for consumers with different levels of annual drug spending. Moreover, Einav et al.'s aim is to estimate a short-run elasticity of demand with respect to an end-of-the-year increase in the spot price of a drug, and their elasticity estimates are local to the variation used. In the paper, the authors caution that the ordinal ranking of their 150 drug elasticities is more important than the cardinal value of these elasticities.

Another explanation for the high elasticities I estimate is that people view prescription painkillers as substitutes for OTC drugs, at least to some extent. This would mean that people who were previously using more OTC drugs to treat their pain substitute to opioids and other prescription painkillers, once their OOP prescription prices drop. Indeed, my analysis of the impact of Part D on OTC purchases shows that cross-price elasticity estimates between prescription and OTC painkillers are significantly positive (elasticity = 0.11).

I acknowledge the limitations of this work. The estimates in this paper are picking up uncompensated responses that are a mix of the price effects, substitution effects, income effects, and information effects of Part D. It is not possible to disentangle these effects with a reduced form model. Nevertheless, my findings provide important evidence that prescription opioids are have a relatively high price elasticity compared to other drugs. This implies that people are

[24] Einav et al. reports that the average Medicare Part D enrollee spends $1,910 on drugs per year, but the spending level to enter the donut hole (i.e. the Einav et al. study sample) is $2,250 to $2,840, which is around the 75th percentile of the expenditure distribution.

sensitive to the price of opioids and that they likely have close substitutes that they are willing to trade off. As such, policies to increase the OOP price of opioids would likely reduce the flow of new opioid use, and the welfare losses associated with such restrictions would likely be small.

References

Agency for Healthcare Research and Quality. (2015). Medical Expenditure Panel Survey - Household Component. Retrieved from https://meps.ahrq.gov/mepsweb/survey_comp/household.jsp

Alpert, A. (2016). The anticipatory effects of Medicare Part D on drug utilization. *Journal of Health Economics*, *49*, 28–45.

Alpert, A., Lakdawalla, D., & Sood, N. (2015). *Prescription Drug Advertising and Drug Utilization: The Role of Medicare Part D* (NBER Working Paper Series No. 21714).

Bao, Y., Pan, Y., Taylor, A., Radakrishnan, S., Luo, F., Pincus, H. A., & Schackman, B. R. (2016). Prescription Drug Monitoring Programs Are Associated With Sustained Reductions In Opioid Prescribing By Physicians. *Health Affairs*, *35*(6), 1045–1051.

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

Becker, G. S., & Murphy, K. M. (1988). A Theory of Rational Addiction. *Journal of Political Economy*, *96*(4), 675–700.

Bradford, A. C., & Bradford, W. D. (2016). Medical Marijuana Laws Reduce Prescription Medication Use In Medicare Part D. *Health Affairs*, *35*(7), 1230–1236.

Buchmueller, T., & Carey, C. (2017). The Effect of Prescription Drug Monitoring Programs on Opioid Utilization in Medicare, *10*(1), 77–112.

Carey, C. (2017). Technological Change and Risk Adjustment: Benefit Design Incentives in Medicare Part D. *American Economic Journal: Economic Policy*, *9*(1), 38–73.

Carroll, A. (2016). The Science of Opioids. Retrieved January 15, 2018, from https://www.nihcm.org/categories/project_links/healthcare-triage-the-science-of-opioids

Case, A., & Deaton, A. (2015). Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century. *Proceedings of the National Academy of Sciences*, *112*(49), 15078–15083.

Cawley, J., & Ruhm, C. (2011). The Economics of Risky Health Behaviors. In A. J. Culyer & J. P. Newhouse (Eds.), *Handbook of Health Economics* (pp. 95–199). Elsevier.

Centers for Disease Control and Prevention. (2016). CDC Releases Guideline for Prescribing Opioids for Chronic Pain. Retrieved January 3, 2018, from https://www.cdc.gov/media/releases/2016/p0315-prescribing-opioids-guidelines.html

Chaloupka, F. J., Grossman, M., & Tauras, J. A. (1999). The Demand for Cocaine and Marijuana by Youth. In F. J. Chaloupka, M. Grossman, W. K. Bickel, & H. Saffer (Eds.), *The Economic Analysis of Substance Use and Abuse: An Integration of Econometrics and Behavioral Economic Research*. University of Chicago Press.

Chaloupka, F. J., & Wechsler, H. (1997). Price, tobacco control policies and smoking among young adults. *Journal of Health Economics*, *16*(3), 359–373.

Chandra, A., Gruber, J., & McKnight, R. (2010). Patient Cost-Sharing and Hospitalization Offsets in the Elderly. *American Economic Review*, *100*(1), 193–213.

Chang, A. K., Bijur, P. E., Esses, D., Barnaby, D. P., & Baer, J. (2017). Effect of a Single Dose of Oral Opioid and Nonopioid Analgesics on Acute Extremity Pain in the Emergency Department. *JAMA*, *318*(17), 1661.

Chetty, R., Looney, A., & Kroft, K. (2009). Salience and Taxation: Theory and Evidence. *American Economic Review*, *99*(4), 1145–1177.

Contoyannis, P., Hurley, J., Grootendorst, P., Jeon, S.-H., & Tamblyn, R. (2005). Estimating the price elasticity of expenditure for prescription drugs in the presence of non-linear price schedules: an illustration from Quebec, Canada. *Health Economics*, *14*(9), 909–923.

Coulson, N. E., & Stuart, B. C. (1995). Insurance Choice and the Demand for Prescription Drugs. *Southern Economic Journal*, *61*(4), 1146.

Council of Economic Advisers. (2017). *The Underestimated Cost of the Opioid Crisis*. Retrieved from https://www.whitehouse.gov/sites/whitehouse.gov/files/images/The Underestimated Cost of the Opioid Crisis.pdf

Dave, D. M., Grecu, A. M., & Saffer, H. (2017). *Mandatory Access Prescription Drug Monitoring Programs and Prescription Drug Abuse* (NBER Working Paper Series No. 23537). Retrieved from http://www.nber.org/papers/w23537

DeCicca, P., Kenkel, D., & Mathios, A. (2008). Cigarette taxes and the transition from youth to adult smoking: Smoking initiation, cessation, and participation. *Journal of Health Economics*, *27*(4), 904–917.

Duggan, M., Healy, P., & Scott Morton, F. (2008). Providing Prescription Drug Coverage to the Elderly: America's Experiment with Medicare Part D. *Journal of Economic Perspectives*, *22*(4), 69–92.

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

Duggan, M., & Scott Morton, F. (2011). The Medium-Term Impact of Medicare Part D on Pharmaceutical Prices. *American Economic Review*, *101*(3), 387–392.

Dunn, A., & Shapiro, A. H. (2017). Does Medicare Part D Save Lives? *American Journal of Health Economics*.

Einav, L., Finkelstein, A. N., & Polyakova, M. (2018). Private provision of Social Insurance: Drug-Specific Price Elasticities and Cost Sharing in Medicare Part D. In *American Economic Journal: Economic Policy*.

Engelhardt, G. V. (2011). *Prescription Drug Insurance Coverage, Drug Utilization, and Cost-Related Non-Adherence: Evidence from the Medicare Part D Expansion* (CRR Working Paper No. 2011–19).

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

Frean, M., Gruber, J. H., & Sommers, B. D. (2016). *Premium Subsidies, the Mandate, and*

Medicaid Expansion: Coverage Effects of the Affordable Care Act (NBER Working Paper No. 22213). Retrieved from http://www.nber.org/papers/w22213.pdf

Gallet, C. A., & List, J. A. (2003). Cigarette demand: a meta-analysis of elasticities. *Health Economics*, *12*(10), 821–835.

Gatwood, J., Gibson, T. B., Chernew, M. E., Farr, A. M., Vogtmann, E., & Fendrick, A. M. (2014). Price Elasticity and Medication Use: Cost Sharing Across Multiple Clinical Conditions. *Journal of Managed Care & Specialty Pharmacy*, *20*(11), 1102–1107.

Gaynor, M., Li, J., & Vogt, W. B. (2007). Substitution, Spending Offsets, and Prescription Drug Benefit Design. *Forum for Health Economics & Policy*, *10*(2).

Gilleskie, D. B., & Strumpf, K. S. (2005). The Behavioral Dynamics of Youth Smoking. *Journal of Human Resources*, *XL*(4), 822–866.

Gold, M. (2001). Medicare+Choice: An Interim Report Card. *Health Affairs*, *20*(4), 120–138.

Goldman, D. P., Joyce, G. F., Escarce, J. J., Pace, J. E., Solomon, M. D., Laouri, M., … Teutsch, S. M. (2004). Pharmacy Benefits and the Use of Drugs by the Chronically Ill. *JAMA*, *291*(19), 2344–2350.

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

Gruber, J. (2001). Youth Smoking in the 1990's: Why Did It Rise and What Are the Long-Run Implications? *American Economic Review*, *91*(2), 85–90.

Gruber, J., & Zinman, J. (2000). *Youth Smoking in the U.S.: Evidence and Implications* (NBER Working Paper Series No. 7780). Cambridge, MA. https://doi.org/10.3386/w7780

Hill, S. C., Roemer, M., & Stagnitti, M. N. (2014). *Outpatient Prescription Drugs: Data Collection and Editing in the 2011 Medical Expenditure Panel Survey. Methodology Report #29*. Rockville, MD. Retrieved from https://meps.ahrq.gov/data_files/publications/mr29/mr29.pdf

Hillman, A. L., Pauly, M. V, Escarce, J. J., Ripley, K., Gaynor, M., Clouse, J., & Ross, R. (1999). Financial incentives and drug spending in managed care. *LDI Issue Brief*, *4*(1), 1–4. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12523336

Huh, J., & Reif, J. (2016). *Did Medicare Part D Reduce Mortality?* (Working Paper).

Jones, C. M. (2013). Heroin use and heroin use risk behaviors among nonmedical users of prescription opioid pain relievers – United States, 2002–2004 and 2008–2010. *Drug and Alcohol Dependence*, *132*(1–2), 95–100.

Joyce, G. F., Escarce, J. J., Solomon, M. D., & Goldman, D. P. (2002). Employer Drug Benefit Plans and Spending on Prescription Drugs. *JAMA*, *288*(14), 1733–1739.

Kaestner, R., & Khan, N. (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.

Kaiser Family Foundation. (2016). The Medicare Part D Prescription Drug Benefit. Retrieved

September 12, 2017, from http://www.kff.org/medicare/fact-sheet/the-medicare-prescription-drug-benefit-fact-sheet/

Kaplan, C. M., & Zhang, Y. (2017). Anticipatory Behavior in Response to Medicare Part D's Coverage Gap. *Health Economics*, *26*(3), 338–351.

Ketcham, J. D., & Simon, K. (2008). Medicare Part D's Effects on Elderly Drug Costs and Utilization. *American Journal of Managed Care*, *14*(11).

Landsman, P. B., Yu, W., Liu, X. F., Teutsch, S. M., & Berger, M. L. (2005). Impact of 3-tier pharmacy benefit design and increased consumer cost-sharing on drug utilization. *American Journal of Managed Care*, *11*(10), 621–628.

Lee, J. S.-J., Hu, H. M., Edelman, A. L., Brummett, C. M., Englesbe, M. J., Waljee, J. F., … Dossett, L. A. (2017). New Persistent Opioid Use Among Patients With Cancer After Curative-Intent Surgery. *Journal of Clinical Oncology*, *35*(36), 4042–4049.

Leibowitz, A. (1989). Substitution between Prescribed and Over-the-Counter Medications. *Medical Care*, *27*(1), 85–94.

Levy, H., & Weir, D. R. (2009). Take-up of Medicare Part D: Results From the Health and Retirement Study. *Journal of Gerontology: Social Sciences*, *65B*(4), 492–501.

Lewit, E. M., Coate, D., & Grossman, M. (1981). The Effects of Government Regulation on Teenage Smoking. *The Journal of Law and Economics*, *24*(3), 545–569.

Lichtenberg, F. R., & Sun, S. X. (2007). The Impact Of Medicare Part D On Prescription Drug Use By The Elderly. *Health Affairs*, *26*(6), 1735–1744.

Liu, F. X., Alexander, G. C., Crawford, S. Y., Pickard, A. S., Hedeker, D., & Walton, S. M. (2011). The Impact of Medicare Part D on Out-of-Pocket Costs for Prescription Drugs, Medication Utilization, Health Resource Utilization, and Preference-Based Health Utility. *Health Services Research*, *46*(4), 1104–1123.

Manning, W. G., Blumberg, L., & Moulton, L. H. (1995). The demand for alcohol: the differential response to price. *Journal of Health Economics*, *14*(2), 123–48. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/10154654

Manning, W. G., Newhouse, J. P., Duan, N., Keeler, E. B., & Leibowitz, A. (1987). Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment. *American Economic Review*, *77*(3), 251–277.

National Center for Injury Prevention and Control. (2017). *CDC compilation of benzodiazepines, muscle relaxants, stimulants, zolpidem, and opioid analgesics with oral morphine milligram equivalent conversion factors, 2017 version*. Atlanta, GA. Retrieved from https://www.cdc.gov/drugoverdose/resources/data.html

National Governors Association. (2013, July 13). A Compact to Fight Opioid Addiction. Retrieved from https://www.nga.org/cms/news/2016/opioid-compact

Nielsen. (2015). Nielsen Consumer Panel Data. Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. Retrieved from https://research.chicagobooth.edu/nielsen/datasets

O'Brien, B. (1989). The effect of patient charges on the utilisation of prescription medicines. *Journal of Health Economics*, *8*(1), 109–32. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/10293367

Patrick, S. W., Fry, C. E., Jones, T. F., & Buntin, M. B. (2016). Implementation Of Prescription Drug Monitoring Programs Associated With Reductions In Opioid-Related Death Rates. *Health Affairs*, *35*(7), 1324–1332.

Pellitt, S. (2017, November 9). National Council Joins Commitment to Improve Access and Quality of Addiction Treatment. *National Council for Behavioral Health*. Retrieved from https://www.thenationalcouncil.org/capitol-connector/2017/11/national-council-joins-commitment-improve-access-quality-addiction-treatment/

Porter, J., & Jick, H. (1980). Addiction Rare in Patients Treated with Narcotics. *New England Journal of Medicine*, *302*(2), 123. Retrieved from https://www.nejm.org/doi/pdf/10.1056/NEJM198001103020221

Potter, G., & Mulvihill, K. (2018, April 28). At least 15 states are pushing for laws to tax opioids. Drugmakers are pushing back. *Associated Press*. Retrieved from http://www.chicagotribune.com/news/nationworld/ct-opioid-crisis-tax-battle-20180428-story.html

Powell, D., Pacula, R. L., & Taylor, E. A. (2017). *How Increasing Medical Access to Opioids Contributes to the Opioid Epidemic: Evidence from Medicare Part D* (Working Paper).

Purves, D., Augustine, G. J., Fitzpatrick, D., Hall, W. C., LaMantia, A.-S., McNamara, J. O., & Williams, S. M. (Eds.). (2004). *Neuroscience* (3rd ed.). Sunderland, MA: Sinauer Associates.

Qato, D. M., Wilder, J., Schumm, L. P., Gillet, V., & Alexander, G. C. (2016). Changes in Prescription and Over-The-Counter Medication and Dietary Supplement Use Among Older Adults in the United States, 2005-2011. *JAMA Intern Med*, *60612*(4), 473–482.

Quinones, S. (2015). *Dreamland: The True Tale of America's Opiate Epidemic*. New York, NY: Bloomsbury Press.

Radakrishnan, S. (2014). *The impact of information in health care markets: prescription drug monitoring programs and abuse of opioid pain relievers* (Working Paper).

Saffer, H., & Chaloupka, F. (1999). The Demand for Illicit Drugs. *Economic Inquiry*, *37*(3), 401–411.

Shah, A., Hayes, C. J., & Martin, B. C. (2017). Characteristics of Initial Prescription Episodes and Likelihood of Long-Term Opioid Use — United States, 2006–2015. *MMWR. Morbidity and Mortality Weekly Report*, *66*(10), 265–269.

Solomon, D. H., Rassen, J. A., & Glynn, R. J. (2010). The Comparative Safety of Analgesics in Older Adults With Arthritis. *Archives of Internal Medicine*, *170*(22), 1968–76.

Stuart, B. C., & Grana, J. (1995). Are Prescribed and Over-the-Counter Medicines Economic Substitutes? A Study of the Effects of Health Insurance on Medicine Choices by the Elderly. *Medical Care*, *33*(5), 487–501.

Temple, J. (2015). *American Pain*. Guilford, CT: Lyons Press.

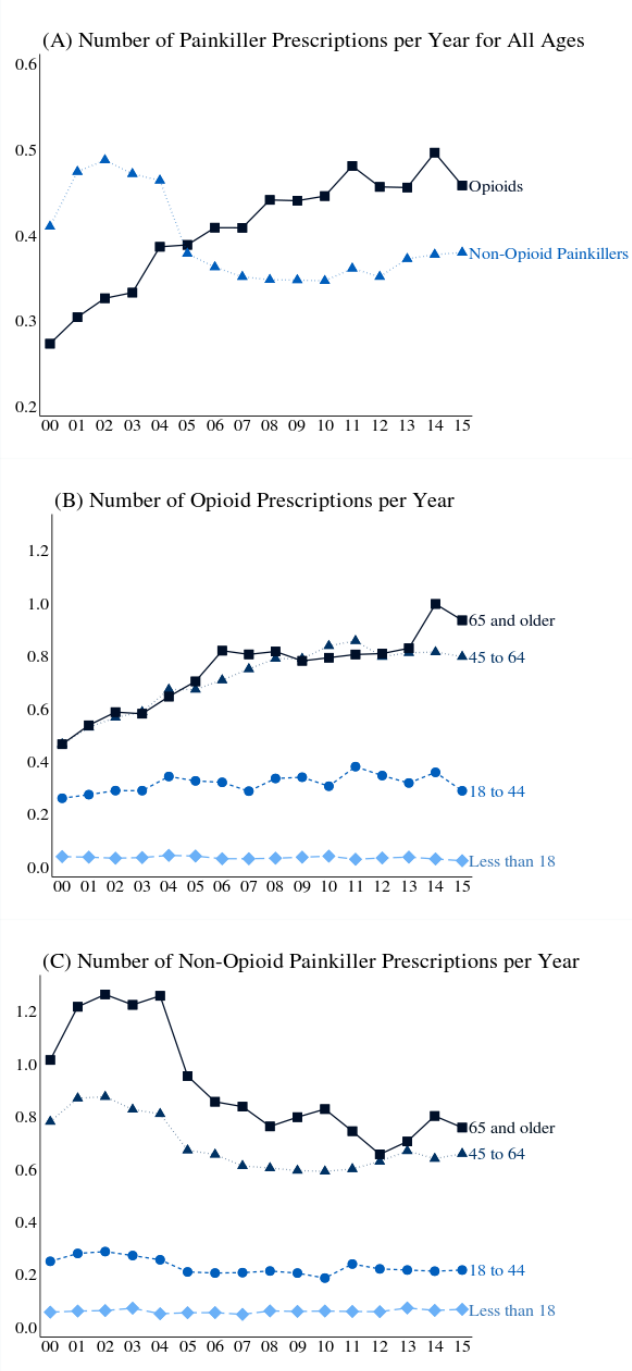
White House. (2018, March 1). President Donald J. Trump is Combatting the Opioid Crisis. *Whitehouse.Gov*. Retrieved from https://www.whitehouse.gov/briefings-statements/president-donald-j-trump-combatting-opioid-crisis/

Yin, W., Basu, A., Zhang, J. X., Rabbani, A., Meltzer, D. O., & Alexander, G. C. (2008). The Effect of the Medicare Part D Prescription Benefit on Drug Utilization and Expenditures. *Annals of Internal Medicine*, *148*(3), 169.

Zhou, C., Florence, C. S., & Dowell, D. (2015). Payments For Opioids Shifted Substantially To Public And Private Insurers While Consumer Spending Declined, 1999–2012. *Health Affairs*, *35*(5), 824–831.

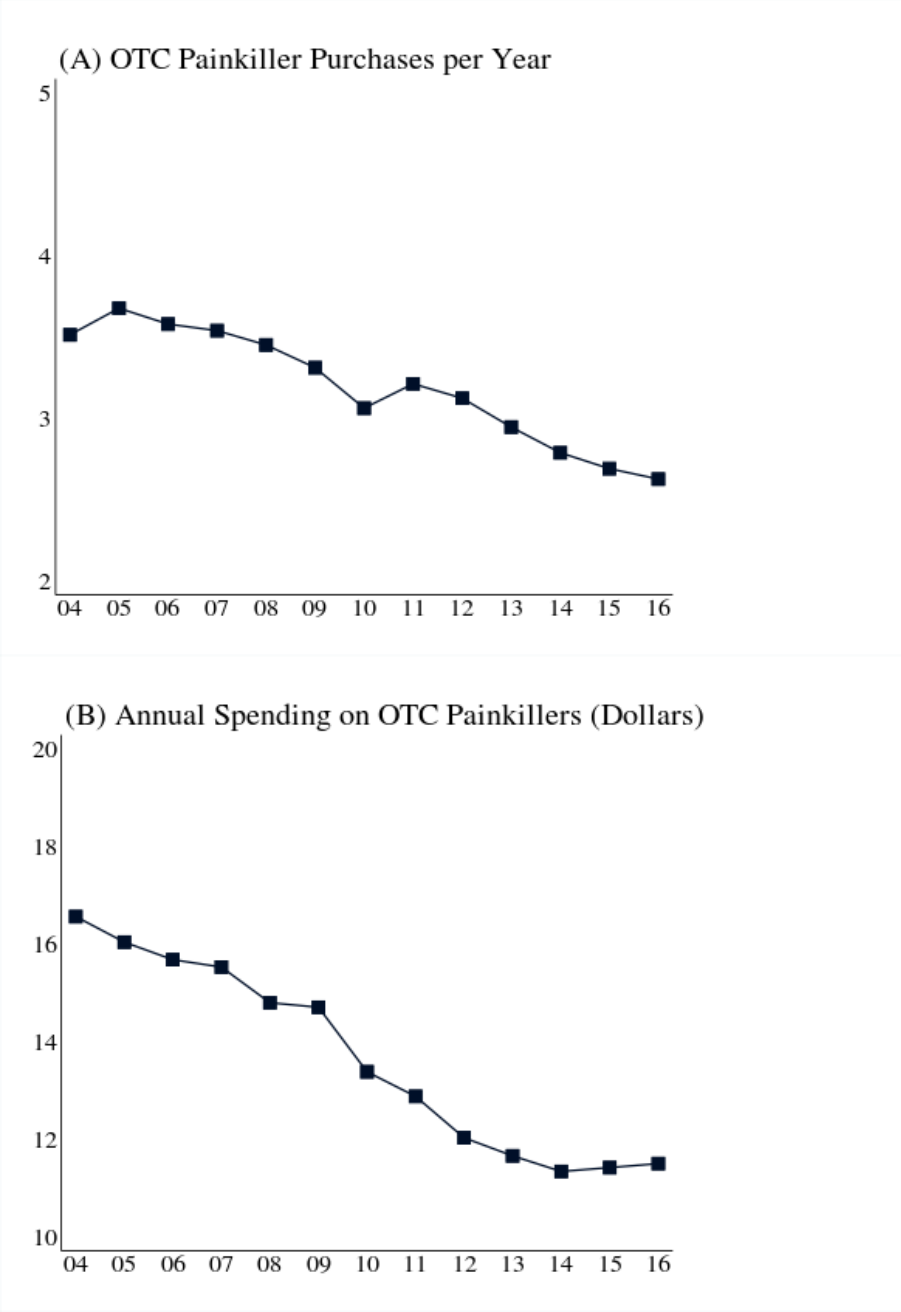
Figures

Figure 1. Annual Utilization of Prescription Painkillers per Person



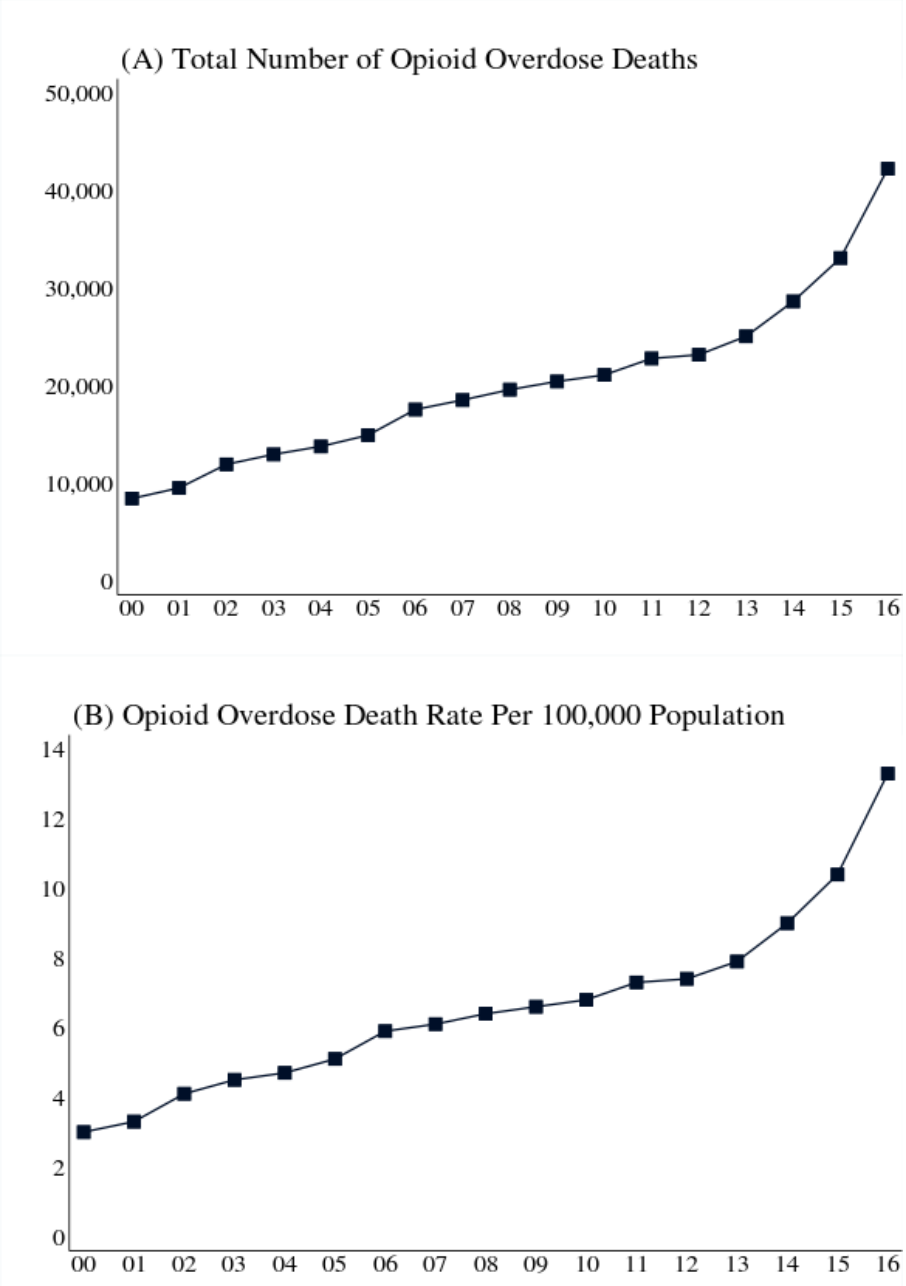
Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2015. Sample is restricted to respondents with non-missing age (N=545,665). Figures display the mean number of painkiller prescriptions per person, adjusted by MEPS survey weights.

Figure 2. Annual Utilization of Over-the-Counter Painkillers per Household



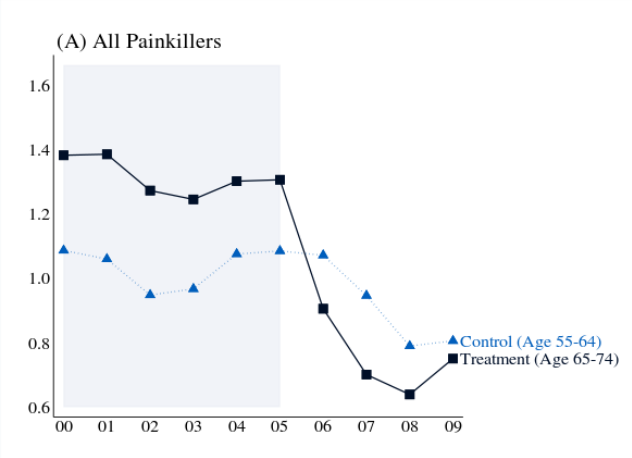
Source: Author's calculations based on Nielsen Household Consumer Panel 2004 to 2016. Figure displays mean annual spending per household, adjusted by Nielsen survey weights. Spending outcomes has been adjusted for inflation.

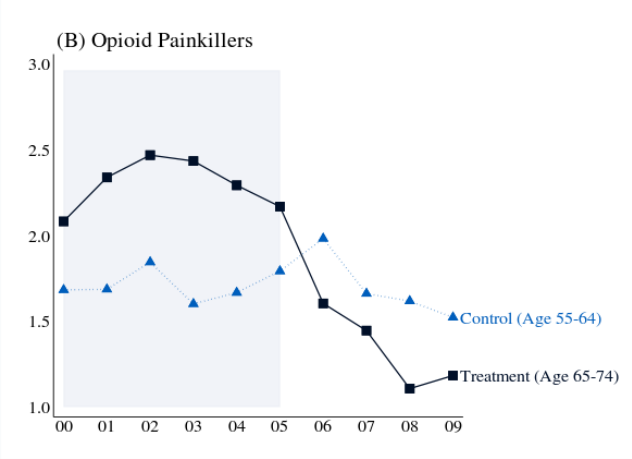
Figure 3. Opioid Overdose Deaths

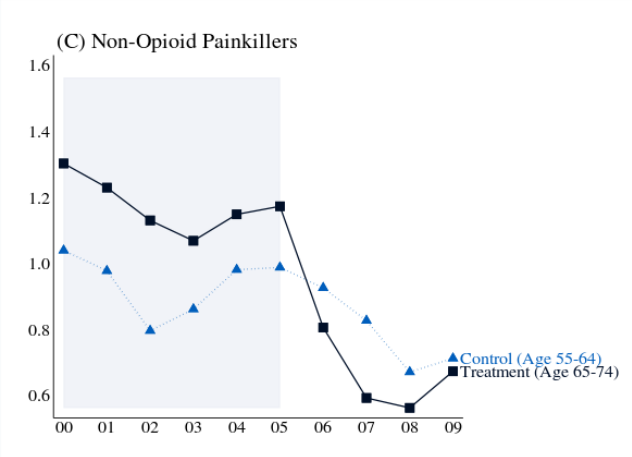


Source: Author's calculations based on data from the Henry J. Kaiser Family Foundation.

Figure 4. Out-of-Pocket Prices of Prescription Painkillers over Time

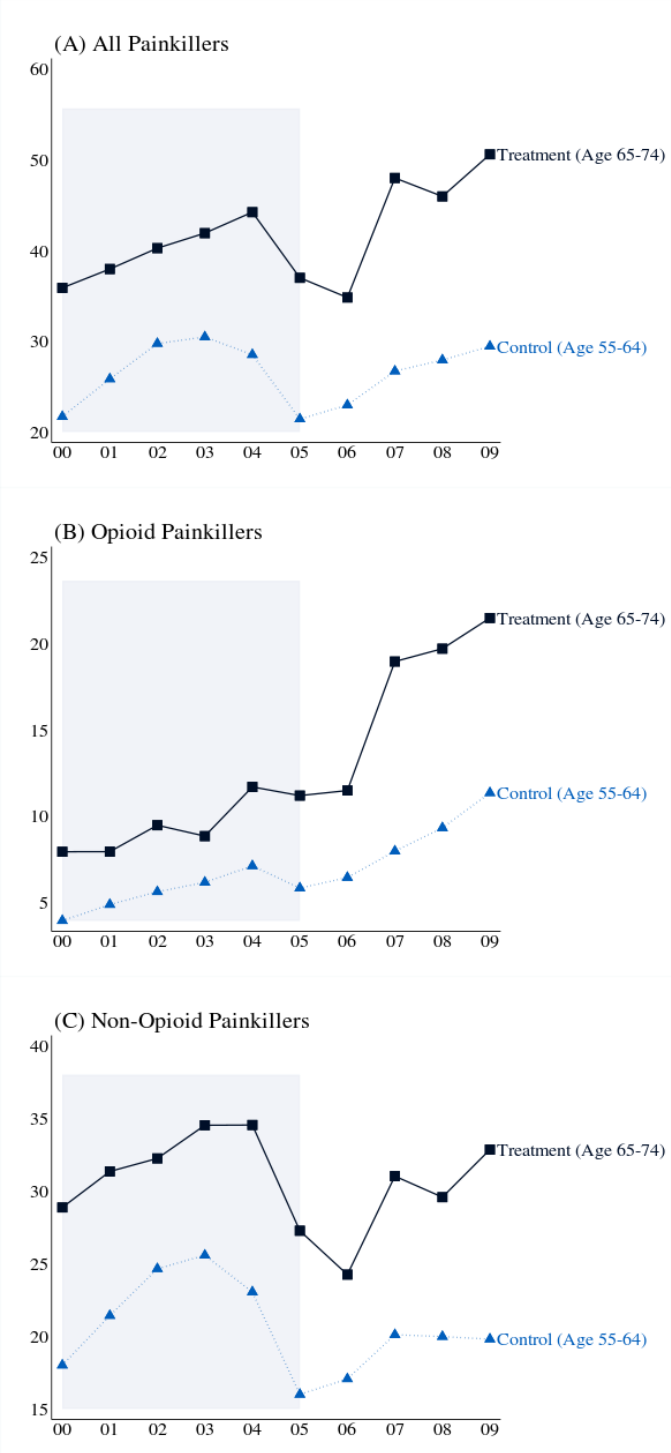






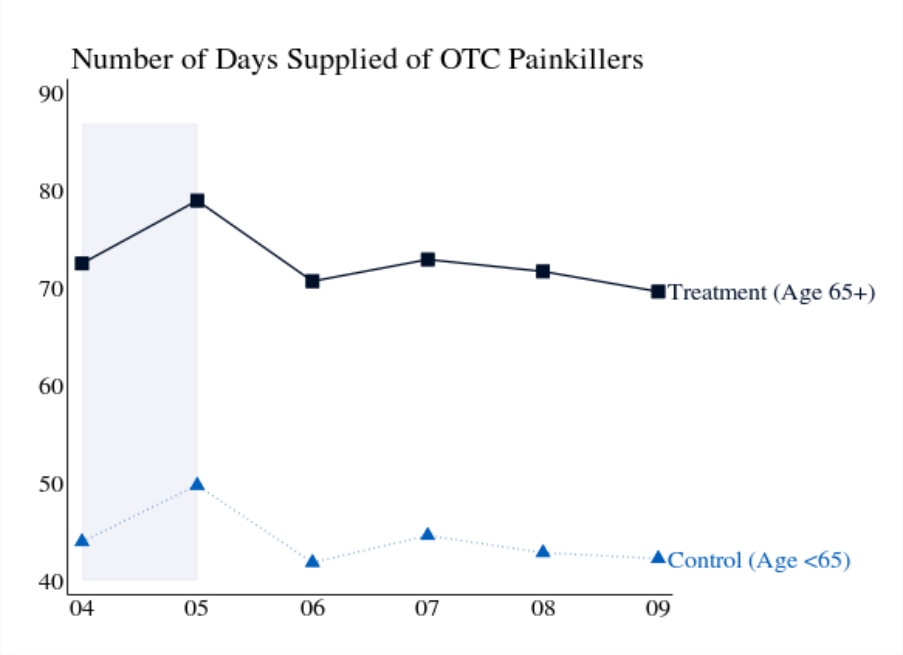
Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Figures display the mean OOP spending per day supply of each NDC, weighted by 2003 utilization of the NDC. Prices are adjusted to 2009 dollars using the Bureau of Labor Statistics' Pharmaceutical Producer Price Index.

Figure 5. Utilization of Prescription Painkillers over Time



Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Sample is restricted to adults aged 55 to 74 (N=50,579). Figures display the mean annual number of days supplied per person, adjusted by MEPS survey weights.

Figure 6. Utilization of OTC Painkillers over Time



Source: Author's calculations based on Nielsen Household Consumer Panel 2004 to 2009. Figure displays the mean annual number of days supplied per person, adjusted by Nielsen survey weights.

Tables

Table 1. Descriptive Statistics of the MEPS Sample

	Treatment Group (Ages 65-74) (1)	Control Group (Ages 55-64) (2)	Difference (3)
Male	0.47	0.48	-0.01**
Married	0.63	0.70	-0.07***
Household Income			
Less than 100% FPL	0.10	0.08	0.02***
100 to 124% FPL	0.06	0.02	0.03***
125 to 199% FPL	0.17	0.09	0.08***
200 to 399% FPL	0.30	0.26	0.04***
Greater than 400% FPL	0.38	0.55	-0.17***
Educational Attainment			
Less than high school	0.25	0.14	0.11***
High school	0.35	0.32	0.03***
Some college	0.18	0.22	-0.04***
College or more	0.22	0.32	-0.10***
Race/Ethnicity			
White, Non-Hispanic	0.78	0.77	0.01
Black, Non-Hispanic	0.10	0.09	0.01
Other, Non-Hispanic	0.05	0.05	-0.01**
Hispanic	0.07	0.08	-0.01**
Region			
Northeast	0.19	0.19	-0.00
Midwest	0.22	0.23	-0.01
South	0.39	0.36	0.03***
West	0.20	0.22	0.01**
N	22,265	28,314	

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Sample is restricted to adults aged 55 to 74. Means are adjusted by MEPS survey weights. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2. Descriptive Statistics of the Nielsen Sample

	Treatment Group (Ages 65+) (1)	Control Group (Age <65) (2)	Difference (3)
Male Householder	0.61	0.74	-0.13***
Female Householder	0.80	0.81	-0.01***
Married	0.38	0.52	-0.14***
Household Income			
Less than 100% FPL	0.05	0.07	-0.01***
100 to 124% FPL	0.04	0.03	0.01***
125 to 199% FPL	0.17	0.11	0.05***
200 to 399% FPL	0.41	0.30	0.10***
Greater than 400% FPL	0.33	0.48	-0.15***
Educational Attainment of Male Householder			
No male householder	0.39	0.26	0.13***
Less than high school	0.08	0.05	0.03***
High school	0.24	0.24	0.00
Some college	0.15	0.22	-0.07***
College or more	0.14	0.23	-0.10***
Educational Attainment of Female Householder			
No female householder	0.20	0.19	-0.01***
Less than high school	0.07	0.03	0.04***
High school	0.39	0.26	0.12***
Some college	0.22	0.27	-0.04***
College or more	0.12	0.25	-0.13***
Race/Ethnicity			
White, Non-Hispanic	0.82	0.72	0.10***
Black, Non-Hispanic	0.09	0.12	-0.03***
Other, Non-Hispanic	0.03	0.05	-0.02***
Hispanic	0.06	0.10	-0.05***
Region			
Northeast	0.21	0.20	0.01**
Midwest	0.24	0.25	-0.00
South	0.33	0.32	0.01**
West	0.22	0.23	-0.01***
N	97,276	237,784	

Source: Author's calculations based on Nielsen Household Consumer Panel 2004 to 2009. Means are adjusted by Nielsen survey weights. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. Classification of Prescription Painkillers in MEPS

	Examples (1)	Any Prescription (2)	Prescriptions Per Year (3)	Total Price Per Prescription (4)	OOP Price Per Prescription (5)
All Drugs		0.90	27.91	68.07	27.77
All Painkillers		0.35	1.96	47.08	18.86
Opioids					
All Opioids		**0.19**	**0.87**	**32.36**	**13.23**
Hydrocodone	Vicodin, Lortab, Lorcet	0.08	0.30	19.43	9.32
Propoxyphene	Darvocet, Darvon, Propacet	0.04	0.15	25.61	13.74
Oxycodone	Oxycontin, Percocet, Endocet	0.04	0.14	51.81	17.04
Tramadol	Ryzolt, Ultram, Ultracet	0.02	0.12	43.29	18.12
Codeine	Codeine & Tylenol	0.02	0.06	15.63	8.35
Morphine	MS Contin, Kadian, Avinza	0.01	0.03	71.08	19.36
Fentanyl	Duragesic, Actiq	0.00	0.03	249.83	75.58
Methadone	Methadose, Dolophine	0.00	0.02	27.17	11.33
Other Opioids	Hydromorphone, Meperidine, Pentazocine, Dihydrocodeine	0.00	0.01	35.05	18.74
Non-Opioid Painkillers					
All Non-Opioid Painkillers		**0.23**	**1.09**	**57.56**	**23.05**
Acetylsalicylic Acid	Aspirin, Ecotrin	0.04	0.20	7.71	3.63
Celecoxib	Celebrex	0.05	0.20	122.18	45.38
Rofecoxib	Vioxx	0.03	0.09	82.17	40.69
Diclofenac	Arthrotec, Voltaren	0.02	0.09	64.05	25.25
Ibuprofen	Advil, Motrin	0.03	0.09	17.54	7.49
Naproxen	Aleven, Naprelan, Anaprox	0.03	0.09	42.38	15.80
Meloxicam	Mobic	0.02	0.07	78.31	32.15
Acetaminophen	Tylenol, Fioricet, Mapap	0.02	0.06	12.74	6.59
Nabumetone	Relafen	0.01	0.04	60.97	26.80
Valdecoxib	Bextra	0.01	0.03	103.45	61.56
Indomethacin	Indocin	0.01	0.03	31.39	11.66
Etodolac	Lodine	0.01	0.03	47.16	15.66
Piroxicam	Feldene	0.00	0.02	46.80	17.14
Sulindac	Clinoril, Disalcid	0.00	0.01	46.31	18.05
Oxaprozin	Daypro	0.00	0.01	54.21	17.00
Other Non-Opioid Painkillers	Sumatriptan, Salsalate, Ketoprofen	0.01	0.03	92.99	25.67
N		22,265	22,265	22,265	22,265

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. The data in the last four columns displays means for the treatment group (elderly individuals) across all years, adjusted by MEPS survey weights.

Table 4. DD Results and Own-Price Elasticity Estimates for Prescription Painkillers

	Utilization (Days Supplied)			Price (OOP Price per Day Supplied)			Elasticity
	Pre-2006 Mean (1)	DD Coefficient (2)	Percent Change (3)	Pre-2006 Mean (4)	DD Coefficient (5)	Percent Change (6)	(7)
Painkillers							
All Painkillers	39.57	4.33* (2.29)	10.9%	1.34	-0.51*** (0.13)	-38.1%	-0.29
Opioids	9.54	4.81*** (1.23)	50.4%	2.31	-1.30** (0.56)	-56.5%	-0.89
Non-Opioid Painkillers	31.50	0.02 (2.03)	-	1.17	-0.40*** (0.14)	-34.2%	-
Opioids, by Dosage							
Total MME	540.10	401.82** (162.18)	74.4%	0.03	-0.02** (0.01)	-66.7%	-1.12
High Dose Opioids	1.58	0.77* (0.47)	48.7%	5.41	-4.31 (3.67)	-	-
Low Dose Opioids	8.04	4.72*** (1.16)	58.7%	1.73	-0.72** (0.31)	-41.6%	-1.41
Opioids, by Release							
Extended Release Opioids	2.04	1.54** (0.72)	75.5%	2.98	-0.57 (1.55)	-	-
Immediate Release Opioids	7.71	4.03*** (1.00)	52.2%	1.84	-1.02** (0.51)	-55.4%	-0.95
N		50,579			3,454		

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Columns 1-3 are based on results from Equation 2. Sample is restricted to adults aged 55 to 74. Column 1 displays the pre-2006 mean for the treatment group. Column 2 displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS. For statistically significant point estimates, column 3 displays percent change from pre-2006 mean.

Columns 4-6 based on results from Equation 3. Sample is restricted to painkiller NDCs for which at least one year of pre-2006 and one year of post-2006 data is available. Column 4 displays the pre-2006 mean for the treatment group. Column 2 displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions include a treatment group indicator and year fixed effects. Data are weighted by 2003 level of utilization of the NDC. For statistically significant point estimates, column 6 displays percent change from pre-2006 mean.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Event Study Results for Prescription Painkillers

	Utilization (Days Supplied)			Price (OOP Price per Day Supplied)		
	All Painkillers (1)	Opioids (2)	Non-Opioid Painkillers (3)	All Painkillers (4)	Opioids (5)	Non-Opioid Painkillers (6)
Year 2000 X Treatment	-1.47	-1.26	-0.55	0.30	0.40	0.26
	(3.62)	(1.83)	(3.38)	(0.27)	(0.45)	(0.30)
Year 2001 X Treatment	-3.98	-2.15	-1.96	0.33	0.65	0.25
	(3.42)	(1.53)	(3.02)	(0.33)	(0.90)	(0.31)
Year 2002 X Treatment	-5.61*	-1.45	-4.24	0.32	0.62	0.33
	(3.29)	(1.77)	(2.95)	(0.22)	(0.88)	(0.24)
Year 2003 X Treatment	-4.65	-2.82	-2.69	0.28	0.83	0.21
	(3.71)	(1.79)	(3.26)	(0.30)	(0.88)	(0.37)
Year 2004 X Treatment	0.09	-0.62	0.05	0.23	0.63	0.17
	(3.11)	(1.57)	(2.97)	(0.21)	(0.94)	(0.26)
Year 2006 X Treatment	-4.79	-0.70	-4.85*	-0.17	-0.38	-0.12
	(3.15)	(1.68)	(2.69)	(0.25)	(1.21)	(0.25)
Year 2007 X Treatment	5.03	5.20**	-0.67	-0.25	-0.22	-0.23
	(4.06)	(2.11)	(3.46)	(0.26)	(1.03)	(0.27)
Year 2008 X Treatment	1.55	4.50*	-2.10	-0.15	-0.51	-0.11
	(4.35)	(2.39)	(3.69)	(0.16)	(0.48)	(0.22)
Year 2009 X Treatment	4.85	4.50**	1.27	-0.06	-0.34	-0.04
	(4.11)	(2.19)	(3.50)	(0.23)	(0.56)	(0.30)
p-value for test that all pre-2006 terms jointly equal 0	0.57	0.48	0.79	0.26	0.68	0.54
N	50,579	50,579	50,579	3,454	1,664	1,790

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Table displays the coefficient on the interaction of the treatment group indicator and each year indicator. The year 2005 is omitted as the base year. Regressions in columns 1-3 control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS. Regressions in columns 4-6 include a treatment group indicator and year fixed effects. Data are weighted by 2003 level of utilization of the NDC.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Heterogeneous Effects for Impact of Part D on Prescription Painkiller Utilization by Reported Condition

	Individuals with the condition			Individuals without the condition		
	Pre-2006 Mean (1)	DD Coefficient (2)	Percent Change (3)	Pre-2006 Mean (4)	DD Coefficient (5)	Percent Change (6)
Cancer						
All Painkillers	43.31	4.39 (5.96)	-	38.97	3.84 (2.45)	-
Opioids	14.13	6.36** (3.23)	45.0%	8.80	4.31*** (1.33)	49.0%
Non-Opioid Painkillers	30.91	-2.29 (5.19)	-	31.59	0.13 (2.15)	-
N		5,069			45,510	
Joint or Back Pain						
All Painkillers	76.66	8.52* (4.61)	11.1%	15.62	-1.43 (1.57)	-
Opioids	19.05	7.05*** (2.72)	37.0%	3.40	0.44 (0.71)	-
Non-Opioid Painkillers	61.04	2.13 (4.02)	-	12.43	-1.94 (1.46)	-
N		18,813			31,766	
Poisoning by medical and non-medical substances						
All Painkillers	62.24	-3.63 (21.89)	-	39.15	4.51** (2.27)	11.5%
Opioids	21.75	6.33 (14.04)	-	9.32	4.87*** (1.22)	52.3%
Non-Opioid Painkillers	45.42	-18.55 (19.99)	-	31.24	0.27 (2.03)	-
N		663			49,916	

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Sample is restricted to adults aged 55 to 74. Columns 1 and 4 display the pre-2006 mean for the treatment group. Columns 2 and 5 display the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS. For statistically significant point estimates, columns 3 and 6 displays percent change from pre-2006 mean.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7. Heterogeneous Effects for Impact of Part D on Prescription Painkiller Utilization for New vs. Existing Users

	Utilization (Days Supplied)			Price (OOP Price per Prescription)		
	Pre-2006 Mean (1)	DD Coefficient (2)	Percent Change (3)	Pre-2006 Mean (4)	DD Coefficient (5)	Percent Change (6)
Pooled Sample						
All Painkillers	13.83	2.70** (1.22)	19.5%			
Opioids	4.11	1.46** (0.68)	35.5%			
Non-Opioid Painkillers	9.92	1.17 (0.99)	-			
All Drugs				31.92	-5.99*** (1.24)	-18.8%
N		12,068			12,068	
New Users						
All Painkillers	0.00	3.62***	-			
Opioids	0.00	1.79***	-			
Non-Opioid Painkillers	0.00	2.48***	-			
All Drugs				33.59	-5.86*** (1.38)	-17.4%
N		8,791			8,791	
Existing Users						
All Painkillers	48.66	1.58 (3.93)	-			
Opioids	24.89	1.52 (3.88)	-			
Non-Opioid Painkillers	57.49	-3.16 (5.46)	-			
All Drugs				30.76	-6.57*** (2.43)	-21.4%
N		3,277			3,277	

Source: Author's calculations based on Medical Expenditure Panel Survey 2005 to 2006. Sample is restricted to adults aged 55 to 74. Columns 1 and 4 display the pre-2006 mean for the treatment group. Columns 2 and 5 display the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS. For statistically significant point estimates, columns 3 and 6 displays percent change from pre-2006 mean.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8. DD Results and Cross-Price Elasticity Estimates for OTC Painkillers

	Utilization (Days Supplied)			Cross-Price Elasticity
	Pre-2006 Mean (1)	DD Coefficient (2)	Percent Change (3)	
OTC Painkillers	75.68	-3.27*** (1.01)	-4.3%	0.11
N		335,060		

Source: Author's calculations based on Nielsen Household Consumer Panel 2004 to 2009. Column 1 displays the pre-2006 mean for the treatment group. Column 2 displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for householder's sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include household fixed effects and year fixed effects. Data are adjusted by Nielsen survey weights, and standard errors are clustered on household.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

A1 Background on Opioids and Other Pain Relief Drugs

Pain relief drugs—which include opioids (also known as narcotics), non-steroidal anti-inflammatory drugs (NSAIDs, such as Ibuprofen), and Acetaminophen (such as Tylenol)—are among the most frequently prescribed therapeutic classes in the United States. These drugs are also known as analgesics, meaning that they produce a reduction in the perception of pain. In 2015, pain relief drugs accounted for nearly 8% of total prescriptions taken by adults in the United States, and 24% of adults used a prescription analgesic at least once during the year. Over the past 15 years, there has been a shift in the type of painkillers prescribed: opioids accounted for only 38 percent of total painkiller prescriptions in 2000 but 51 percent of prescriptions by 2015 (author's calculations based on Medical Expenditure Panel Survey). This is a worrisome trend because opioids are not only the strongest pain medications but also pose the highest risk for addiction.

Spending on prescription opioids has grown rapidly over the past 15 years (Appendix Figure A- 1). Panel A shows that average annual opioid spending was $9 per person in 2000 and more than tripled to $32 per person in 2015. Over the same time period, the share of spending attributable to public sources more than doubled from 24 percent in 2000 to 51 percent in 2015. Panel B of the Appendix Figure A- 1 shows that this increase was even more pronounced for the elderly population. Among people over age 65, average annual opioid spending increased from $17 per person in 2000 to $63 per person in 2015. Meanwhile, the share of spending attributable to public sources nearly tripled from 24 percent in 2000 to 66 percent in 2015.

How Pain Relief Drugs Work

This section briefly describes the biochemistry of pain and pain relief drugs (Carroll, 2016; Purves et al., 2004). The human brain and nervous system consist of nerve cells called neurons. Neurons communicate with each other by firing electrical signals to release chemical messengers, called neurotransmitters, across the tiny spaces between cells; this process is called neurotransmission. Nerve receptors are located all over the human body and send signals to the

brain when they are exposed to certain stimuli, such as temperature. Nociceptors are specialized nerve receptors that only fire when something is causing damage to the body (e.g. if the skin is cut, a muscle is pulled, etc.). Nociceptors are located in skin, organ walls, and within body tissues such as muscles and joints. When the body encounters a noxious stimulus, nociceptors transmit electrical signals to the spinal cord, where neurotransmitters are released to send the signal up to the brain, where it is interpreted as pain. These pain signals are transmitted in a fraction of a second; their purpose is to alert the body to potential harm.

Opioids are effective painkillers because they inhibit the pain signal at multiple steps in the pathway from the nociceptors to the brain. In the brain, opioids cause sedation and alter moods that decrease the emotional response to pain. At the nociceptor level, opioids block the signaling from the nociceptors to secondary neurons. Along the spinal cord, opioids chemically bind to specific opioid receptors on neurons, which decreases the release of neurotransmitters that are trying to communicate the pain signal. This results in less pain experienced by the brain. The reason human spinal cords have opioid receptors is because the body has a built-in analgesic system that regulates pain signals. The human body produces endogenous opioids, known as endorphins, which bind to neurons and produce pain relief. Opioid drugs bind to opioid receptors in a similar way that endorphins produced by the body do, but with more powerful side effects, such as intense euphoria, severe respiratory depression, sedation, urinary retention, nausea, dizziness, and constipation.

Moreover, opioid medications are associated with tolerance (with time, higher doses are required to get the same level of pain relief) and severe withdrawal symptoms if one stops the drug. This can lead to physical and psychological dependence on the drug. An opioid overdose refers to toxicity due to excessive opioids; an overdose can lead to insufficient breathing, loss of consciousness, and death. Because of the drug's dangerous potential for addiction, opioid sales are controlled by the US Drug Enforcement Authority (DEA).

Since 1970, the DEA has classified certain drugs and other substances, called controlled substances, into five schedules based on risk of abuse or harm. Schedule I drugs, such as heroin, have high risk and no counterbalancing benefit and are banned from medical use. Schedule II drugs have high potential for abuse and can lead to severe psychological or physical dependence;

examples include hydromorphone, methadone, meperidine, oxycodone, fentanyl, morphine, opium, and codeine. Schedule III drugs have less potential for abuse but can still lead to moderate/low physical dependence or high psychological dependence. Schedule III opioids include combination products containing less than 16 mg of hydrocodone per dose and less than 90 mg of codeine per dose (for example, Tylenol with Codeine). Schedule IV drugs have low potential for abuse (for example, Tramadol), and Schedule V drugs have even lower potential for abuse (for example, Robitussin AC).

NSAIDs – which include Ibuprofen, Aspirin, and COX-2 inhibitors – work differently from opioids. When cells and tissues are damaged, they prompt the body's COX-1 and COX-2 enzymes to produce chemicals known as prostaglandins. Prostaglandins lower the threshold required for nearby nociceptors to fire (i.e. reduce the body's pain threshold); this results in more pain signals being transmitted to the brain. NSAIDs work by competitively inhibiting production of prostaglandins from the COX enzymes; the drug competes for the binding sites on the COX enzymes. Reduced production of prostaglandins diminishes the intensity of pain signals being sent to the brain, and as a result, the body experiences pain relief. Side effects of long-term NSAID use can include heartburn and stomach ulcers.

Acetaminophen – which includes Tylenol – is another class of commonly-used pain relief drugs, but researchers have not yet determined exactly how the drug works. The physician's directions that come with Acetaminophen prescriptions usually include the note, "Although the analgesic effect of Acetaminophen is well established, the site and mode of action have not been clearly elucidated." Side effects of long-term use of Acetaminophen can include liver damage and trouble passing urine.

The side effects associated with NSAIDs and Acetaminophen are substantially less severe than those of opioids. Moreover, neither NSAIDs nor Acetaminophen share the addictive properties associated with opioids. The Centers for Disease Control and Prevention (CDC) therefore recommends NSAIDs and Acetaminophen as first-line therapies for chronic pain outside of cancer treatment and end-of-life care (Centers for Disease Control and Prevention, 2016). Neither NSAIDs nor Acetaminophen are controlled by the DEA, unless combined with opioids.

Causes of Opioid Growth

Researchers have proposed several possible explanations for the rapid growth of opioids since the late 1990s. One school of thought focuses on the increased demand for opioids. Economic studies point out that certain population cohorts in the United States (particularly middle-aged White men) have experienced relative declines in permanent income in recent decades; this phenomenon may push the struggling cohorts to opioid addiction, suicide, and other "deaths of despair" (Case & Deaton, 2015). Ignorance about the addiction potential of opioids and increased prevalence of physical pain are other potential reasons for growth in the demand for opioids.

Another set of explanations faults the increased supply of opioids. During the 1990s, new attitudes in medicine promoted the treatment of pain as the fifth vital sign and destigmatized the prescription of opioids for non-cancer pain. Meanwhile, drug manufacturers initiated aggressive marketing campaigns for opioids, often funding continuing medical education seminars for physicians and offering other in-kind perks to doctors. When asked about the addictive potential of opioids, sales representatives often pointed to a 1980 study which found that less than 1 percent of patients taking narcotics developed addiction to them (Porter & Jick, 1980); however, that one-paragraph publication was based on a study of hospitalized patients, not those going home with opioid prescriptions. In particular, Purdue Pharmaceutical aggressively marketed its time-release formula of oxycodone – Oxycontin – as a virtually non-addictive pain relief drug. In 2005, Purdue pled guilty to false branding and paid a $634 million fine. Moreover, there was little regulation of pain management clinics ("pill mills"), making prescription opioids even easier to access. On the illicit side, heroin became cheaper and more pure in quality, fueled by the rampant growth of the black tar heroin from the Xalisco region of Mexico. This eased the transition from prescription to illicit opioids for those who became addicted.

Consequences of Opioid Misuse

One of the most devastating consequences of opioid misuse is the elevated rate of overdose deaths in the United States. By the year 2010, drug overdoses – driven by opioids – became the leading cause of death from injury, surpassing motor vehicle accidents. Panel A of Appendix Figure A- 2 shows that the number of opioid overdose deaths increased from 8,400 per

year in 2000 to 42,200 per year in 2016. Opioid overdoses may be from licit prescription opioids as well as illicit opioids such as heroin and illegally produced fentanyl. According to Panel A, prescription opioids have played an increasingly larger role in overdose deaths over time: prescription opioids were responsible for 52 percent of overdose deaths in 2000 and 77 percent by 2016. However, the underlying mortality data cannot distinguish deaths from pharmaceutical fentanyl and those from illegally produced fentanyl. Therefore, the prescription opioids bar may contain deaths from both prescription and illicit fentanyl.

Panel B of Appendix Figure A- 2 provides an alternative way to describe the split between prescription and illicit opioid deaths.[1] The "semisynthetic and natural opioids" and the "heroin" bars refer unambiguously to prescription and illicit opioids, respectively. The "synthetic opioids" bar consists of deaths from both prescription and illicit fentanyl. In the year 2016, semisynthetic and natural (prescription) opioids accounted for 34 percent, synthetic (prescription and illicit) accounted for 37 percent, and (illicit) heroin accounted for 29 percent of total opioid overdose deaths. The most common drugs involved in prescription opioid deaths include methadone, oxycodone, and hydrocodone.

There are several other health and economic consequences of opioid misuse, in addition to deaths from overdose (Quinones, 2015; Temple, 2015). Shared needles increase the incidence of HIV and Hepatitis C. Opioid use by women during pregnancy can lead to neonatal abstinence syndrome: babies develop addiction in the womb and experience withdrawal after birth, leading to conditions such as seizures, breathing problems, and diarrhea. Prescription opioid abuse has also been linked to increased drug diversion, crime, emergency department utilization, and demand for illicit opioids (Council of Economic Advisers, 2017; Jones, 2013; Powell et al., 2017).

Policy Responses to the Opioid Crisis

Reducing prescription opioid misuse is a top public health priority for policymakers at all levels of government, as well as leaders of the private sector. At the federal level, the White

[1] The aggregate numbers in Panel B are slightly higher than those in Panel A because the three categories presented in Panel B are not mutually exclusive; deaths that involve more than one type of opioid are included in every applicable category.

House declared the opioid crisis “a national public health emergency under federal law” (White House, 2018). The Centers for Disease Control and Prevention (CDC) has issued new guidelines urging providers to reduce opioid prescribing and substitute toward other non-opioid therapies (Centers for Disease Control and Prevention, 2016). At the state level, 46 state governors have signed a compact promising to take steps to reduce inappropriate opioid prescribing (National Governors Association, 2013); already several states have strengthened prescription drug monitoring programs (PDMPs) and expanded Naloxone access as ways to reduce opioid overdose deaths. Recently, insurance companies have also taken steps: in 2017, 16 major health insurance companies representing 245 million covered lives adopted eight National Principles of Care and pledged to increase access to treatment for substance use disorder (Pellitt, 2017).

Policy responses to the opioid crisis can be classified into two categories. The first set of policies intends to mitigate harm for existing users by increasing access to treatment for opioid use disorder. Pharmacotherapy programs to treat opioid use disorder typically use one of three drugs. (1) Naltrexone is an opioid antagonist; it prevents the effects of opioids (euphoria, pain relief, etc) and decreases the desire to take opioids. (2) Methadone is a synthetic opioid agonist, meaning that it acts as other opioid drugs by binding to opioid receptors. However, unlike other opioids, Methadone stays in the system for up to 59 hours (compared to six hours for normal-release opioids) and does not demand increasing doses every few hours. Methadone can relieve withdrawal symptoms and cravings for other opioids, and is often used as a replacement drug in treatment for opioid addiction. (3) Buprenorphine is a partial opioid agonist that works by occupying opioid receptors but without stimulating a strong euphoric effect associated with other opioids; it can also reduce cravings and withdrawal symptoms. In addition to these three pharmacotherapy programs, another drug can effectively act as an overdose antidote: Naloxone is an opioid antagonist, meaning that it blocks opioid receptors by binding to the receptors in place of opioid drugs, and can reverse an overdose. Recent policies attempt to increase access to these drugs by making Naloxone available over the counters, increasing waivers for physicians to prescribe Buprenorphine, and expanding access to addiction cessation therapy through insurance expansions.

The second category of policies focuses on preventing future misuse by restricting access to prescription opioids. In recent years, many states have strengthened their prescription drug

monitoring programs (PDMPs), databases in which retail pharmacists enter information about controlled substance prescriptions. Providers can access PDMP databases before providing a patient with a prescription to ensure that the patient is not doctor shopping. Some studies have found that mandatory access PDMP laws reduce opioid prescribing (Bao et al., 2016; Buchmueller & Carey, 2017; Dave, Grecu, & Saffer, 2017; Patrick, Fry, Jones, & Buntin, 2016; Radakrishnan, 2014). Other policies include the increased regulation of pain management clinics, the promotion of abuse-deterrent opioid formulations, tougher prescriber guidelines from the CDC, and 7-day limits on initial opioid prescriptions for opioid-naïve patients prescribed the drugs to treat acute pain.

A2 Review of Literature on Price Elasticities of Demand for Prescription Drugs

Appendix Table A- 1 summarizes methods, data sources, and results of 31 studies that estimate price elasticities of demand for prescription drugs. The empirical methods used in these studies exploit exogenous changes in out-of-pocket (OOP) drug prices, such as those caused by the introduction of Medicare Part D in 2006, entering the Part D coverage gap (donut hole), changes in benefit design of private insurance, the RAND Health Insurance Experiment, and the introduction of drug copayments in the United Kindgom's National Health Service. Within each category, studies are sorted by year of publication. It should be noted that the studies listed in Appendix Table A- 1 include only those that provide estimates for the policy's impact on OOP costs as well as drug utilization and are thus able to calculate implied elasticities.

There exist a large number of studies that assess the impact of prescription drug coverage or other policy changes on utilization alone; these are not included in Appendix Table A- 1. Notable papers in this category include a study that uses panel data from the Health and Retirement Study Prescription Drug Study and finds that gaining prescription drug coverage through Part D leads to a 15 percent increase in the number of prescription drugs taken (Engelhardt, 2011). Another paper uses an instrumental variables approach to assess the impact of prescription drug coverage on drug utilization; the authors use data from the Medicare Current Beneficiary Survey and find that drug coverage through Part D increases drug utilization by 30 percent (Kaestner & Khan, 2012). Neither of these studies calculates implied elasticities of prescription drugs.

Appendix Table A- 1: Studies that Estimate Price Elasticities of Demand for Prescription Drugs

Paper	Methods	Results
Studies Based on the Introduction of Medicare Part D		
Lichtenberg & Sun. (2007). "The Impact of Medicare Part D on Prescription Drug Use by the Elderly." *Health Affairs*.	The authors use a sample of the 2004-06 Walgreens pharmacy data (N=585 million prescriptions) and estimate DD models to compare drug use (measured in units of days of therapy) and OOP costs (per days of therapy) among those aged 65 and older to those under 65.	Part D reduced OOP costs by 18.4 percent and increased quantity by 12.8 percent. The elasticity of demand for prescription drugs is **-0.70**.
Yin et al. (2008). "The Effect of the Medicare Part D Prescription Benefit on Drug Utilization and Expenditures." *Annals of Internal Medicine.*	DD models and a sample of pharmacy data from Walgreens for the years 2004-07 are used to compare prescription utilization (measured in pill-days) and out-of-pocket expenditures for those aged 66 to 79 with a control group aged 60 to 63 (N=177,311 individuals), before and after January 2006.	From January to May 2006, Part D increased use of medications by 1.1 percent and decreased OOP costs by 8.8 percent (implied elasticity of **-0.13**). From June 2006 to April 2007, utilization increased 5.9 percent and OOP costs decreased 13.1 percent (implied elasticity of **-0.45**). The effect over the earlier period represents the effect of increasing enrollment and the selection effect of early enrollees (who were unhealthier on average) than late enrollees. The effect over the later period represents the steady-state effect of Part D.
Ketcham & Simon. (2008). "Medicare Part D's Effect on Elderly Drug Cost and Utilization." *American Journal of Managed Care.*	The authors use 2005-07 pharmacy records from Wolters Kluwer Health (N=1.4 billion prescription records filled by 34 million patients aged 58 and older) and estimate DD models comparing individuals 66 and older vs those aged 58-64, before and after January 2006. Outcomes include OOP cost per day's supply of a medication, the days of medication supplied per capita, and the number of individuals filling prescriptions.	Part D reduced OOP cost per day's supplied of medication by 21.7 percent and increased use of prescription drugs by 4.7%, implying a price elasticity of demand of **-0.22**.
*Schneeweiss et al. (2009).	Using 2005-06 pharmacy claims data, the authors assess changes in drug utilization (measured by daily doses of medication) before and after 2006 among a group of previously drug uninsured elderly individuals (N=114,766). The authors impute insurance status based on medication costs and patients' OOP spending. However, this study only examines utilization of four essential drug classes.	Utilization increased by between 3 and 37 percent, and OOP spending decreased by between 37 and 58 percent, depending on the drug class. The demand elasticities are **-0.35** for warfarin, **-0.44** for statins and clopidogrel, and **-0.76** for PPIs.
Duggan & Scott-Morton. (2010). "The Effect of Medicare Part D on Pharmaceutical Prices and Utilization." *American*	This study investigates the effect of Part D on price and utilization of branded drugs. The empirical strategy exploits variation across drugs in their pre-2006 Medicare market shares and compares	In addition to reducing the share of the drug price paid by the patient, Part D also reduced gross prices of prescription drugs about 20 percent lower than they otherwise would have

Economic Review.	growth in drug prices for drugs that are more reliant on Medicare customers with drugs that are less reliant on Medicare customers. The authors use MEPS data to calculate Medicare market shares and 2001 to 2006 IMS Health data to obtain data on price and utilization outcomes.	been. Prices of brand-name drugs with close substitutes decreased because insurers could structure their formularies to drive demand toward generics and thus had substantial bargaining power with pharmaceutical companies. The study estimates a price elasticity of **-0.38** for prescription drugs.
Liu et al. (2011). "The Impact of Medicare Part D on Out-of-Pocket Costs for Prescription Drugs, Medication Utilization, Health Resource Utilization, and Preference-Based Health Utility." *Health Services Research.*	The authors use DD models and the MEPS 2005-06 panel data to estimate price and utilization outcomes (measured in units of prescriptions) for those aged 65 and older with those aged 55 to 63 (N=1,105), before and after January 2006. The study sample excludes those with Tricare, VA, Medicaid, other state and government subsidies, those with income <125% FPL, and those with cognitive limitations.	OOP costs for prescription drugs increased by $180 (or 21.1 percent from 2005 levels) and utilization increased by 2.05 prescriptions (or 9.3 percent) per patient year. The implied elasticity is **-0.44**.
Studies that Exploit the Medicare Part D Coverage Gap (Donut Hole)		
Einav, Finkelstein, & Schrimpf. (2015). "The Response of Drug Expenditure to Nonlinear Contract Design: Evidence from Medicare Part D." *Quarterly Journal of Economics.*	The authors use administrative data of 2007-09 Part D formularies and Part D claims (N=3.9 million beneficiary years) to study the response of drug use to the future out-of-pocket price. They exploit variation in beneficiaries' birth months, which generates variation in contract duration in their first year of eligibility, which in turn predicts their probability of reaching the Part D coverage gap.	The implied elasticity of drug spending with respect to price ranges from **-0.75 to -0.5**, depending on the magnitude of the price change.
Aron-Dine et al. (2015). "Moral Hazard in Health Insurance: Do Dynamic Incentives Matter?" *Review of Economics and Statistics.*	Part D claims data for the years 2007-09 (N=138,000 individuals) are used to analyze how individuals' initial drug utilization responds to future OOP prices. The authors take advantage of the fact that enrollees can enroll in Medicare at age 65 but their plan resets on January 1 regardless of the month in which they enroll. They exploit variation in birth month, which predicts enrollees' probability of reaching the coverage gap.	The implied elasticity of initial prescription drug claims with respect to the future price is **-0.25.**
Kaplan & Zhang. (2016). "Anticipatory Behavior in Response to Medicare Part D's Coverage Gap." *Health Economics.*	The authors examine whether individuals anticipate copayment changes in their Part D plans and adjust consumption in advance. They exploit variation in beneficiaries' birth months, which generates variation in contract duration in their first year of eligibility, which in turn predicts their probability of reaching the Part D coverage gap. They also use DD models to compare their main study group with those who receive low-income subsidies and do not	The implied elasticity of drug utilization (measured as number of prescriptions) with respect to future price ranges from **-0.2 to -05.**

	face the coverage gap.	
*Einav, Finkelstein, & Polyakova. (2018). "Private Provision of Social Insurance: Drug-Specific Price Elasticities and Cost Sharing in Medicare Part D." *American Economic Journal: Economic Policy.*	This study exploits sharp increases in OOP prices created by the Part D coverage gap to estimate price elasticities of demand across more than 150 drugs and more than 100 therapeutic classes. The authors use administrative data of Part D formularies and Part D claims from 2007 to 2011 (N=6.5 million beneficiary-years).	There is considerable heterogeneity in the price elasticity of demand across products; the average elasticity of the probability of any December purchase with respect to OOP price is **-0.24** and standard deviation is 0.49. The elasticity of opiate agonists is **-0.04**. For NSAIDs, the elasticity is **-0.33** for non-maintenance NSAIDs, **+0.07** for maintenance NSAIDs, and **-0.15** for other NSAIDs.
Studies that Exploit Cost-Sharing Changes in non-Medicare Part D Settings		
Harris, Stergachis, & Ried. (1990). "The Effect of Drug Copayments on Utilization and Cost of Pharmaceuticals in a Health Maintenance Organization." *Medical Care.*	Exploiting the 1983 implementation of a cost-sharing prescription drug plan in Washington, the authors analyze the effect of copay increases on the number of prescriptions utilized.	A $1.50 copay led to a 10.7 percent decrease in the number of prescriptions. Increasing the copay from $1.50 to $5 led to an additional 10.6 percent decrease. The price elasticity of demand for drugs is **-0.05 to -0.08**.
Smith. (1993). "The Effects of Copayments and Generic Substitution on the Use and Costs of Prescription Drugs." *Inquiry.*	This study assesses the effect of increases in drug copayments from $2 to $5 for a set of employer groups covered by a national managed care company.	The price elasticity of demand is **-0.10**. Physicians compensated for the increased price to consumers by prescribing larger amounts per prescription.
Coulson & Stuart. (1995). "Insurance Choice and the Demand for Prescription Drugs." *Southern Economic Journal.*	The authors use panel data based on a survey of 4,066 elderly Pennsylvanians enrolled in Medicare. They study the effect of Pennsylvania's PACE program, which provides subsidized drug coverage for elderly Medicare beneficiaries and imposes a $4 copayment per prescription.	The average subsidy was 82.2 percent, and the quantity of prescriptions purchased increased 27.6 percent. The own-price elasticity of drugs is thus **-0.34**.
*Ellison et al. (1997). "Characteristics of Demand for Pharmaceutical Products: An Examination of Four Cephalosporins." *RAND Journal of Economics.*	The authors model demand for four cephalosporins using a multistage budgeting approach. Three of the drugs lost patent protection during this period, which enables the study of generic substitution.	Own-price elasticities of the generic versions of the drugs are relatively larger and range from **-1.07 to -4.34**. Own-price elasticities of demand for the branded version of the drugs are smaller and range from **-0.39 to -2.97**. Cross-price elasticities between branded and generic versions of each drug are positive.
Johnson et al. (1997). "The Effect of Increased Prescription Drug Cost-Sharing on Medical Care Utilization and Expenses of Elderly Health Maintenance Organization Members." *Medical Care.*	The authors assess the effects of a copayment change among enrollees of the Kaiser-Permanente Northwest division in the 1980 to 1990 time period. They used administrative data from the insurer on benefit design and medical and drug claims and estimated changes in drug utilization after the copayment change.	A $2 (66 percent) increase in copayment resulted in an 8 percent decrease in prescription use. The implied price elasticity of demand is **-0.12**.
Hillman et al. (1999). "Financial Incentives and Drug Spending in Managed	A large sample of members enrolled in nine different United HealthCare Corporation's insurance plans	For individuals in IPA plans, a 50 percent increase in drug copayments led to a 12.3 percent decrease in drug

Care." *Health Affairs.*	(N=134,937) is used to study the effect of higher copayments on drug utilization. The authors assess effects separately for physicians who are compensated under independent practice association (IPA) models and network-model HMOs. Analyses include plan fixed effects to control for potential selection that may bias results.	spending (implied elasticity is **-0.25**). For individuals in network plans, a 50 percent increase in drug copayments led to only a 3.4 percent (statistically insignificant) reduction in drug spending (implied elasticity is **-0.07**).
Joyce et al. (2002). "Employer Drug Benefit Plans and Spending on Prescription Drugs." *JAMA.*	The authors study the effect of copayment changes on total drug spending, using 1997-99 data on non-elderly beneficiaries who worked at large firms with insurance benefits (N=420,786 beneficiaries). In the sample, only two of the 25 firms gave employees a choice of drug plans, which minimizes potential selection bias.	The price elasticity of drug expenditures was **-0.22** for single-tier plans and **-0.33** for two-tier plans.
*Goldman et al. (2004). "Pharmacy Benefits and the Use of Drugs by the Chronically Ill." *JAMA.*	The authors estimate how changes in cost sharing affect drug utilization (measured in drug days) of the most commonly used drug classes among the privately insured and chronically ill. They use 1997 to 2000 pharmacy claims data linked with health plan benefit designs from 30 employers (N=528,969 non-elderly beneficiaries).	For all 8 therapeutic classes analyzed, doubling copayments is associated with reductions in utilization. The largest decreases were for NSAIDs (elasticity estimate was **-0.45**) and antihistamines (elasticity was **-0.44**). Patients with at least one chronic illness were less responsive to price changes. Patients with arthritis, for example, had a price elasticity of demand for NSAIDs of **-0.27**.
*Landsman et al. (2005). "Impact of 3-Tier Pharmacy Benefit Design and Increased Consumer Cost-Sharing on Drug Utilization. *American Journal of Managed Care.*	The authors estimate price responsiveness of prescription demand for nine therapeutic classes using 1999 to 2001 data on three managed care populations whose pharmacy benefits changed from a 2-tier to a 3-tier design, compared with a managed care population that had no change in benefit design. Utilization was measured as the average monthly number of prescriptions.	The study found lower elasticities for drugs used in asymptomatic conditions **(-0.10 to -0.16** for statins, ACE inhibitors, CCBs, and ARBs) and higher elasticities for drugs used in symptomatic conditions (**-0.24 to -1.15** for triptans, SSRIs, Cox-e inhibitors, NSAIDs, and TCAs). The elasticity for NSAIDs was **-0.60**.
Gibson, McLaughlin, & Smith. (2005). "A Copayment Increase for Prescription Drugs: The Long-Term and Short-Term Effects on Use and Expenditures." *Inquiry.*	The study exploits a natural experiment in which a large firm increases drug copayments. The authors use a panel dataset that provides information on medical and drug claims for the firm that changed copayments and a control firm that did not change copayments for the years 1995 to 1998 (N=263,000 employee quarters).	The overall elasticity of demand for drugs **is -0.04**. The own-price elasticity of demand for multisource brand-name drugs is **-0.27**, more elastic than that of single-source brand name drugs (elasticity is **-0.03**). The study does not find evidence that brand-name and generic drugs are substitutes.
Gaynor, Li, & Vogt. (2007). "Substitution, Spending Offsets, and Prescription Drug Benefit Design." *Forum for Health Economics & Policy.*	The authors use the 1997 to 2003 MarketScan panel dataset of insurance claims and benefit design (N=1.7 million person years) to assess the effects of changes in employer-provided drug benefits on drug spending. During this time, a number of employers reduced	The short-run price elasticity of demand for drug spending with respect to price is **-0.6** and long-run elasticity is **-0.8**.

	generosity of drug coverage. The model includes individual fixed effects approach to control for potential selection bias.	
Shea et al. (2007). "Estimating the Effects of Prescription Drug Coverage for Medicare Beneficiaries." *Health Services Research.*	The authors use the 1999 Medicare Current Beneficiary Survey (N=5,270 beneficiaries) to identify the effect of insurance coverage on prescription utilization by Medicare beneficiaries. The authors use a multistage residual inclusion method using instrumental variables to control for selection bias.	Prescription drug insurance increased the number of prescriptions filled by 50 percent. The estimated price elasticity of demand for prescription drugs for Medicare beneficiaries is **-0.54.**
Chernew et al. (2008). "Effects of Increased Patient Cost Sharing on Socioeconomic Disparities in Health Care." *Journal of General Internal Medicine*.	This study explores whether the impact of increased drug copayments for diabetes and heart disease drugs differs between high- and low-income areas. The authors use MarketScan claims data which provide information on insurance coverage and claims for people covered by large employer plans (N=43,000 individuals with diabetes or heart disease).	The elasticity of demand on drug adherence ranges from **-0.03 to -0.05**. Those with lower income were more price-sensitive.
Gilman & Kautter. (2008). "Impact of Multitiered Copayments on the Use and Cost of Prescription Drugs Among Medicare Beneficiaries." *Health Services Research.*	This paper studies the impact of multi-tiered copayments on the cost and use of prescription drugs among Medicare beneficiaries. The authors use 2002 Marketscan data to link plan enrollment and benefits with medical and drug claims for 352,760 Medicare beneficiaries. They use cross-sectional variation in copayment structures among firms that offer employer-sponsored retiree health plans. To reduce potential selection bias, the authors ensure that each firm in their sample offers only one prescription drug plan, either a one-tiered plan or a three-tiered plan.	Beneficiaries in three-tiered plans had lower drug utilization and higher OOP costs than individuals in lower-tiered plans. The price elasticity of demand for prescription drug expenditures is **-0.23.**
Chandra, Gruber, & McKnight. (2010). "Patient Cost-Sharing and Hospitalization Offsets in the Elderly. *American Economic Review*.	The authors exploit a policy change that raised cost sharing for patients covered by insurance plans for retired public employees in California. They use administrative data that provides information on medical utilization (N=70,912 continuously-enrolled individuals), and estimate DD models to identify the impact of increased copayments on drug utilization.	For PPO enrollees, the arc-elasticity of drug utilization (measured by number of prescriptions) with respect to patient cost is **-0.08**, and for HMO enrollees, the arc-elasticity is **-0.15.**
*Gatwood et al. (2014). "Price Elasticity and Medication Use: Cost-Sharing Across Multiple Clinical Conditions." *Journal of Managed Care & Specialty Pharmacy.*	The study sample consists of about 11.5 million privately insured enrollees aged 18 to 64 in the 2005-09 MarketScan claims database. The authors estimate negative binomial fixed effects models with patient cost sharing as the key independent variable and prescription fills as the outcome variable, separately for eight categories of drugs. Models	Elasticities range from **-0.02 to -0.16**, with the largest (in magnitude) price elasticity for smoking deterrents and the smallest for NSAIDs/opioids. Demand for antiplatelet agent was not responsive to price.

	include plan fixed effects, and thus focused on longitudinal changes in cost-sharing over time.	
Yeung et al. (2016). "Price Elasticities of Pharmaceuticals in a Value-Based-Formulary Setting." NBER Working Paper.	The authors exploit a natural experiment that involved a large nonprofit insurance company transitioning its cost-based formulary to a value-based formulary, which tries to incentivize patients to use drugs that are likely to produce better value. This led to exogenous increases in cost-sharing for some drugs and decreases for others.	The overall price elasticity of demand for drugs is **-0.16**, but there is substantial variation across the formulary tiers, ranging from **-0.09 to -0.87**. Patients were more price-sensitive to drug placed in higher cost-sharing tiers.
Studies Based on the RAND Health Insurance Experiment		
Newhouse & the Insurance Experiment Group. (1993). *Free For All? Lessons from the Health Insurance Experiment.*	The Health Insurance Experiment randomly assign 5,800 non-elderly individuals to insurance plans with four different levels of coinsurance (ranging from 0 to 95 percent) and three different levels of maximum OOP expenditures.	Individuals in the free care plan spent nearly twice as much on prescription drugs as individuals in the 95 percent coinsurance plan ($82 and $46, respectively). However, the increase was attributable to a larger number of physician visits for individuals in the generous plan.[2] The overall elasticity estimate for prescription drugs is **-0.17**, similar to the elasticity of demand for health care in general.
Studies Based on Natural Experiments in non-US Settings		
O'Brien. (1989). "The Effect of Patient Charges on the Utilization of Prescription Medicines." *Journal of Health Economics.*	The United Kingdom's National Health Service implemented copayments for prescription drugs in 1968. This study exploits the natural experiment to study the effect of OOP price increases on the number of prescriptions.	The price elasticity of demand for drugs was **-0.23** for the initial period (1969-1977) and later rose to **-0.64** (1978-1986). The study also found a positive cross-price elasticity of 0.22 between prescription and OTC drugs.
Hughes & McGuire. (1995). "Patient Changes and the Utilization of NHS Prescription Medicines." *Health Economics.*	The authors exploit the 1968 implementation of copayments for prescription drugs in the United Kingdom's National Health Service. They use cointegration models to estimate price elasticities of demand for prescription drugs.	The price elasticity of demand for drugs is **-0.35.**
Contoyannis et al. (2005). "Estimating the Price Elasticity of Expenditure for Prescription Drugs in the Presence of Non-Linear Price Schedules: An Illustration from Quebec, Canada. *Health Economics*.	This study uses an exogenous change in cost-sharing within the Quebec public prescription drug insurance program to estimate price elasticity of expenditure for drugs using an instrumental variables approach. The instrument is based on the price an individual would face under the new policy if their consumption remained at the pre-policy level. The authors use administrative data on the	Expenditure elasticities range from **-0.12 to -0.16**.

[2] The insurance plans in the RAND Health Insurance Experiment did not vary cost-sharing for prescription drugs independently of other medical services. Since prescription drugs may serve as substitutes or complements to other services, it is difficult to isolate the effect of drug prices on drug utilization using the RAND data.

	Quebec program (N=120,000 elderly beneficiaries). Those without a prescription in the pre-policy period are not included in the analysis.

*Studies that estimate elasticities for specific drug classes.

A3 Additional Details about the MEPS Data

Construction of the MEPS Analytical Dataset

This section describes how I edited the original MEPS Prescribed Medicines files for the analysis in this paper. Step 1 describes how I merged the MEPS and CDC files. Steps 2 to 9 outline how I identified the opioid and non-opioid painkillers in MEPS. I could not simply use the Multum Lexicon codes provided by MEPS because the classification scheme changed over time (Hill, Roemer, & Stagnitti, 2014). I also could not use the NDCs because they were missing for 8 percent of the observations. I instead used the drug names provided by MEPS to identify opioids and non-opioid painkillers. Appendix Table A- 2 displays a comprehensive list of each of the generic drug names in the opioid and non-opioid painkillers categories. Steps 10-15 explain how I imputed missing information on opioids' MME, DEA schedule, etc. for the observations that were missing this information.

- **Step 1**: The original MEPS Prescribed Medicines files contained 5,652,749 observations for the years 1996 to 2015, where each observation represented the purchase or refill of a prescription medicine. Using the NDCs, I merged in additional information on MME, DEA schedule, extended vs immediate release, etc. for the opioid observations using the CDC Oral MME Equivalents file (https://www.cdc.gov/drugoverdose/data-files/CDC_Oral_Morphine_Milligram_Equivalents_Sept_2017.xlsx). The CDC file successfully matched with 89 percent of the opioid observations in the MEPS file (where opioid observations were defined as those in the Multum classes "Narcotic Analgesics" and "Narcotic Analgesic Combinations").
- **Step 2**: I browsed through the 486,003 observations that were classified as "Analgesics" by the Multum Lexicon codes and identified 510 observations that were misclassified as analgesics. These were primarily birth control pills, antibiotics, statins, vitamins, eyedrops, and antihistamines. I reclassified them in their correct categories. The sample now consisted of 485,493 analgesic observations.
- **Step 3**: Of the 485,493 analgesic observations, 3,661 were missing both NDCs and drug names. For these observations, I renamed the drug names to "Unknown Opioids" and "Unknown Non-Opioid Painkillers" according to their Multum codes.

- **Step 4**: There were 726 analgesic observations for which the drug names were missing but the NDCs were not. For these observations, I used the FDA's NDC database (https://www.accessdata.fda.gov/scripts/cder/ndc/) to look up the drug names.
- **Step 5**: For the remaining 481,106 analgesic observations, I streamlined the product names to correct misspellings, abbreviations, and other inconsistencies in the original MEPS drug names. For example, the drug "Acetaminophen" was spelled almost 70 different ways in the MEPS files ("ACEMINOPHEN", "ACETAMIN 120MG", "ACETAMINOPHEN DROP", "ACETAMI", etc). I created a variable called Product_Name that was spelled "Acetaminophen" for all such observations. I repeated this for all 481,106 analgesic observations and ended up with 663 distinct product names.
- **Step 6**: For each of the 485,493 analgesic observations, I created a variable to identify the generic drug names by looking up the drugs on the FDA's NDC database (https://www.accessdata.fda.gov/scripts/cder/ndc/). I ended up with 132 distinct generic drug names.
- **Step 7**: I browsed through all 5,652,749 observations and identified 1,071 observations that were actually analgesics based on their drug names but had been misclassified as non-analgesics by the MEPS Multum Lexicon codes. For example, in some cases, drugs like Aspirin and Vicodin were classified as muscle relaxants rather than analgesics. For these observations, I reclassified them as analgesics and streamlined their product names and generic drug names as described in Steps 5-6. I also browsed through the analgesic observations and reclassified treatment drugs for opioid use disorder (Buprenorphine, Naloxone) as non-analgesics. I had now identified a total of 486,392 analgesic observations in the MEPS (485,493 correctly classified analgesics + 1,071 analgesics that had previously been misclassified – 172 opioid treatment drugs).
- **Step 8**: I used the generic drug names (a variable which I had manually created) to categorize all 5,652,749 observations into three categories: opioid painkillers (229,921 observations), non-opioid painkillers (256,471 observations), and other drugs (5,166,357 observations). I did not use the Multum Lexicon codes to distinguish opioid vs non-opioid painkillers because the Multum Lexicon codes were not consistent over time. For example, the drugs "Tramadol" and "Tramadol & Acetaminophen" were classified as "Miscellaneous Analgesics" from 1996 through 2011 but as "Narcotic Analgesics" from 2012 onwards.
- **Step 9**: I used the generic drug names (which had 132 distinct values) to create a binary variable that identified each individual drug. (For example, the variable "presc_tapen" was equal to 1 for all observations of Tapentadol prescriptions.)
- **Step 10**: Of the 229,921 opioid observations that I had identified in the MEPS, 89 percent had successfully matched with the CDC file (from Step 1). For the remaining 11 percent of opioid observations, I identified whether they were immediate release or extended release drugs through an imputation process. If an observation was missing immediate vs extended release information, I first used information provided in the MEPS drug name. (For example, I coded "MORPHINE IR" and "OXYCODONE 15MG IMM REL TABLETS" as immediate release formulations.)

- For those that were still missing, I searched for drugs with the same name, form, and strength level in the CDC file. (For example, in the CDC file, all Fentanyl tablets were immediate release and all Fentanyl patches were extended release, so I identified missing Fentanyl tablets as immediate release and missing Fentanyl patches as extended release formulations.
- For those that were still missing, I looked up the NDCs on the FDA website (https://www.fda.gov/Drugs/DrugSafety/InformationbyDrugClass/ucm251735.htm) and the Bioportal website (http://bioportal.bioontology.org/ontologies). Finally, for the 3,000 opioid observations that were missing both drug names and NDCs ("Unknown Opioids"), I identified them as "immediate release" because these were more prevalent in the data. I ended up with 185,748 "immediate release" opioids and 44,173 "extended release" opioids.

- **Step 11**: I identified DEA schedules of the 229,921 opioid observations. For 89 percent of the observations, this information was already available from the CDC file (from Step 1). For the remaining 11 percent of opioid observations, I imputed this information using steps similar to those described in Step 10. I ended up with 153,516 Schedule II opioid observations, 21,065 Schedule III, 53,904 Schedule IV, and 1,436 Schedule V.
- **Step 12**: I identified the drug form, strength per unit, and unit of measurement for the 229,921 opioid observations. If needed, I converted strength per unit from the given units to a consistent unit for all observations (MG for tablets, MG/ML for solutions, and MG/patch for patches). For 89 percent of the observations, this information was already available from the CDC file (from Step 1). For the remaining 11 percent of opioid observations, I imputed this information. I first used the rxstreng and rxstrunt variables provided by MEPS to fill in missing information for strength per unit. (For example, if observations with an rxname of "Codeine" and rxstreng of "30 MG" did not match with the CDC file, I filled in "30" for the strength per unit and "MG" for the unit of measurement. This process allowed me to identify the drug form and strength per unit of 76 percent of the missing data.
    - For observations that had missing values for rxstreng and rxstrunt, I searched for drugs with the same name and form in the CDC file and used the modal values. (For example, the drug "Stadol" in its tablet form always had a strength per unit of 10 and unit of measurement of 10 MG/ML in the CDC file. So for Stadol observations with missing rxstreng values, I filled in "10" for the strength per unit and "MG/ML" for the unit of measurement.)
    - Finally, for the 3,000 opioid observations that were missing both drug names and NDCs ("Unknown Opioids"), 28 percent of them did have nonmissing information for rxstreng. For the remaining 72 percent, I identified the missing information using the modal values of all the opioid observations (i.e. "tablet" drug form, 5 for strength per unit, and MG for unit).
    - Through this process, I was also able to identify drug names for 26 percent of the 3,000 opioid observations that were missing both drug names and NDCs (for example, if the drug form was weekly patch and the category was narcotic

analgesic, I knew the drug must be fentanyl). I now had only 2,210 opioid observations that were missing both drug names and NDCs ("Unknown Opioids").
    - I discovered that some of the "Unknown Opioids" were actually treatment drugs such as Buprenorphine or Naloxone. I reclassified these observations as non-analgesics. I now had 229,280 opioid observations.
- **Step 13**: For each of the opioid observations, I identified the active opioid ingredient (e.g. morphine, hydrocodone, fentanyl, tramadol, etc) using the generic drug names. For the 2,210 opioid observations that were missing both drug names and NDCs ("Unknown Opioids"), I listed the active opioid ingredient as "Unknown."
- **Step 14**: For each of the opioid observations, I identified the MME conversion factor. I had obtained this data from the CDC file for 89 percent of the opioid observations (see Step 1). For the remaining 11 percent, I used the active opioid ingredients and obtained this information from the CMS website (https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/Opioid-Morphine-EQ-Conversion-Factors-Aug-2017.pdf). For the 2,210 opioid observations that were missing both drug names and NDCs ("Unknown Opioids"), I identified the MME conversion factor as the modal MME (1).
- **Step 15**: MEPS provided the total amount spent on each prescription, as well as the breakdown by source of payment (amount paid by self, private insurance, other private sources, workers' compensation, Medicare, VA, Champus, Tricare, other federal sources, Medicaid, other state/local sources, other public sources, and other sources). These variables were all nonmissing in the original data because they had already been imputed by MEPS for missing cases. I used these variables to calculate amount paid by all public sources (sum of workers' compensation, Medicare, VA, Champus, Tricare, other federal sources, Medicaid, other state/local sources, and other public sources) and amount paid by all private sources and self (sum of private insurance, other private sources, self, and other).
- **Step 16**: I imputed quantities and days supplied for the opioid and non-opioid painkillers, ensuring that the units matched the unit of measurement from Step 12. Of the 485,751 painkiller observations, the MEPS quantity variable (rxquanty) was nonmissing for 99.9 percent of observations. For those 561 observations that were missing quantities, I imputed the quantity by using the modal quantity of the same NDC in other cases.
    - The days supplied variable was only provided for the years 2010 onwards. Of the 485,751 painkiller observations, I had days supplied information for only 23 percent. Before any imputations, the mean (median) days supplied per prescription was 18 (16) for opioids and 31 (30) for non-opioid painkillers.
    - For observations that were missing days supplied, I imputed using the modal quantity per day supplied of the same NDC in cases for which I did have days supplied. (For example, for NDC 00054024425 (Codeine 30 mg tablets), the mode number of tablets patients were prescribed per day in the post-2010 period was 6. Therefore, for NDC 00054024425 in the pre-2010 period, I coded the days

supplied variable as the quantity of tablets in the prescription divided by 6.) After this imputation, I had days supplied information for 61 percent of the painkiller observations.
    - For cases where the NDC was not observed again in the post-2010 period, I imputed using the modal quantity per day supplied for observations that had the same product name, drug form, and strength level. After this imputation, I had days supplied information for 90 percent of the painkiller observations.
    - For cases where days supplied was still missing, I imputed using the modal quantity per day supplied for observations that had the same generic drug name, drug form, and strength level. After this imputation, I had days supplied information for 95 percent of the painkiller observations.
    - For cases where days supplied was still missing, I imputed using the modal quantity per day supplied for observations that had the same generic drug name and drug form. After this imputation, I had days supplied information for 100 percent of the painkiller observations.
    - After all the imputations, the mean (median) days supplied per prescription was 16.5 (10) for opioids and 28.2 (30) for non-opioid painkillers.
- **Step 17**: For each opioid observation, I multiplied the Quantity variable (from MEPS) with the Strength Per Unit variable and the MME conversion factor (from the CDC file) to obtain the total MMEs in each prescription. Prior to calculating the product, I ensured that all three variables were measured in the same units.
    - Based on the total MME per day supplied, I identified high-dose opioid prescriptions as those that had more than 90 MMEs per day supplied and low-dose prescriptions as those that had 90 or fewer MMEs per day supplied.
- **Step 18**: Before collapsing the data, I created additional spending variables that described the amount spent (in that transaction) by each payment source on each of the generic drugs, extended release opioids, immediate release opioids, high-dose opioids, and low-dose opioids.
- **Step 19**: I collapsed the data at the prescription level to obtain a person-year level dataset that provided the number of prescriptions and amount of money spent for each drug type. I then calculated the amount spent per prescription for each drug type.
- **Step 20**: I collapsed the data at the days supplied level to obtain a person-year level dataset that provided the number of days supplied and amount of money spent for each drug type. I then calculated the amount spent per day supplied for each drug type.

MEPS Limitations

This subsection describes how I handle limitations of the MEPS data in my analysis. The text in italics comes from the MEPS codebook and methodology report (Agency for Healthcare Research and Quality, 2015; Hill et al., 2014), and subsequent paragraphs explain the extent to which the methodological issue does or does not threaten the validity of my results.

1. *"Users should carefully review the data when conducting trend analyses or pooling years or panels because Multum's therapeutic classification has changed across the years of the MEPS…Analysts should use caution when using the Cerner Multum therapeutic class variables for analysis and should always check for accuracy."*

I do not use the Multum therapeutic variable to classify drugs, since the Multum codes change over the time period of my analysis. Rather, I carefully identify opioid and non-opioid painkillers by using the original drug names provided by MEPS.

2. *"…beginning with the 2007 data, the rules MEPS uses to identify outlier prices for prescription medications became much less stringent than in prior years. Starting with the 2007 Prescribed Medicines file, there was: less editing of prices and quantities reported by pharmacies, more variation in prices for generics, lower mean prices for generics, higher mean prices for brand name drugs, greater differences in prices between generic and brand name drugs, and a somewhat lower proportion of spending on drugs by families, as opposed to third-party payers."*

The DD model estimates the treatment effect as the difference between the treatment group (individuals aged 65-74) and the control group (individuals aged 55-64) after 2006, relative to the difference between the two groups before 2006. Presumably, the 2007 MEPS methodological changes were applied to all respondents without age-based discrimination. As long as the rules were not applied differentially to my treatment group and control group after 2007, the DD results should not be affected.

3. *"Starting with the 2008 Prescribed Medicines file, improvements in the data editing changed the distribution of payments by source: (1) more spending on Medicare beneficiaries is by private insurance, rather than Medicare, and (2) less out-of-pocket payments and more Medicaid payments among Medicaid enrollees."*

My interest is in OOP drug prices, so the shift from Medicare to private insurance among Medicare beneficiaries is not relevant for my analysis. I estimate a sensitivity analysis in which I omit Medicaid enrollees from analysis, and I find that the substantive results are similar (results available on request).

4. *"Starting with the 2009 data, additional improvements increased public program amounts and reduced out-of-pocket payments and, for Medicare beneficiaries with both Part D and Medicaid, decreased Medicare payments and increased Medicaid and other state and local government payments."*

Regarding the reductions in OOP payments, so long as the methodology for calculating OOP payments did not change differentially for the treatment and control groups in 2009, my DD model should still capture the causal effect of Part D. I am primarily interested in the OOP gap between the treatment and control groups, not the raw levels of OOP payments. Regarding the second issue (decreased Medicare payments and increased Medicaid payments), my interest is in OOP prices, so the shift from Medicare to Medicaid among dual eligibles is not relevant for my analysis.

Other methodological changes were made beginning with the 2010 data, such as improvements to account for price discounts in the Part D donut hole and improvements in the price imputation methodology. However, since my period of analysis covers only through 2009, these later changes do not affect my results.

A4 Background on Medicare Part D

Established in 1966, Medicare provides health insurance for individuals over age 65. For the first 40 years of its existence, however, the Medicare program did not provide prescription drug coverage, with the exception of drugs administered in institutional settings such as hospitals and physicians' offices. Before 2006, the elderly had limited access to drug coverage: some low-income "dual-eligible" Medicare beneficiaries received coverage through Medicaid or state-sponsored drug programs; others received coverage through their employers or purchased coverage themselves through Medigap policies offered by private firms. However, these plans were often expensive and had caps on drug spending; one study found that before 2006, nearly one-third of elderly enrollees with drug coverage faced annual caps of $500 or less (Gold, 2001). Because of all these challenges, nearly one-third of Medicare beneficiaries lacked drug coverage before 2006 (Kaestner & Khan, 2012). Without insurance, these adults faced considerable cost barriers in accessing drugs and were more likely to engage in cost-related nonadherence (Duggan, Healy, & Scott Morton, 2008).

Motivated by the high proportion of elderly adults without drug coverage, high out-of-pocket spending burdens for the uninsured, and growing clinical importance of drugs in preventing and treating disease, the federal government established a prescription drug benefit for the elderly as part of the Medicare Modernization Act of 2003 (MMA). As of January 1,

2006, Medicare beneficiaries gained access to drug coverage through Medicare Part D (henceforth referred to as "Part D"). Insurance was delivered through private Part D plans and subsidized by the federal government. The MMA also provided a means-tested subsidy to help cover premiums and cost sharing for low-income individuals with limited assets.

How Part D Works

The enactment of Part D affected Medicare beneficiaries differently depending on their prior drug coverage (Levy & Weir, 2009):

1. Those who already had creditable drug coverage (e.g. through their current or former employers) were instructed to keep that coverage, and employers received subsidies from the government to continue offering it. (This was intended to reduce the likelihood that Part D would crowd out existing sources of drug coverage.)
2. Those on Medicaid (dual eligibles) were automatically enrolled in Part D and the subsidy.
3. Eighty-six percent of those on Medicare Advantage plans already had drug coverage before Part D. After 2006, nearly all Medicare Advantage plans included Part D plans as part of their benefit.
4. Those without coverage or with privately purchased drug coverage (including Medigap plans) could decide whether to enroll in Part D and whether to apply for the subsidy.

Part D beneficiaries could choose from three types of drug plans: 1) stand-alone plans that offered only drug coverage, 2) Medicare Advantage plans that provided all Medicare benefits including prescription drugs, or 3) creditable employer-sponsored coverage (for which the government would subsidize the employer). Enrollment in Part D plans was voluntary, but recipients were subject to a financial penalty for each month that they delay enrollment after reaching the eligible age (to lessen adverse selection).

For a typical Part D plan in 2006, the enrollee was responsible for paying 100 percent of their drug spending until reaching a $250 annual deductible. For the next $2,250 of spending, the plan covered 75 percent and the enrollee paid the remainder out of pocket. For the next $3,600 of spending, the plan paid 0 percent and the enrollee paid 100 percent (this part was known as the

"coverage gap" or "doughnut hole"). After spending reached $5,100, the plan paid 95 percent and the enrollee paid only 5 percent out of pocket (Engelhardt & Gruber, 2011). Insurers had substantial flexibility in plan design, so long as the plan was actuarially equivalent to the one described above and covered certain therapeutic classes of drugs.

Relevance of Part D for Researchers

The introduction of Part D represented the most significant expansion to Medicare since the program's inception. Appendix Figure A- 3 shows that the prescription drug coverage rate for the elderly jumped from 74 percent before 2006 up to 92 percent in the years following Part D. Coverage for a control group of near-elderly individuals, on the other hand, increased only marginally from 81 percent to 84 percent over the same time period. Part D currently serves 41 million Medicare beneficiaries and spends $94 billion ($2,300 per beneficiary) each year (Kaiser Family Foundation, 2016). The policy has had large-scale impacts on prescription drug utilization, out-of-pocket spending, drug prices, and inpatient hospitalizations among elderly individuals.

The implementation of Part D is of particular interest to researchers because it generated substantial variation in drug coverage rates across age groups and over time. Those above age 65 received a positive shock in their out-of-pocket price of prescription drugs after 2006, whereas those below 65 did not. Appendix Figure A- 4 shows that after 2006, the share of elderly individuals' prescription spending attributable to Medicare increased substantially from 9 percent before 2006 to 49 percent after the implementation of Part D; meanwhile, the share of total spending spent out of pocket fell from 49 percent before Part D to 25 percent after. Spending shares for the control group of near-elderly individuals, on the other hand, remained largely constant before and after 2006. This suggests that Part D led to a large change in out-of-pocket drug spending for Medicare eligibles.

Prior research has exploited the implementation of Part D as a natural experiment for understanding the causal effects of prescription drugs on various health, financial, and social outcomes. Although Part D is an older policy, it continues to be used as a setting for studying prescription drug coverage even in recent studies (Bradford & Bradford, 2016; Buchmueller &

Carey, 2017; Carey, 2017; Dunn & Shapiro, 2017; Huh & Reif, 2016; Kaplan & Zhang, 2017; Powell et al., 2017).

A5 Additional MEPS Analysis

Appendix Figure A- 5 displays trends in OOP prices of prescription painkillers over time for the outcomes not presented in Figure 4 in the main paper: price per MME and price per day supplied of high dose opioids, low dose opioids, extended release opioids and immediate release opioids. For the majority of outcomes, OOP prices appeared to follow similar trends for the treatment and control groups before 2006 and declined substantially for the treatment group after 2006. Appendix Figure A- 6 displays similar trends for the utilization outcomes (comparable to Figure 5 in the main paper). Although levels of utilization are always higher for elderly individuals, the trends are largely similar for the treatment and control groups before 2006, followed with a large uptick in utilization for the treatment group after 2006.

In Appendix Table A- 4, I use my baseline DD model to model the effect of Part D on utilization of all prescription drugs (not just painkillers). I find that Part D led to an increase in 2.95 prescriptions utilized per year ($p<0.01$), which represents an 11 percent increase over pre-2006 levels. The policy also reduced OOP prices by $7.61 per prescription, which represents a 24 percent decline from pre-2006. This implies a price elasticity of demand of -0.45, which aligns with findings from previous studies (Duggan & Scott Morton, 2010; Ketcham & Simon, 2008; Liu et al., 2011; Yin et al., 2008).

Appendix Table A- 5 displays regression results for the impact of Part D on prescription opioid utilization by drug (to be compared with Table 4 in the main paper). The increased opioids utilization can be traced to large increases in hydrocodone (2.94 increase in days supplied or 134 percent increase from pre-2006) and morphine (1.00 increase in days supplied of 417 percent increase from pre-2006).

In Appendix Table A- 6 through Appendix Table A- 12, I present results from numerous parallel trends tests, falsification tests, and sensitivity analyses that provide confidence in the causal interpretation of my results. I discuss these results in detail in the main paper.

Appendix Table A- 13 shows results from a specification in which the outcome variable is measured as an indicator for whether the respondent made any purchase of the prescription that year. The estimated treatment effects are close to zero and not statistically significant, suggesting that there was no impact of Part D on the extensive margin of painkiller utilization. This may be because painkiller utilization was already relatively among elderly individuals even before 2006. Thirty-five percent of elderly individuals used prescription painkillers, even before the introduction of Part D.

In Appendix Table A- 14, I use my DD model to assess the effects of Part D on the number of prescriptions individuals receive as "free" samples. Providers or manufacturers may offer free samples as a way to market their drugs, and so if I were to find increases in the number of opioids offered as free samples, it may raise concerns about the possibility of non-price mechanisms influencing the purchase of painkillers after Part D. However, I find that there was no significant impact of Part D on the number of free samples of opioids. Moreover, while there was an impact for non-opioid painkillers, it was in the opposite direction as expected. Part D led to a 25 percent decline in the number of free samples of non-opioid painkillers, suggesting that advertising through this avenue actually fell.

A6 Additional Nielsen Analysis

Before 2006, the average price per day supplied of an OTC painkiller was $0.37. Appendix Table A- 15 shows that there was no detectable effect of Part D on the prices of OTC painkillers for older households relative to younger households. The DD coefficient is close to zero and statistically insignificant.

Appendix Table A- 16 displays results from an event study specification that assesses differential trends in OTC utilization between the treatment and control group in each year, relative to the base year 2005. Older households purchase more painkillers than younger households. In the years 2004 and 2006, the gap between older and younger households increased, whereas during 2007-09, this gap shrunk substantially.

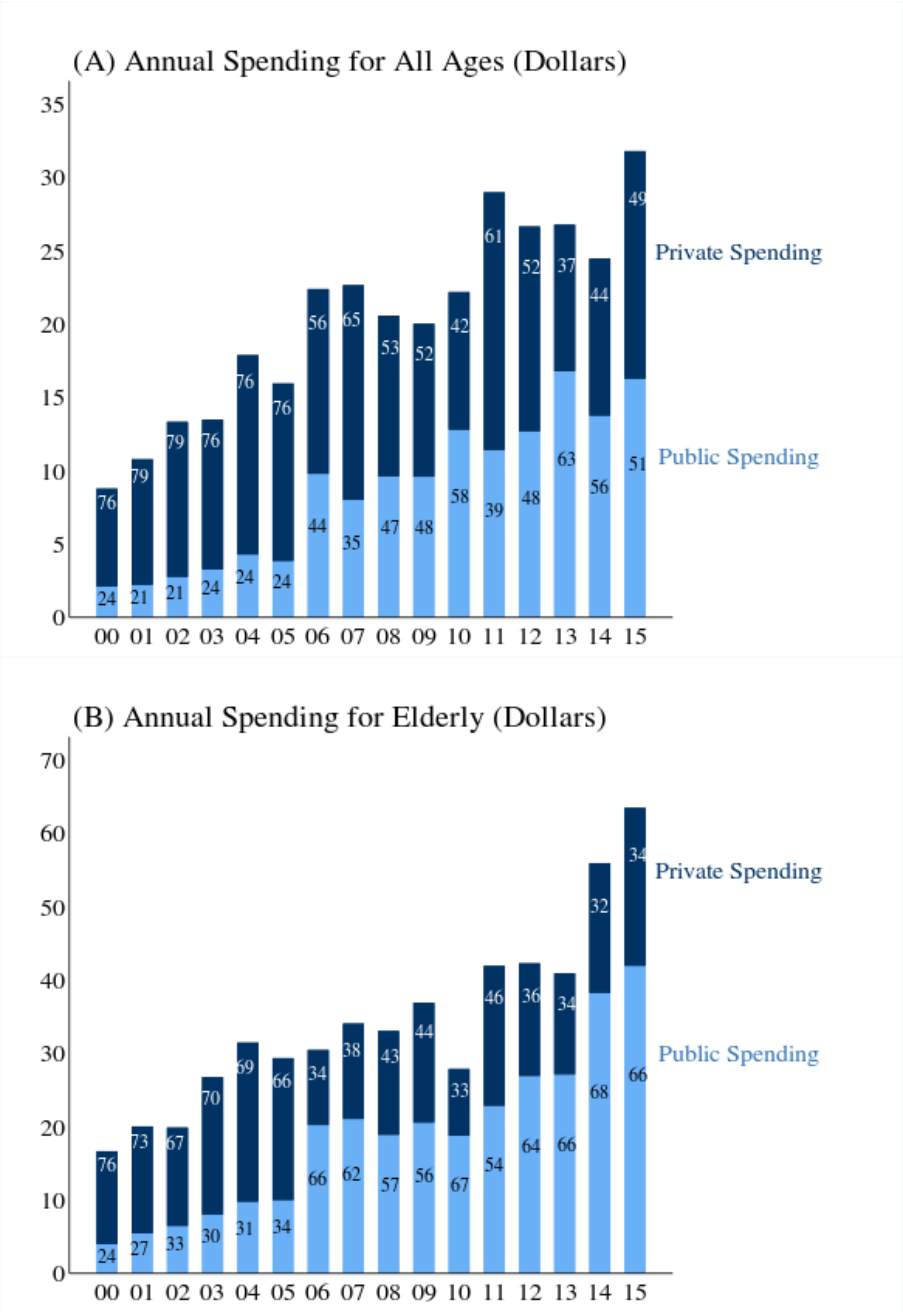
I expose the baseline DD model to a number of sensitivity analyses, and results are displayed in Appendix Table A- 17. The baseline DD model presented in the main paper yields a

treatment effect of -3.27 ($p<0.01$). Column 1 displays results from a specification that omits demographic control variables from the right hand side; in this specification, the treatment effect is -3.46 ($p<0.01$). Column 2 shows that if Nielsen survey weights are omitted, the treatment effect is -3.46 ($p<0.01$). Both these results are remarkably similar to that presented in the original baseline model. However, when I omit household fixed effects from the right hand side, the DD coefficient is 0.18 and imprecisely measured. This suggests that the results are sensitive to the inclusion of household fixed effects. In Column 4, I show that Part D led to a 0.01 percentage point or 1.3 percent decline in the probability of purchasing any OTC painkillers in a given year.

Finally, I explore heterogeneous effects of the policy by income. Appendix Table A- 18 shows that the decline in OTC painkillers was concentrated among high-income households with income greater than 400 percent of the poverty level and middle-income households with incomes between 125 and 400 percent of the poverty level. As expected there was no detectable effect of Part D on OTC painkiller utilization of low-income households because these individuals were more likely to have drug coverage through Medicaid even before Part D.

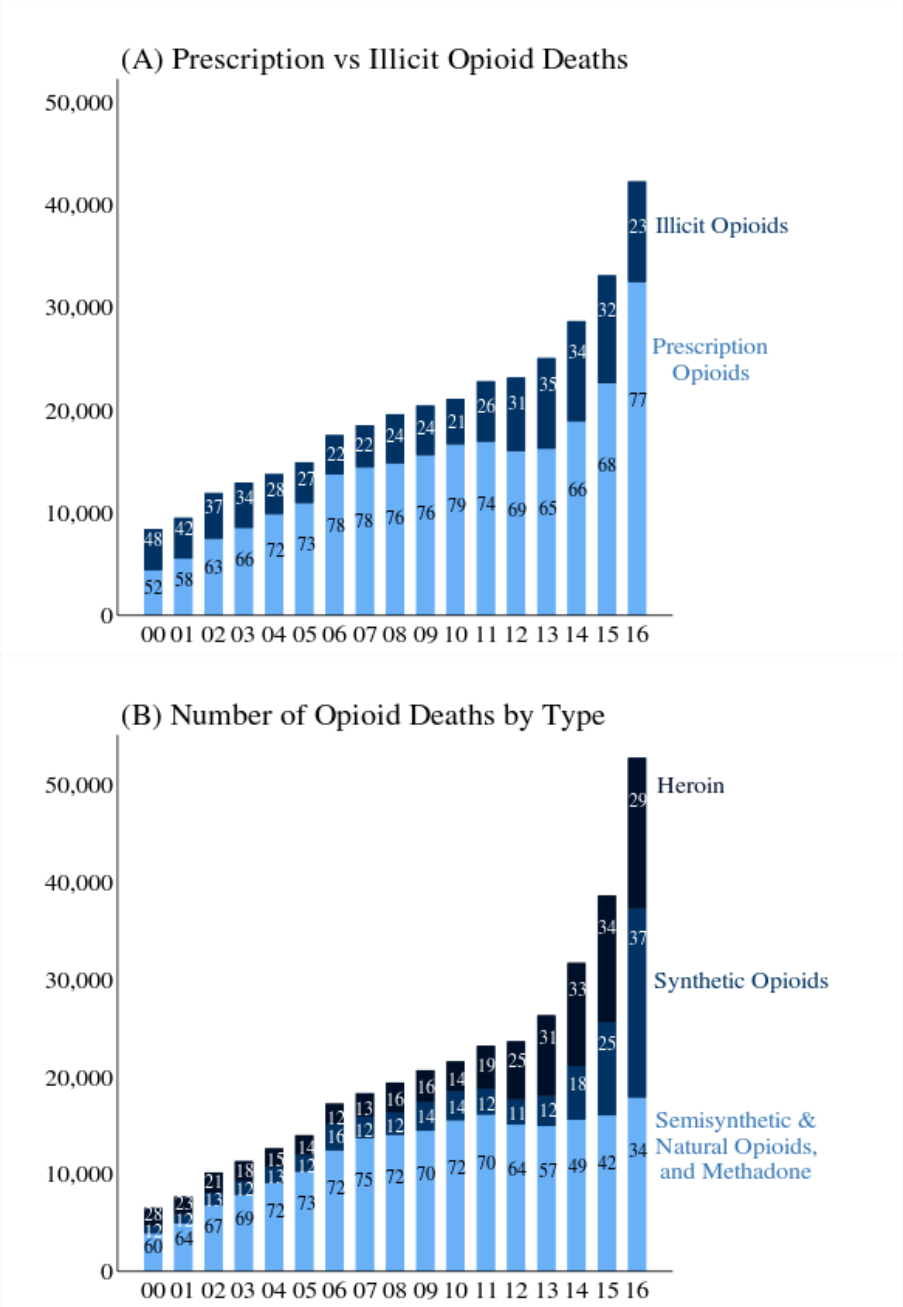
A7 Appendix Figures

Appendix Figure A- 1: Prescription Opioid Spending per Person



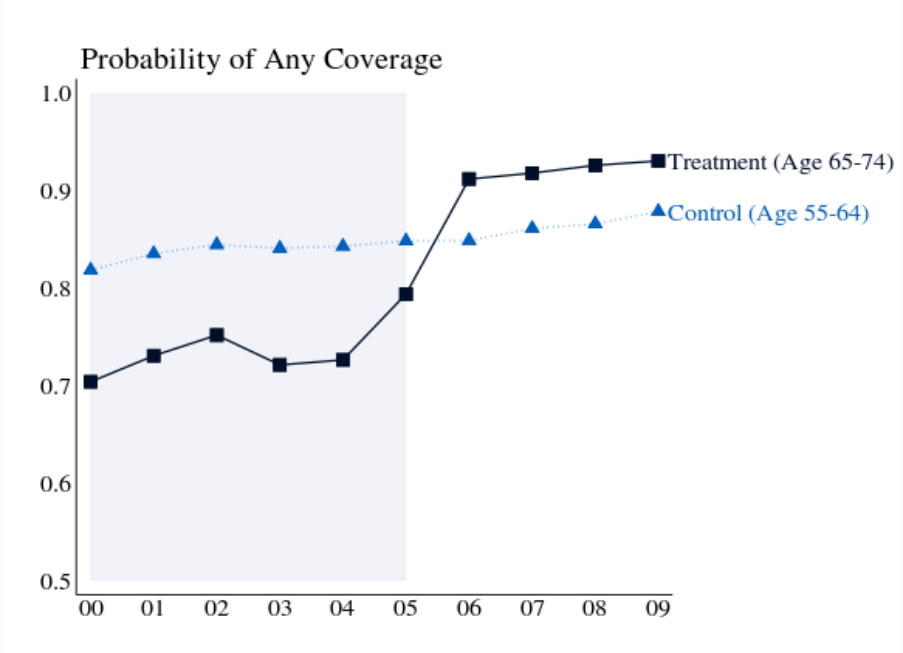
Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2015. Panel A includes all respondents (N=549,801), and Panel B includes respondents over age 65 (N=60,798). Figures display the mean number of painkiller prescriptions per person, adjusted by MEPS survey weights.

Appendix Figure A- 2: Opioid Overdose Deaths by Type



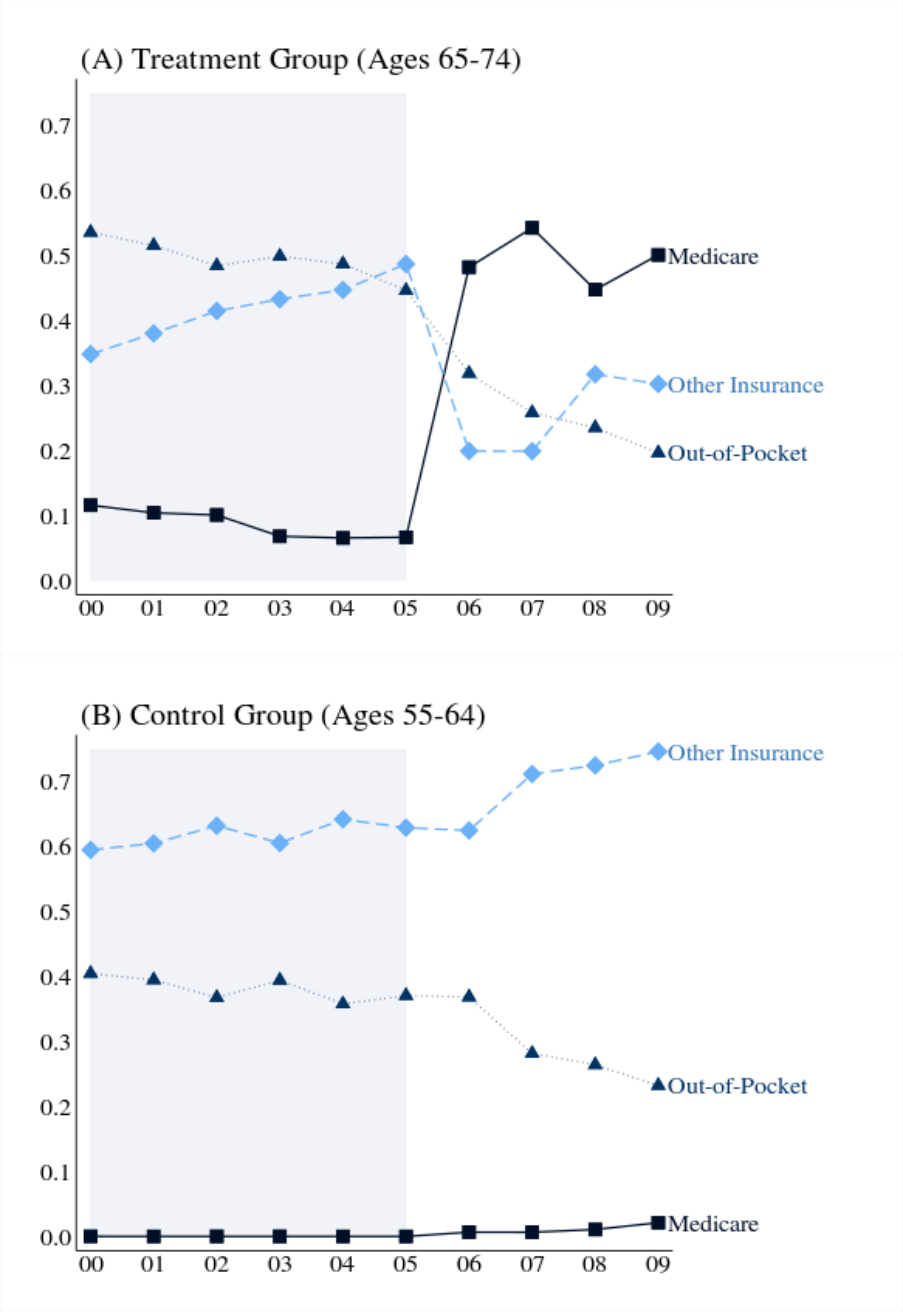
Source: Author's calculations based on data from the Henry J. Kaiser Family Foundation. Figures display the number of opioid overdose deaths in the United States by category. The numbers inside each bar indicate the percent of total opioid overdose deaths attributable to that category.

Appendix Figure A- 3. Impact of Part D on Prescription Drug Insurance Rates



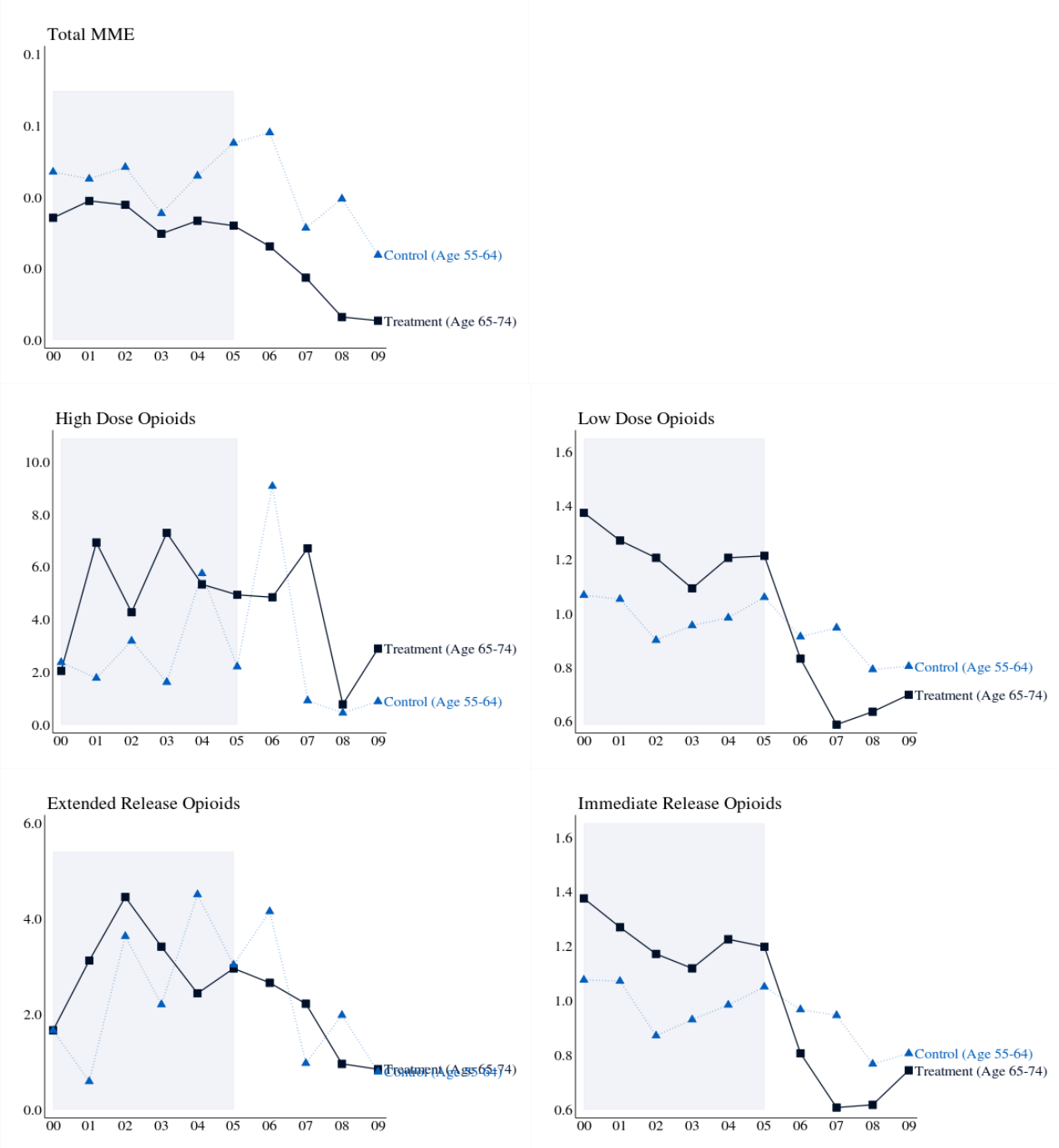
Source: Author's calculations based on Medical Expenditure Panel Survey. Sample is restricted to adults aged 55 to 74 (N=50,579). Figure displays probability of having any prescription drug coverage at any point during the year, adjusted by MEPS survey weights. Individuals are defined as having prescription drug coverage if at least one of the following is true: 1) they have a private source of insurance coverage, 2) they reported positive third party payments for prescriptions purchased during the year, or 3) they have a Medicare Part D plan.

Appendix Figure A- 4. Proportion of Total Prescription Drug Spending by Source



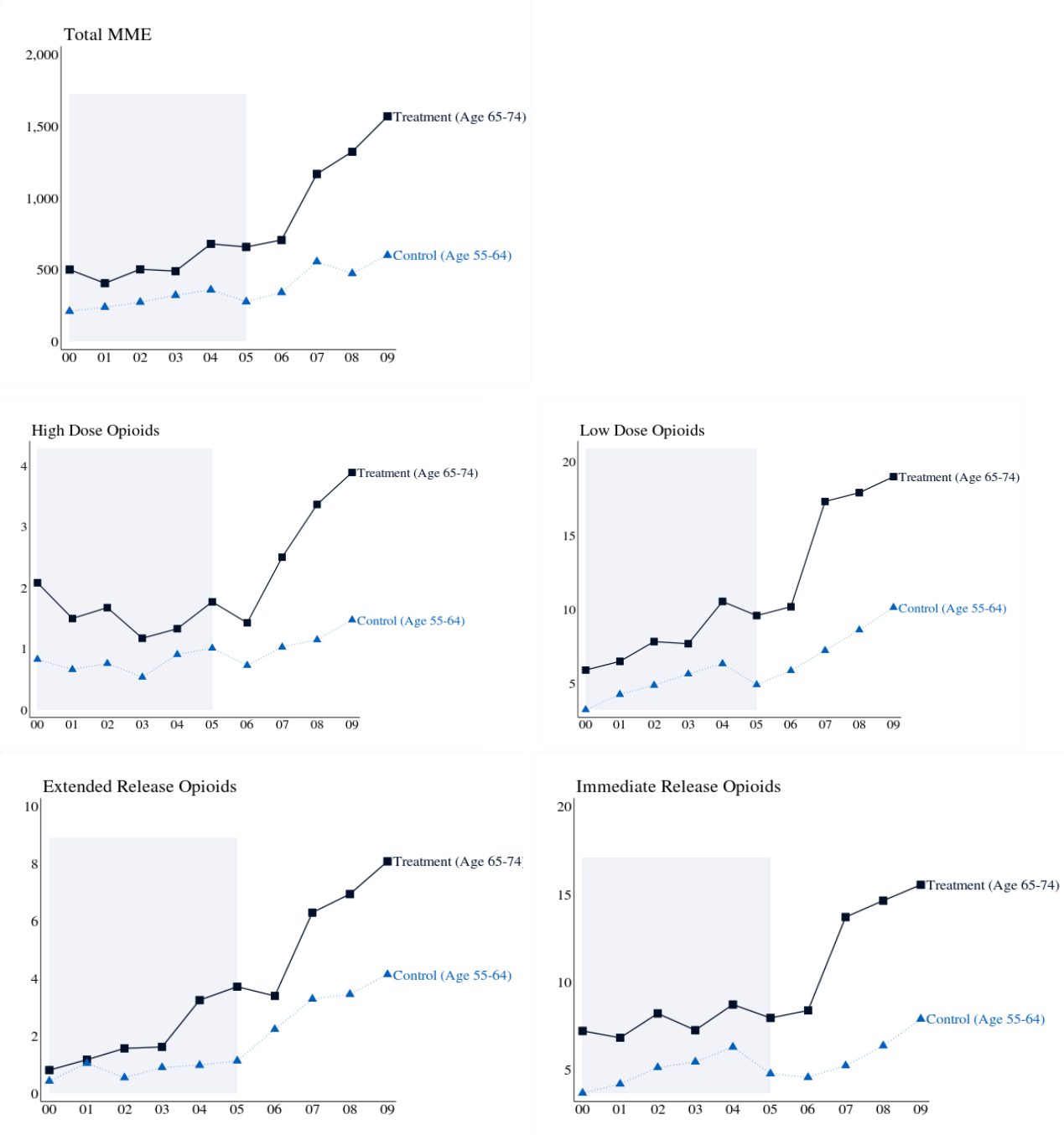
Source: Author's calculations based on Medical Expenditure Panel Survey. Sample is restricted to adults aged 55 to 74 (N=50,579). Figures display percentage of total prescription drug spending paid by each source, adjusted by MEPS survey weights.

Appendix Figure A- 5. Out-of-Pocket Prices of Prescription Painkillers over Time



Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Figures display the mean OOP spending per day supply of each NDC, weighted by 2003 utilization of the NDC. Prices are adjusted to 2009 dollars using the Bureau of Labor Statistics' Pharmaceutical Producer Price Index.

Appendix Figure A- 6. Utilization of Prescription Painkillers over Time



Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Sample is restricted to adults aged 55 to 74 (N=50,579). Figures display the mean number of days supplied per person, adjusted by MEPS survey weights.

A8 Appendix Tables

Appendix Table A- 2: Classification of Prescription Painkillers in MEPS

Drug	Common Brands
Opioids – Prescription pain relief drugs whose distribution is controlled by the DEA because they have potential for abuse and may lead to psychological or physical dependence	
Butorphanol	Stadol
Codeine	
Codeine & Acetaminophen	
Dihydrocodeine & Acetaminophen	
Dihydrocodeine & Aspirin	
Fentanyl	Durageic, Actiq
Hydrocodone	Hysingla
Hydrocodone & Acetaminophen	Lortab, Lorcet, Vicodin, Norco
Hydrocodone & Aspirin	Damason
Hydrocodone & Ibuprofen	Vicoprofen
Hydromorphone	Dilaudid
Levorphanol	Levo Dromoran
Meperidine	Demerol
Meperidine & Promethazine	Meprozine
Morphine	MS Contin, Kadian, Avinza
Nalbuphine	Nubain
Opium	
Oxycodone	Oxycontin, Roxicodone
Oxycodone & Acetaminophen	Percocet, Endocet, Roxicet
Oxycodone & Aspirin	Endodan, Percodan
Oxycodone & Ibuprofen	Combunox
Oxymorphone	Opana
Pentazocine & Acetaminophen	Talacen
Propoxyphene	Darvon
Propoxyphene & Acetaminophen	Darvocet, Propacet
Propoxyphene & Aspirin	
Tapentadol	Nucynta
Tramadol	Ryzolt
Tramadol & Acetaminophen	Ultracet
Unknown Opioids	
Non-opioid painkillers – Pain relief drugs that are not controlled by the DEA but require a physician's prescription	
Acetaminophen & Acetaminophen Combinations	Fioricet, Mapap, Midrin, Tylenol
Almotriptan	Axert
Aspirin & ASA Combinations	Aspirin, Ecotrin, Fiorinal
Bromfenac	Duract
Celecoxib	Celebrex
Choline Magnesium Trisalicylate	Trilisate
Diclofenac	Arthrotec, Cataflam, Voltaren
Diflunisal	Dolobid
Dihydroergotamine mesylate	Migranal
Eletriptan	Relpax
Ergotamine	Cafergot

Etodolac	Lodine
Fenoprofen	
Flurbiprofen	Ansaid
Frovatriptan	Frova
Ibuprofen	Advil, Motrin
Indomethacin	Indocin
Ketoprofen	Oruvail
Ketorolac	Toradol
Magnesium salicylate	
Meclofenamate	
Mefenamic acid	Ponstel
Meloxicam	Mobic
Methylprednisolone	
Methysergide maleate	Sansert
Nabumetone	Relafen
Naproxen	Naprelan, Anaprox, Aleve
Naratriptan	Amerge
Oxaprozin	Daypro
Piroxicam	Feldene
Prednisone	
Rizatriptan	Maxalt
Rofecoxib	Vioxx
Salsalate	
Sulindac	Clinoril
Sumatriptan	Imitrex
Tolmetin	
Valdecoxib	Bextra
Zolmitriptan	Zomig
Unknown Non-Opioid Painkillers	

Source: Author's classification of drugs in Medical Expenditure Panel Survey Prescribed Medicines files.

Appendix Table A- 3: Composition of the 2003 Basket of Pain Relief Drugs

Generic Drug Name	Sample NDCs	Proportion of All Painkillers	
		Treatment Group	Control Group
Opioids			
Hydrocodone & Acetaminophen	00406035705, 52544063401	0.031	0.051
Methadone	00406345434, 00054457025	0.025	0.007
Oxycodone	59011010010, 58177004104	0.021	0.015
Propoxyphene & Acetaminophen	00378015505, 00603546628	0.014	0.016
Oxycodone & Acetaminophen	00054465029, 00406053201	0.013	0.011
Tramadol	00045065960, 00378415105	0.010	0.005
Fentanyl	50458003405, 50458003505	0.008	0.001
Codeine & Acetaminophen	00045051360, 63304056201	0.007	0.008
Hydrocodone & Ibuprofen	00093516101	0.001	0.001
Codeine	00054415625	0.001	0.001
Morphine	60951065270	0.001	0.007
Hydromorphone	00406324301	0.001	0.001
Meperidine & Promethazine	00603442421, 58177002704	0.001	0.001
Propoxyphene	00603545921	0.001	0.001
Tramadol & Acetaminophen	00045065060	0.001	0.020
Non-Opioid Painkillers			
Celecoxib	00025152031, 00025152051	0.364	0.374
Aspirin & ASA Combos	00182044810, 15127022894	0.303	0.183
Diclofenac	00781178901, 00591033801	0.055	0.053
Meloxicam	00597002901, 00597003001	0.040	0.037
Naproxen	00093014901, 67253062210	0.028	0.070
Ibuprofen	00009738701, 49884077705	0.026	0.058
Acetaminophen & Combos	00603026321, 00143111501	0.010	0.018
Nabumetone	00093101501, 00029485120	0.010	0.029
Indomethacin	00172403060, 00378014301	0.013	0.001
Diflunisal	00093075506	0.004	0.001
Etodolac	51672401801, 00093112201	0.004	0.002
Oxaprozin	00185014101, 49884072301	0.004	0.012
Piroxicam	00093075701, 00378202001	0.003	0.006
Sulindac	00378053101, 00591566001	0.003	0.005
Flurbiprofen	00378009301, 00093071101	0.002	0.006
Ketoprofen	00378575001	0.001	0.001
Ketorolac	00378113401, 58177030104	0.001	0.001

Source: Author's calculations based on Medical Expenditure Panel Survey 2003. This table excludes drugs that were removed from the market before 2006 (i.e. Vioxx, Bextra, etc).

Appendix Table A- 4. Impact of Part D on Utilization of All Prescription Drugs

	Utilization (Prescriptions)			Price (OOP Price per Prescription)			Elasticity
	Pre-2006 Mean (1)	DD Coefficient (2)	Percent Change (3)	Pre-2006 Mean (4)	DD Coefficient (5)	Percent Change (6)	(7)
All Drugs	26.27	2.95*** (0.82)	11.2%	31.52	-7.61*** (0.92)	24.1%	-0.45
N		50,579			50,579		

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Sample is restricted to adults aged 55 to 74. Columns 1 and 4 display the pre-2006 mean for the treatment group. Columns 2 and 5 display the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS. Columns 3 and 6 displays percent change from pre-2006 mean.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix Table A- 5. Regression Results for Impact of Part D on Prescription Opioid Utilization (Days Supplied) by Drug

	Pre-2006 Mean (1)	DD Coefficient (2)	Percent Change (3)
Hydrocodone	2.20	2.94*** (0.67)	133.6%
Propoxyphene	2.64	0.67 (0.51)	-
Oxycodone	1.44	0.42 (0.58)	-
Tramadol	1.60	0.50 (0.52)	-
Codeine	0.56	0.03 (0.16)	-
Morphine	0.24	1.00*** (0.32)	416.7%
Fentanyl	0.34	0.32 (0.35)	-
Methadone	0.55	-0.32 (0.30)	-
Other Opioids	0.32	-0.24* (0.13)	-75.0%
N		50,579	

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Sample is restricted to adults aged 55 to 74. Column 1 displays the pre-2006 mean for the treatment group. Column 2 displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS. For statistically significant point estimates, column 3 displays percent change from pre-2006 mean.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A- 6. Event Study Results for Impact of Part D on Prescription Painkillers

Panel A: Utilization (Days Supplied)

	Total MME (1)	High Dose Opioids (2)	Low Dose Opioids (3)	Extended Release Opioids (4)	Immediate Release Opioids (5)
Year 2000 X Treatment	-74.74	0.54	-1.93	-2.16**	0.46
	(153.40)	(0.71)	(1.60)	(0.87)	(1.68)
Year 2001 X Treatment	-195.01	0.13	-2.36*	-2.42***	-0.44
	(139.42)	(0.67)	(1.37)	(0.87)	(1.36)
Year 2002 X Treatment	-142.99	0.18	-1.70	-1.51*	-0.09
	(189.07)	(0.70)	(1.56)	(0.91)	(1.52)
Year 2003 X Treatment	-221.74	-0.14	-2.79*	-1.93**	-1.46
	(147.02)	(0.58)	(1.64)	(0.93)	(1.56)
Year 2004 X Treatment	-46.92	-0.30	-0.35	-0.27	-0.63
	(123.19)	(0.53)	(1.50)	(0.87)	(1.43)
Year 2006 X Treatment	-54.51	-0.20	-0.65	-1.60	0.38
	(219.06)	(0.47)	(1.57)	(1.01)	(1.39)
Year 2007 X Treatment	186.37	0.49	5.18***	0.23	5.02***
	(250.61)	(0.71)	(1.98)	(1.35)	(1.69)
Year 2008 X Treatment	423.59	1.33	4.21*	0.78	4.69**
	(309.02)	(0.98)	(2.19)	(1.45)	(1.99)
Year 2009 X Treatment	568.72**	1.60	3.94*	1.23	4.30**
	(256.24)	(1.03)	(2.09)	(1.34)	(1.85)
p-value for test that all pre-2006 terms jointly equal 0	0.51	0.82	0.32	0.03	0.87
N	50,579	50,579	50,579	50,579	50,579

Panel B: OOP Price (per Day Supplied)

	Total MME (1)	High Dose Opioids (2)	Low Dose Opioids (3)	Extended Release Opioids (4)	Immediate Release Opioids (5)
Year 2000 X Treatment	-0.01	-0.33	0.57	0.00	0.53
	(0.02)	(0.84)	(0.50)	(0.57)	(0.57)
Year 2001 X Treatment	-0.01	5.16	-0.12	2.53	-0.26
	(0.03)	(3.68)	(0.72)	(1.89)	(0.66)
Year 2002 X Treatment	-0.01	1.09	0.38	0.82	0.24

	(0.01)	(3.97)	(0.55)	(3.17)	(0.43)
Year 2003 X Treatment	-0.01 (0.01)	5.68* (3.26)	-0.30 (0.46)	1.21 (2.45)	0.26 (0.40)
Year 2004 X Treatment	-0.01 (0.02)	-0.41 (5.40)	0.65 (0.47)	-2.07 (4.21)	1.16** (0.55)
Year 2006 X Treatment	-0.03 (0.02)	-4.22 (6.96)	0.23 (0.55)	-1.50 (4.59)	-0.49 (0.52)
Year 2007 X Treatment	-0.01 (0.01)	5.79 (5.41)	-1.25** (0.63)	1.25 (2.24)	-0.97 (0.62)
Year 2008 X Treatment	-0.03** (0.01)	0.33 (0.26)	-0.57 (0.53)	-1.02 (0.79)	-0.33 (0.50)
Year 2009 X Treatment	-0.02*** (0.01)	2.01** (0.89)	-0.70 (0.56)	0.05 (0.49)	-0.34 (0.69)
p-value for test that all pre-2006 terms jointly equal 0	0.88	0.39	0.53	0.80	0.29
N	1,664	308	1,356	223	1,441

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Table displays the coefficient on the interaction of the treatment group indicator and each year indicator. The year 2005 is omitted as the base year. Regressions in Panel A control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS. Regressions in Panel B include a treatment group indicator and year fixed effects. Data are weighted by 2003 level of utilization of the NDC.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A- 7. Falsification Tests for Impact of Part D on Prescription Painkiller Utilization (Days Supplied)

	"Treatment" as Ages 45-54 (1)	"Treatment" as Ages 35-44 (2)	"Treatment" as Ages 25-34 (3)	"Treatment" as Ages 18-24 (4)
All Painkillers	0.99 (1.72)	0.57 (1.39)	0.18 (1.40)	-0.16 (1.42)
Opioids	1.22 (0.98)	-0.79 (0.77)	-1.23 (0.77)	-1.43* (0.76)
Non-Opioid Painkillers	0.22 (1.43)	1.25 (1.15)	1.23 (1.13)	1.28 (1.18)
N	74,703	77,310	74,883	63,708

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. The control group consists of individuals aged 55-64, and the column header provides the definition of the "treatment" group. Each cell displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix Table A- 8. DD Results with Two Post Periods for Impact of Part D on Prescription Painkiller Utilization (Days Supplied)

	Treatment X 2004-05 (1)	Treatment X Post-2006 (2)	N (3)
All Painkillers	4.03* (2.40)	5.76** (2.38)	50,579
Opioids	1.63 (1.17)	5.39*** (1.30)	50,579
Non-Opioid Painkillers	2.43 (2.21)	0.88 (2.10)	50,579

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Sample is restricted to adults aged 55 to 74. Column 1 displays the coefficient on the interaction of the treatment group indicator and the 2004-05 indicator. Column 2 displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A- 9. Sensitivity Analyses for Impact of Part D on Prescription Painkiller Utilization (Days Supplied)

Panel A: Alternative Specifications

	No Demographic Controls (1)	Omit Years 2004-05 (2)	Omit Ages 63-64 (3)	Alternative Treatment (4)	Treatment X Year FE (5)	Control for Health Status (6)	Treatment X Year FE and Control for Health Status (7)
All Painkillers	4.31*	5.90**	4.82**	3.59	4.85	3.87*	4.53
	(2.26)	(2.39)	(2.35)	(2.28)	(4.11)	(2.27)	(4.00)
Opioids	4.72***	5.38***	4.95***	3.11***	4.50**	4.53***	4.30**
	(1.21)	(1.30)	(1.20)	(1.18)	(2.19)	(1.23)	(2.13)
Non-Opioid Painkillers	0.06	1.02	0.29	0.48	1.27	-0.18	1.12
	(2.00)	(2.11)	(2.11)	(2.05)	(3.50)	(2.02)	(3.47)
N	50,579	40,539	45,700	47,929	50,579	50,579	50,579

Panel B: Include Additional Years of Data

	Years 1996-2009 (1)	Years 2000-2015 (2)	Years 1996-2015 (3)
All Painkillers	5.88***	7.73***	9.37***
	(2.14)	(1.86)	(1.65)
Opioids	5.34***	7.23***	7.86***
	(1.17)	(0.97)	(0.91)
Non-Opioid Painkillers	1.18	1.35	2.55*
	(1.86)	(1.71)	(1.50)
N	65,363	87,899	102,683

Source: Author's calculations based on Medical Expenditure Panel Survey. In Panel A, years of analysis are restricted to 2000 to 2009. Each cell displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Unless otherwise specified, regressions control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A- 10. DD Results for Impact of Part D on Number of Painkiller Prescriptions (Number of Prescriptions)

	Utilization (Prescriptions)		
	Pre-2006 Mean (1)	DD Coefficient (2)	Percent Change (3)
Painkillers			
All Painkillers	1.96	0.11 (0.11)	-
Opioids	0.73	0.18*** (0.07)	24.7%
Non-Opioid Painkillers	1.23	-0.07 (0.07)	-
Opioids, by Dosage			
High Dose Opioids	0.15	0.01 (0.03)	-
Low Dose Opioids	0.59	0.17*** (0.06)	28.8%
Opioids, by Release			
Extended Release Opioids	0.12	0.05 (0.03)	
Immediate Release Opioids	0.62	0.13** (0.05)	21.0%
N		50,579	

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Sample is restricted to adults aged 55 to 74. Column 1 displays the pre-2006 mean for the treatment group. Column 2 displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS. For statistically significant point estimates, column 3 displays percent change from pre-2006 mean.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A- 11. Heterogeneous Effects for Impact of Part D on Prescription Painkiller Utilization by Household Income

	Pre-2006 Mean (1)	DD Coefficient (2)	Percent Change (3)
Less than 125% FPL			
All Painkillers	51.70	8.31 (5.66)	-
Opioids	16.50	5.54 (3.44)	-
Non-Opioid Painkillers	38.06	3.29 (4.96)	-
N		9,259	
125-400% FPL			
All Painkillers	41.65	6.37* (3.61)	15.3%
Opioids	9.47	7.88*** (2.08)	83.2%
Non-Opioid Painkillers	33.49	-0.77 (3.08)	-
N		21,191	
Greater than 400% FPL			
All Painkillers	31.45	0.10 (2.96)	-
Opioids	6.58	0.53 (1.46)	-
Non-Opioid Painkillers	25.93	-0.55 (2.59)	-
N		20,129	

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Sample is restricted to adults aged 55 to 74. Column 1 displays the pre-2006 mean for the treatment group. Column 2 displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for sex, marital status, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS. For statistically significant point estimates, column 3 displays percent change from pre-2006 mean.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A- 12. Robustness Checks for Impact of Part D on Prescription Painkiller Utilization

	Ages 50-79 (1)	Ages 51-78 (2)	Ages 52-77 (3)	Ages 53-76 (4)	Ages 54-75 (5)	Ages 55-74 (6)	Ages 56-73 (7)	Ages 57-72 (8)	Ages 58-71 (9)	Ages 59-70 (10)	Ages 60-69 (11)
All Painkillers	4.22** (1.79)	4.01** (1.84)	4.11** (1.91)	4.51** (2.01)	4.75** (2.17)	4.33* (2.30)	4.45* (2.38)	5.00** (2.48)	4.61* (2.66)	3.45 (2.85)	2.17 (3.06)
Opioids	4.71*** (1.00)	4.64*** (1.03)	4.65*** (1.06)	4.78*** (1.09)	4.98*** (1.15)	4.81*** (1.23)	4.91*** (1.29)	5.24*** (1.37)	5.06*** (1.44)	4.28*** (1.53)	3.11* (1.71)
Non-Opioid Painkillers	0.13 (1.60)	-0.07 (1.63)	-0.02 (1.72)	0.18 (1.81)	0.39 (1.94)	0.02 (2.04)	0.15 (2.08)	0.39 (2.15)	0.16 (2.30)	-0.41 (2.45)	-0.80 (2.62)
N	79,033	73,350	67,583	61,851	56,231	50,579	45,128	39,653	34,221	29,118	24,195

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Sample is restricted to ages defined in the column header. Each cell displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A- 13. DD Results for Impact of Part D on Any Purchase of Prescription Painkillers

	Utilization (Any Purchase)		
	Pre-2006 Mean (1)	DD Coefficient (2)	Percent Change (3)
Painkillers			
All Painkillers	0.35	0.01 (0.01)	-
Opioids	0.17	0.01 (0.01)	-
Non-Opioid Painkillers	0.26	-0.01 (0.01)	-
N		50,579	

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Sample is restricted to adults aged 55 to 74. Column 1 displays the pre-2006 mean for the treatment group. Column 2 displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS. For statistically significant point estimates, column 3 displays percent change from pre-2006 mean.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix Table A- 14. Impact of Part D on Free Samples of Prescription Painkillers

	Number of Free Sample Prescriptions		
	Pre-2006 Mean (1)	DD Coefficient (2)	Percent Change (3)
All Drugs	0.96	-0.20*** (0.07)	-20.8%
All Painkillers	0.09	-0.02* (0.01)	-22.2%
Opioids	0.01	-0.00 (0.00)	-
Non-Opioid Painkillers	0.08	-0.02* (0.01)	-25.0%
N		50,579	

Source: Author's calculations based on Medical Expenditure Panel Survey 2000 to 2009. Sample is restricted to adults aged 55 to 74. Column 1 displays the pre-2006 mean for the treatment group. Column 2 displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include age fixed effects and year fixed effects. Data are adjusted by MEPS survey weights, and standard errors account for the complex design of the MEPS. For statistically significant point estimates, column 3 displays percent change from pre-2006 mean.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A- 15. DD Results for Impact of Part D on Prices of OTC Painkillers

	Price (per Day Supplied)		
	Pre-2006 Mean (1)	DD Coefficient (2)	Percent Change (3)
OTC Painkillers	0.37	0.06 (0.06)	-
N		335,060	

Source: Author's calculations based on Nielsen Household Consumer Panel 2004 to 2009. Column 1 displays the pre-2006 mean for the treatment group. Column 2 displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for householder's sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include household fixed effects and year fixed effects. Data are adjusted by Nielsen survey weights, and standard errors are clustered on household.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Appendix Table A- 16. Event Study Results for Impact of Part D on Utilization of OTC Painkillers

	Utilization (Days Supplied) (1)
Year 2004 X Treatment	2.05**
	(0.91)
Year 2006 X Treatment	3.41***
	(0.93)
Year 2007 X Treatment	-3.67***
	(0.96)
Year 2008 X Treatment	-4.01***
	(1.00)
Year 2009 X Treatment	-7.86***
	(1.04)
N	335,060

Source: Author's calculations based on Nielsen Household Consumer Panel 2004 to 2009. Column 1 displays the coefficient on the interaction of the treatment group indicator and each year indicator. The year 2005 is omitted as the base year. Regressions control for householder's sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include household fixed effects and year fixed effects. Data are adjusted by Nielsen survey weights, and standard errors are clustered on household.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A- 17. Sensitivity Analyses for Impact of Part D on Utilization of OTC Painkillers

	No Controls (1)	No Weights (2)	No Household FE (3)	Any Purchase Outcome (4)
OTC Painkillers	-3.46***	-3.46***	0.18	-0.01**
	(0.98)	(0.72)	(1.24)	(0.01)
N	335,060	335,060	335,060	335,060

Source: Author's calculations based on Nielsen Household Consumer Panel 2004 to 2009. Table displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Results should be compared with those in Table 8. The outcome variable is "number of days supplied of OTC painkillers" for columns 1-3 and "any painkiller purchased" for column 4 (pre-2006 mean for "any painkiller purchased" is 0.79). Unless otherwise specified, regressions control for householder's sex, marital status, household income, educational attainment, race/ethnicity, and Census region, and include household fixed effects and year fixed effects. Data are adjusted by Nielsen survey weights, and standard errors are clustered on household.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix Table A- 18. Heterogeneous Effects for Impact of Part D on OTC Painkiller Utilization by Household Income

	Pre-2006 Mean (1)	DD Estimate (2)	Percent Change (3)
Less than 125%			
OTC Painkillers	61.28	-1.97 (3.75)	-
N		20,031	
125 to 400%			
OTC Painkillers	75.72	-2.50* (1.33)	-3.3%
N		153,486	
Greater than 400%			
OTC Painkillers	80.33	-5.81*** (1.96)	-7.2%
N		161,539	

Source: Author's calculations based on Nielsen Household Consumer Panel 2004 to 2009. Column 1 displays the pre-2006 mean for the treatment group. Column 2 displays the coefficient on the interaction of the treatment group indicator and the post-2006 indicator. Regressions control for householder's sex, marital status, educational attainment, race/ethnicity, and Census region, and include household fixed effects and year fixed effects. Data are adjusted by Nielsen survey weights, and standard errors are clustered on household.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$