Prescription Drug Advertising and Drug Utilization: The Role of Medicare Part D*

Abby Alpert†
University of Pennsylvania and NBER

Darius Lakdawalla
University of Southern California and NBER

Neeraj Sood
University of Southern California and NBER

September 2018

ABSTRACT

This paper examines how direct-to-consumer advertising (DTCA) for prescription drugs influences utilization by exploiting a large and plausibly exogenous shock to DTCA driven by the introduction of Medicare Part D. Part D led to larger relative increases in DTCA in geographic areas with higher concentrations of Medicare beneficiaries. We examine the impact of this differential increase in advertising on non-elderly individuals to isolate advertising effects from the direct effects of Part D. We find that exposure to advertising led to large increases in treatment initiation and improved adherence to therapy. Advertising also had positive spillover effects on non-advertised generic drugs.

* We are grateful for helpful comments from numerous colleagues and seminar and conference participants at the Conference of the American Society of Health Economists, Annual Health Economics Conference, Midwest Health Economics Conference, NBER Summer Institute Health Care Meeting, Southern California Conference in Applied Microeconomics, Harvard University, University of California-Irvine, University of Southern California, and Wharton. We thank Sarah Dykstra, Laura Gascue, Karina Hermawan, and Chia-Wei Lin for excellent research assistance and programming. This research was supported by NIA P01AG033559 and AHRQ R01HS025983.
†Address: The Wharton School, University of Pennsylvania, Philadelphia, PA 19104. alpertab@wharton.upenn.edu

1. Introduction

Spending on direct-to-consumer advertising (DTCA) of prescription drugs in the U.S. has increased dramatically in the last few decades from $150 million in 1993 to over $4 billion in 2010 (Dave, 2013; Dave and Saffer, 2012). This rise was precipitated by a 1997 FDA policy change that relaxed restrictions on DTCA.[1] Most DTCA occurs on television, where pharmaceuticals represented the third highest category of advertising expenditures in 2014 (behind automotive and fast food restaurant advertising).[2] Nielsen estimates that an average of 80 pharmaceutical ads air every hour on American television.[3] Since Americans aged 50+ watch an average of more than 40 hours of live television per week (Nielsen, 2014), pharmaceutical advertising may have especially substantial effects on the behavior of older patients with a high rate of prescription drug use. Indeed, Figure 1 shows that the dramatic rise in advertising that occurred over the last two decades has coincided with a similarly striking increase in spending on prescription drugs. While the coincidence of these trends suggests a possible relationship between advertising and drug spending, the causal channel could go in both directions. The 1990s saw the introduction of an unprecedented number of blockbuster drugs that could have induced greater advertising as well as greater drug spending. These confounding factors make it difficult to isolate the independent effect of DTCA.

The rise of DTCA has generated much debate about its effects on patient welfare. Most countries (with the exception of the U.S. and New Zealand) ban this type of advertising. On the one hand, DTCA may be informative if it educates patients about available treatments and

[1] Prior to 1997, ads were required to include essentially all of the information on the product label (which is unlikely to fit in a 30-second television or radio spot), but after 1997 only the *major* risks and benefits needed to be included.
[2] See Nielsen "Tops of 2014: Advertising" available at: http://www.nielsen.com/us/en/insights/news/2015/tops-of-2014-advertising.html
[3] Nielsen estimate reported in FiercePharma "Top 10 DTC Pharma Advertisers – H1 2013" available at: http://www.fiercepharma.com/special-reports/top-10-dtc-pharma-advertisers-h1-2013

encourages individuals to seek care for underdiagnosed conditions. Advertisements may also serve to remind patients to take their existing medications, promoting better drug adherence (Holmer, 2002; Donohue et al., 2004; Wosinska, 2005). On the other hand, the persuasive and product differentiation aspects of DTCA may lead to unnecessary treatments and excessive drug spending by switching consumers from cheaper generics to more expensive advertised branded drugs. There is a lack of consensus on whether DTCA serves primarily to inform or persuade, which matters for assessing its value to patients. This distinction hinges partly on the extent to which DTCA impacts drug utilization and the mechanisms underlying advertising's impacts, such as whether the effects of DTCA stem from the initiation of therapy versus adherence and whether there are spillovers of advertising on non-advertised drugs. However, identifying DTCA's causal effects on utilization has been challenging empirically, since demand factors often influence both the amount of advertising and the timing of advertisements. Some studies have tried to address these endogeneity concerns with instrumental variable strategies, though it is difficult to find appropriate instruments given the close relationship between demand and advertising decisions.

We address these challenges by introducing a new quasi-experimental approach to estimating how DTCA influences drug utilization. We exploit a large shock to DTCA driven by the introduction of Medicare Part D in 2006. Our instrumental variable strategy exploits variation across geographic areas in the share of the population that is covered by Medicare (ages 65+) to predict changes in advertising exposure across areas. We show that there was a large relative increase in advertising exposure immediately following the introduction of Part D in geographic areas with a high share of elderly compared to areas with a low elderly share. Prior to Part D, both the levels and trends in advertising exposure across high and low elderly share areas were

nearly identical. Since advertising cannot be perfectly targeted to the elderly, we use the sudden differential increase in advertising exposure for non-elderly that live in elderly-dominated areas to estimate the effects of advertising on drug use. This strategy hinges on the observation that non-elderly individuals are exposed to the increase in DTCA but do not receive Part D insurance coverage, which may independently impact drug utilization.

This paper makes four main contributions. First, we exploit a major policy change to identify the effects of DTCA on drug utilization. The use of policy shocks as natural experiments has been scarce in the existing advertising literature, although it is a promising approach for obtaining variation in advertising that is unrelated to individual demand. Second, the large policy shock provides an ideal setting for estimating a broad array of behavioral responses to advertising on both the extensive and intensive margins, including drug initiation and adherence. We isolate these responses to explore welfare implications of advertising. Prior studies on the revenue consequences of advertising have largely focused on overall utilization and spending. Third, we use data from two novel sources. We measure pharmaceutical advertising using data on Nielsen "ratings" – a measure of the fraction of people in a target audience that view advertisements. We observe ratings for two target audiences: the non-elderly (under 65) and the elderly (65+). While most of the prior DTCA literature uses advertising expenditures or the volume of ads to quantify advertising, ratings are a more direct measure of actual advertising exposure.[4] This measure is more often used outside of the DTCA literature to measure exposure to other types of television programming (e.g., Kearney and Levine, 2015; Kanazawa and Funk, 2001). We obtain measures of drug utilization using administrative pharmacy claims from a database covering about 18 million person-years. Finally, we quantify

[4] To our knowledge, Saffer et al. (2007) – which studies advertising for nicotine replacement therapy – is the only other pharmaceutical advertising study to use Nielsen ratings data.

spillover effects of Part D on the non-elderly population. Numerous studies have examined the effects of Part D on the elderly but few have considered the effects on the non-elderly.[5] One important mechanism through which Part D may have an effect on the non-elderly is through advertising, and we find strong evidence of these spillovers.

We find that drug utilization is highly responsive to advertising exposure. Following Part D, there was a 6 percent increase in the number of prescriptions purchased by the non-elderly in areas with high elderly share, relative to areas with low elderly share. Event study results using quarterly utilization data show that this differential effect coincided precisely with the implementation of Part D in 2006. The event study also confirms that there were no differential pre-trends in utilization across higher and lower elderly share areas, providing support for the identifying assumption that the trends would have continued to be the same in the absence of Part D. Our results show that a 10 percent increase in advertising views leads to a 5.4 percent increase in total prescriptions filled for advertised chronic drugs, which implies an advertising exposure elasticity of 0.54, and an estimated advertising expenditure elasticity of 0.23.

Expanded take-up of prescription drugs accounts for about 70% of the total effect of advertising, while increased adherence to drug therapy accounts for the remaining 30%. While advertising increased drug adherence for existing patients, we also find that individuals who initiate drug treatments due to advertising are on average less compliant suggesting some potential wasteful spending. We find evidence that advertising also increased the use of non-advertised drugs in the same therapeutic class as advertised drugs. This effect is concentrated among generic drugs. DTCA on net does not cause substitution away from lower-cost generics to higher-cost advertised drugs; it leads to increased use of generics rather than decreased use.

[5] Prior studies on the spillover effects of Part D have examined pharmaceutical R&D investments (Blume-Kohout and Sood, 2013) and negotiated drug prices (Duggan and Scott Morton, 2010; Lakdawalla and Yin, 2015).

Finally, this paper also shows that by increasing insurance coverage for one population, Part D had the unintended effect of generating additional demand for individuals outside of the Medicare program. These demand increases were themselves large and economically important.

While Part D triggered a number of changes in the prescription drug marketplace, the bulk of our estimated effect seems linked to advertising in particular. We find little evidence in favor of alternate causal channels. First, Part D did not differentially reduce drug prices in high elderly share areas, ruling out concurrent price effects that could independently impact drug use. Second, changes in promotion directed to physicians ("detailing") after Part D appear to be unrelated to elderly share. Finally, in a placebo test estimating the differential effects of Part D on drug use for classes of drugs that *do not* advertise, we find effects that are null or small relative to the effects for classes that do advertise, providing evidence that the observed changes in utilization are predominantly due to advertising. Nevertheless, accounting for the potentially small effects of other mechanisms, we compute a lower bound on the advertising expenditure elasticity ranging from 0.14 to 0.19; this is sixty to eighty percent of our estimated elasticity.

2. **Background and Related Literature**

2.1. Why Would Medicare Part D Increase Advertising Exposure?

Medicare is a federal program that provides health insurance to the elderly, ages 65 and over, and to qualifying non-elderly disabled individuals. On January 1, 2006, Medicare expanded to include coverage of outpatient prescription drugs through the introduction of Part D, representing one of the largest expansions of the Medicare program since its inception. Part D substantially lowered out-of-pocket costs and increased drug utilization for the elderly (e.g., Ketcham and Simon, 2008; Yin et al., 2008; Lichtenberg and Sun, 2007).

The widespread changes brought about by Part D significantly altered pharmaceutical firms' incentives to advertise. As shown in earlier theoretical work (Lakdawalla, Sood, and Gu, 2013), insurance expansions such as Part D can increase the return to advertising through two mechanisms. First, prior studies suggest that more profitable markets generate greater returns to capturing new consumers, and in turn stimulate more intense advertising effort. Thus, the returns to advertising are higher when there are more insured consumers in the market, because insured consumers face lower out-of-pocket costs that induce greater spending. Second, insurance coverage might alter the responsiveness of consumers to advertising. Intuitively, an undecided consumer might be more likely to try a new drug after seeing an advertisement if the cost of trying the drug is lower.

Given this result, we would expect drug advertising to increase more after Part D in geographic areas with a higher share of elderly individuals, where there was a greater expansion in insurance coverage. We will show that this prediction is borne out in the data. Previous research (Lakdawalla, Sood, and Gu, 2013) found that Part D led to a relative increase in *national* advertising for the types of drugs differentially used by Medicare beneficiaries. In this paper, we focus on geographic variation in advertising changes and use administrative claims data to identify and characterize the causal utilization effects of advertising.[6]

2.2. Previous Literature on Advertising Effects

Our paper contributes to a large literature on the impacts of DTCA on drug use (see Dave, 2013 for a recent survey). The majority of studies in this literature find positive demand effects of advertising. Although studies consistently find evidence of significant market expansion

[6] While the primary focus of Lakdawalla, Sood, and Gu (2013) was to show how Part D impacted advertising across drugs with varying elderly share (e.g. statins vs. contraceptives), it also examined limited utilization outcomes using the Medical Expenditure Panel Survey (MEPS). We build on this previous work, by exploiting a new strategy based on geographic variation in exposure to Part D and use comparatively rich measures of drug utilization from administrative claims data.

effects from advertising (e.g. Rosenthal et al., 2003; Iizuka and Jin, 2005; Bradford et al., 2006), evidence of market stealing—gaining market share from competitors—is mixed. Some studies find no effect, and others find small but statistically significant effects (e.g. Wosinska, 2002; Dave and Saffer, 2012). In general, the market expansion effects appear to dominate.

A persistent challenge for this literature has been in identifying a source of variation in advertising that is orthogonal to demand factors.[7] Prior studies that do not address this endogeneity concern may find estimates that are biased upwards if firms target advertising to markets (or time periods) where demand for the drug is already high or biased downwards if firms aim to stimulate demand where it would otherwise be low.[8] Our study overcomes this problem by using a natural experiment—the introduction of Part D—to study the effects of DTCA on drug utilization among those unaffected by the insurance expansion. To our knowledge, there are only two other studies that provide natural experiment evidence on the effects of DTCA. Most similar to our study, Sinkinson and Starc (2015) exploit changes in DTCA due to political election advertising (which temporarily displace DTCA) to examine the effects of own and rival advertising on firm revenue for statins. The estimated elasticities in our study tend to be larger. This may be partially explained by differences in identification strategies, with Sinkinson and Starc (2015) exploiting temporary reductions in advertising and our study exploiting a permanent increase. We might expect asymmetry in reductions versus increases in advertising. Given the long-lasting effects of advertising impressions, short

[7] Most previous studies of DTCA have had to rely on cross-sectional or time-series variation in advertising to identify the effect on drug utilization. Studies that attempt to address the endogeneity concern have instrumented for DTCA using variables such as the age of the drug, time until patent expiration, advertising expenditures by the same company in an unrelated drug class, and national advertising costs.

[8] For example, there could be an upward bias if DTCA targets high prevalence diseases (or seasons of the year—e.g., allergy medications) that would naturally have higher sales without advertising. There could be a downward bias if advertising targets under-diagnosed or under-treated diseases. Also, firms may increase advertising when a competing product enters the market. This could also create a downward bias, since, in the absence of advertising, the demand for the older product may have declined as patients substituted towards the new product. It is unclear which of these effects would dominate.

reductions in advertising could have more muted effects on use.[9] In another related study, Shapiro (2018) compares changes in advertising expenditures at discrete television market boundaries to estimate spillover effects of DTCA on rival's demand for antidepressants.

Our study offers several contributions to the literature. First, the size, breadth, and permanence of the DTCA shock related to Part D is unusually large relative to other advertising changes captured in previous studies. Second, we use novel data that measure actual exposure to advertising using Nielsen ratings (discussed below) rather than indirect measures that are used in nearly all DTCA studies such as advertising spending or number of ads.[10] Third, we decompose the total utilization effects of advertising into distinct channels of behavioral response including drug initiation and adherence, which is important for beginning to assess welfare implications of DTCA. Since much of the pharmaceutical advertising literature has focused on the revenue consequences of advertising, little is known about the behavioral mechanisms underlying advertising effects. Specifically, there is little evidence on how advertising impacts drug adherence and the few existing studies find very small or null effects (Donohue et al. 2006; Wosinska, 2005). Fourth, we estimate the effects of DTCA for a large number of drugs across several conditions. Prior studies typically focus on a single drug class or a small subset of brand-name drugs. Given that FDA policy tends to consider all types of prescription drugs uniformly, our estimates are likely more generalizable for such policy considerations. Finally, our results are relevant for understanding the broader consequences of insurance expansions.

[9] Sales decay may occur more slowly than sales growth, since individuals will already have experience with the drug and may continue to get refills. Memories of prior advertising impressions may also decay slowly.

[10] One exception is Avery, Eisenberg, and Simon (2012), which uses survey data from Simmons National Consumer Survey and Kantar/TNS Media Intelligence to construct individual-level exposure to ads for anti-depressants. In contrast to that paper, which studies self-reported anti-depressant use in the past 12 months, we have administrative pharmacy claims that enable us to construct comparatively rich measures of utilization.

3. **Data Sources**

3.1. Advertising Data

We use the Nielsen Ad*Views™ database from 2001-2010 to measure pharmaceutical advertising in local media markets. We focus on television advertising, which accounts for more than two-thirds of total DTCA expenditures (Avery, et al., 2012). Nielsen collects data on the universe of television commercials shown in 210 "Designated Market Areas" (DMAs) that span the entire United States. Each DMA is comprised of one or more counties that share the same home-market television stations. Nielsen viewing stations located in each DMA record all commercials shown and can identify "national" ads shown in all 210 DMAs and "local" ads shown in a subset of markets. We use data on local ads since there is scope for targeting different amounts of advertising to different markets. Local ads can be shown during network (e.g. NBC), syndicated, or local television programming (e.g. local news). We obtained local advertising data for the top 100 DMAs (86.5% of TV viewers) and the top 200 advertised brand-name prescription drugs, which account for 96% of advertising spending.

Our measure of DTCA exposure is Nielsen rating points. Rating points are derived from data collected on actual viewership of television commercials for a sample of television-owning households in each DMA. Using meters attached to participants' televisions or paper diaries, Nielsen records who in the household is watching and what they are watching 24 hours a day. "Rating points" are simply the fraction of the sample that watched a particular commercial. In our data, we observe rating points for each brand-name prescription drug, DMA, quarter, and for two age groups (ages 2-64 and ages 65+), which is defined as follows:

(1) $$Rating\ Points_{jmat} = \frac{\#\ of\ views_{\ jmat}}{\#of\ persons_{mat}} \text{ x } 100$$

Where $Rating\ Points_{jmat}$ are computed as the total number of views of commercials for brand-name drug j in market (DMA) m, in age-group a, and in quarter t divided by the total number of individuals in the sample in that group, multiplied by 100. We divide rating points by 100 in order to interpret this measure as average views per person. Rating points for a brand can increase if the number of commercials increases, the commercials become better targeted (e.g., late night vs. primetime), or individuals watch more television. Nielsen rating points are the industry standard for measuring television viewership and have the advantage of being a more direct measure of advertising exposure than total advertising expenditures or the number of ads, which have been the predominant measures of advertising in the DTCA literature to date.

While in recent years, a variety of alternative methods for watching television programming have been introduced—such as time shifted (DVR) viewing and Internet viewing— traditional live television remains the dominant medium. In 2014, adults ages 50-64 watched on average 43.2 hours of programming per week, of which only 3.8 hours were time-shifted and an additional 1.2 hours were spent watching video on the Internet (Nielsen, 2014).[11]

3.2. Drug Utilization Data

We construct measures of drug utilization using a database of insurance claims from more than 40 large national employers, including many Fortune 500 companies, for 2004-2010.[12] These data were compiled by a prominent health benefits consulting company and cover approximately 18 million person-years during the study period. The claims dataset is described in more detail in several previous studies (e.g. Goldman et al., 2004; Goldman and Joyce, 2007; Joyce et al., 2007). The pharmacy claims include detailed information on all outpatient

[11] Since most of our study period from 2004-2010 precedes the widespread adoption of time-shifted viewing and the introduction of Netflix, YouTube, Hulu, and other Internet streaming services, we expect that the share of our sample that is not watching television live is very small. Moreover, Nielsen does account for most time-shifted viewing by including recorded programming watched within seven days of its initial release.

[12] Data prior to 2004 is not defined in a consistent way with data after 2004, so we cannot use it in our analysis.

prescription drug purchases. Limited demographic information is provided, including gender, age, marital status, and the three-digit ZIP code of residence. We restrict our analysis to individuals with full-year insurance coverage and aged 40-60.[13] This group is closer in age to Medicare eligibility and thus more likely to be using similar types of prescription drugs as Medicare beneficiaries. We only include individuals who live in the top 100 Nielsen DMAs, which represents about 95 percent of pharmacy claims.

Each person in the claims data is assigned to a Nielsen DMA based on their three-digit ZIP code of residence to determine their potential advertising exposure in each quarter. One limitation of our data is that Nielsen DMAs are defined in terms of five-digit ZIP codes, while we observe individuals' three-digit ZIP codes in the claims. Some three-digit ZIP codes overlap multiple DMAs, so it is not possible to assign these individuals to a single DMA with certainty. Instead we assign these individuals the population-weighted[14] average of advertising exposure across all of the possible DMAs where they could reside.[15] Consequently, we use the three-digit ZIP code as the effective advertising market rather than the DMA, since all individuals residing in a three-digit ZIP code have the same advertising exposure. As we will show below, effects are similar if we restrict the data to the subsample with a single DMA match.

The main outcomes are total number of prescriptions purchased and total days supplied. For most analyses, we focus on drugs that treat five chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis. There are 50 drugs for these conditions that advertised during our study period (see list of drugs in Appendix Table B.1). We collapse the data to the three-digit ZIP code level by condition and quarter, computing the mean prescriptions

[13] We exclude ages 61-64 out of concern that individuals close in age to Medicare eligibility may change their drug utilization behavior in anticipation of future Part D coverage (Alpert, 2016).
[14] Population weights for the 5-digit ZIP code level come from the 2000 Decennial Census.
[15] About 30 percent of individuals receive this probabilistic measure of advertising exposure.

purchased and days supplied, to conduct our analyses at the level of variation in advertising exposure (Bertrand et al., 2004). Zeros are included for individuals who were enrolled in health insurance but did not purchase any drugs for the condition.[16] This results in 107,345 ZIPcode-by-condition-by-quarter observations. Since Part D affected advertising incentives for all drugs and due to the possibility of spillovers across drugs treating the same condition, we do not conduct a drug-level analysis and instead perform our analysis at the condition-level.

We also construct a measure of drug adherence for individuals who filled at least one prescription for any of the five chronic conditions. We measure adherence between the individual's first drug claim through their last drug claim for that condition.[17] We consider adherence as receiving continuous treatment for a condition,[18] rather than for a specific brand since this is the more relevant dimension from a welfare perspective. Adherence is measured quarterly as the medication possession ratio (MPR), which is a widely used method for measuring medication compliance with claims data (Hess, et al., 2006). The MPR is calculated as the number of days with drug on-hand (days supplied) divided by the number of days in the quarter. We provide further details on constructing the adherence measures in Appendix A.2.

3.3. Population Data

Our instrument is the elderly share in each DMA. We compute the share of the population that is 65 and over (i.e. eligible for Medicare) in each DMA using the 2000 Census.[19] This share is held constant at the DMA's 2000 value (which pre-dates our study period) so that no identification originates from changes in elderly share. From the advertiser's perspective, the

[16] Each person gets 5 observations for each condition in each quarter. If they do not use a drug for that condition, the observation is zero. We do not condition on having a diagnosis as advertising might affect the rate of diagnosis.
[17] In some specifications, we account for discontinuation by computing an alternative measure of adherence where we assume that a person is non-adherent after their last observed drug claim.
[18] Specifically, we combine utilization for advertised drugs with the non-advertised drugs in the same therapeutic classes as the advertised drugs.
[19] Individuals who cannot be matched to a single DMA are assigned the population-weighted average of the elderly share across all possible DMAs where they could reside.

DMA is the relevant market. There is substantial heterogeneity in elderly share across markets, ranging from 8% in the Houston DMA to 26% in Fort Myers-Naples DMA (see Table 1).

3.4. Descriptive Statistics

In Appendix Table B.2, we present sample means for the advertising variables by elderly share before and after Part D. We split the 100 DMAs into above vs. below-median elderly share markets. Average views per person of pharmaceutical ads are much greater for elderly viewers relative to non-elderly viewers. For example, in low elderly share markets in 2005, elderly viewers saw on average 1,184 pharmaceutical ads per year compared to 387 ads for the non-elderly. This difference is not surprising as ads are targeted to programming with elderly viewers and older viewers watch more hours of television. There was a larger increase in ads viewed in high elderly share markets after Part D than in low elderly share markets.

We also observe that high elderly share markets are less populated than low elderly share markets. This may be partially due to retiree preferences for less urban areas. Because of differences across high and low elderly share areas, we condition on market fixed effects in all of the analyses. While baseline differences across markets could, in principle, drive differential trends in advertising or utilization, our event-study analyses will demonstrate similar trends until immediately after Part D. To further mitigate concerns that these immediate differences might reflect confounding factors we also present results of placebo tests in Section 5.2.4.

4. **Empirical Strategy**

To understand the impact of DTCA on drug utilization, we exploit quasi-experimental variation in advertising exposure after the introduction of Part D for non-elderly adults living in high elderly share areas. Specifically, we capture the differential change in DTCA exposure

across high and low elderly share areas by estimating the following difference-in-difference equation, our first-stage relationship:

(2) $DTCA_{mct,<65} = \beta(Share65_m \times Post_t) + \gamma_t + \mu_m + \alpha_c + \epsilon_{mct}$

Where $DTCA_{mct,<65}$ is per capita views (rating points) for non-elderly individuals ages 2-64 in market m in quarter t for ads related to condition c. The market m is the three-digit ZIP code.[20] $Share65_m$ is the share of population[21] 65+ in market m in 2000, and $Post_t$ is an indicator that equals 1 in the post-Part D period (2006-2010). Thus $Share65_m \times Post_t$ is our instrument for DTCA exposure for the non-elderly. In some specifications we use an alternative form of this instrument, $HighElderlyShare_m \times Post_t$, where $HighElderlyShare_m$ is an indicator that equals 1 if the market m has an above-median elderly share. This latter instrument does not restrict the impact of elderly share to have a linear relationship with advertising but, instead, considers the possibility of non-linear effects. We use the share of the population 65+ as our instrument to reflect advertising incentives. We aim to estimate the effect of per capita advertising views on per capita demand for drugs. Pharmaceutical firms have greater incentives to increase per capita views in markets with greater per capita demand for drugs.[22] Our identification strategy exploits the fact that Part D coverage raised per capita demand for the elderly, but not for the non-elderly. Thus, the extent to which it increased total per capita demand is determined by the share of elderly in the market. We expect that the greater increase in per capita demand in high elderly share areas after Part D led to a greater increase in per capita

[20] As discussed in Section 3.2, we collapse the data to the 3-digit ZIP code level rather than the DMA-level, since a subset of the sample resides in 3-digit ZIP codes that cross multiple DMAs and cannot be matched to a single DMA. For this subset, we assign them the population-weighted average advertising exposure across all DMAs where they might reside. Thus, our constructed advertising exposure measure is constant across individuals within the same 3-digit ZIP code, but not always within a DMA, which necessitates the analysis at the 3-digit ZIP code level.

[21] The 65+ share is computed at the DMA level since this is the relevant market from the advertiser's perspective. For individuals whose 3-digit ZIP code cannot be matched to a single DMA, they receive the population weighted average of the 65+ share across all the DMAs where they might reside.

[22] We focus on per capita views as our outcome variable (which is what Nielsen ratings measure) so per capita demand is the relevant measure of the returns to advertising rather than total demand under this specification.

advertising views.[23] Our empirical estimates will test this hypothesis. Since geographic areas with a high versus low concentration of elderly are potentially different, all of our analyses condition on market fixed effects (μ_m), which account non-parametrically for cross-sectional differences in 2000 elderly share. We also include time fixed effects (γ_t) to account for secular time trends and condition fixed effects (α_c) to account for differences in utilization and returns to advertising across conditions. Standard errors are clustered at the three-digit ZIP code level (market m) to account for serial correlation within areas as well as correlation across conditions.

Next, we estimate a reduced form equation comparing changes in drug utilization for the non-elderly across areas with a high elderly share relative to a low elderly share. By focusing on the non-elderly population, we can isolate the effects of advertising on drug utilization from the direct effects of Part D on utilization. The equation for the reduced form is as follows:

(3) $Y_{mct,<65} = \theta(Share65_m \times Post_t) + \rho_t + \sigma_m + \tau_c + \epsilon_{mct}$

Where $Y_{mct,<65}$ is mean total prescriptions or days supply for non-elderly individuals in market m in quarter t for advertised drugs that treat condition c. We use this reduced form model to estimate effects on other measures of drug utilization including prescriptions purchased (or days supplied) conditional on use, the probability of any drug use, and drug adherence. We also obtain the 2SLS estimate: the effect of advertising on prescriptions purchased.[24]

5. Results

[23] Other factors may also affect advertising decisions, which will add noise to the relationship between elderly share and changes in advertising, but this should not affect the validity of elderly share as an instrument.

[24] It should be noted that the Nielsen data on advertising exposure is only available to us for the 2-64 age group, while we select on ages 40-60 (individuals who are likely to be using similar drugs as Medicare beneficiaries) in the utilization data. Our advertising elasticity estimates will not be biased by this age-group selection if the proportional change in advertising exposure after Part D is the same across ages. As shown below, individuals 2-64 and 65+ have the same proportional change in advertising exposure after Part D, which supports this assumption.

Our analysis proceeds in three steps. We first provide evidence that our instrument predicts changes in advertising exposure. Second, we estimate the causal impact of advertising exposure on total drug utilization for the non-elderly using two-stage least squares. We conduct event-study analyses and several robustness and placebo analyses which show that pre-trends, composition changes and alternative mechanisms do not meaningfully contribute to our results. Third, we investigate the causal pathways along which advertising operates by decomposing the total utilization effect into intensive and extensive margin effects including drug adherence and take-up. We also investigate spillovers on non-advertised drugs.

5.1. First-Stage Effects of Part D on Advertising Exposure

5.1.1. Overall Sample of Drugs

We begin by showing graphically that the share of the population that is 65+ in an area is strongly predictive of differential changes in advertising exposure after Part D. Figure 2 plots mean annual views per person (rating points) of ads for the top 200 brand-name pharmaceuticals from 2001-2010, comparing DMAs with above-median and below-median elderly shares. The figures show views by the non-elderly. Prior to 2006, both the levels and trends in advertising exposure for the non-elderly are nearly identical across geographic areas. That is, a non-elderly person would view the same number of pharmaceutical ads whether they lived in a market with a high or low concentration of elderly. However, after Part D began in 2006, advertising exposure increases sharply for non-elderly living in areas with a high elderly share relative to those living in areas with a low elderly share. This difference persists through the end of the study period.[25]

[25] The patterns in advertising exposure are similar for elderly viewers, as seen in Appendix Figure B.1. Prior to Part D, the trends are parallel but there is less advertising exposure in high elderly share areas, perhaps due to the lower rates of drug insurance coverage (and income) in these areas. After Part D, the pattern flips with an immediate relative increase in advertising exposure in areas with a high elderly share.

Since we are following a balanced panel of brand-name drugs, there is a secular downward trend in overall advertising over this time period due to the "aging" of these drugs. This pattern mimics the decline in national advertising expenditures shown in Figure 1. Several popular drugs lost patent protection over the study period.[26] Since off-patent drugs typically do not advertise (Dave, 2013), patent expirations reduce advertising expenditures. After excluding drugs that lost patent protection during this period (see Appendix Figure B.2), we find an upward trend in overall advertising, but still find a similar divergence in trends after Part D. This verifies that the change is not driven by differential effects of patent expirations across areas.[27]

We estimate the magnitude of the differential change in advertising exposure using a difference-in-difference model similar to Equation 2 at the DMA level (see Appendix Table B.3). Comparing non-elderly individuals in areas with high elderly share to low elderly share areas, Part D generated an additional 25 ads viewed per year[28], or about one additional ad every other week. This represents a 6 percent increase.[29] For the elderly, the effect of Part D on the number of ads viewed is much larger, since Medicare beneficiaries are likely the intended target for these ads. We find that Part D generated an additional 72 ads viewed per year, or an additional ad every 5 days (6.3 percent increase). These results confirm that the introduction of Part D is associated with a large relative increase in advertising exposure for the elderly in high elderly share areas and that there are substantial spillover effects for the non-elderly.

5.1.2. Chronic Drugs

[26] There were 4 major patent expirations that occurred around 2006 among the top 200 drugs (Pravachol, Wellbutrin XL, Zocor, and Zoloft) and a wave of patent expirations in the late 2000s which has been termed the "patent cliff."
[27] We assume that markets with a low-share of elderly and a high-share of elderly are similarly affected by common nationwide shocks such as those driven by drugs losing patent protection. Given the similar pre-trends in advertising exposure across markets, this assumption likely holds.
[28] In Appendix Table B.3, the coefficients from the binary instrument (which are estimated at the quarterly-level), imply an additional 25 ads viewed per year (6.233*4) for the non-elderly and 72 for the elderly (18.055*4).
[29] Percent change is (6.233*4)/413=0.06 using the mean for high elderly share areas in 2005 in Appendix Table B.2.

We also assess the predictive power of the instrument for our primary analysis sample of chronic drugs for five conditions (depression, diabetes, hyperlipidemia, hypertension, osteoporosis) that are prevalent among Medicare beneficiaries[30] and account for a large share of advertising. Since these drugs are predominantly used by the elderly, they would likely experience the largest increase in advertising from Part D.

First, we replicate the graphical evidence from above for the chronic drugs sample. In Panel A of Figure 3, we plot advertising exposure for the selected brand-name chronic drugs at the quarterly level and for 2004-2010, which corresponds to the claims data. Although the quarterly data are noisier, the patterns are similar to the full sample of drugs. Levels and trends in non-elderly advertising exposure are nearly identical across high and low elderly share areas prior to Part D and then diverge sharply in 2006.

We estimate the analogous first-stage difference-in-differences regression model shown in Equation 2. Panel A of Table 2 presents the first-stage results using the continuous instrument (Post interacted with Share 65+), while Panel B uses the binary instrument (Post interacted with indicator for above-median elderly share) mirroring the graphical evidence.[31] We find a strong positive relationship between the introduction of Part D and differential changes in advertising across areas. Panel A (using the continuous instrument) shows that a geographic area with a one percentage point higher elderly share experiences an increase in quarterly advertising exposure of 0.064 views per person after Part D (significant at the 1% level). Panel B compares above-

[30] These five conditions are among the most common conditions for Medicare beneficiaries: 58% have hypertension, 45% hyperlipidemia, 28% diabetes, 14% depression, 7% osteoporosis (CMS, 2012).
[31] The F-statistics for the binary and continuous instruments are 30.86 and 32.69, respectively, which are well above conventionally accepted levels (Stock, Wright, and Yogo, 2002).

median to below-median elderly share areas and shows markedly similar results.[32] Advertising exposure for chronic drugs increased by 8.1 percent relative to the baseline mean.

5.1.3. Validity of the Instrument

We implement a simple placebo test to test for other differential shocks to advertising incentives by estimating the effect of Part D on exposure to advertising for contraceptive drugs. Since contraceptives are unlikely to be used by the elderly, their advertising should be unaffected by Part D. In fact, Figure 4 shows no differential effect of Part D on advertising exposure for the non-elderly across high versus low elderly share markets. We also showed above that changes in advertising exposure after 2006 were larger for the elderly compared to the non-elderly, as would be expected if the change in advertising were due to Part D. Taken together, this evidence provides reassurance that Part D, not another confounder, is driving the differential changes in advertising. In Section 5.2.4, we will provide evidence in support of the exclusion restriction that the estimated utilization effects are also not driven by confounding factors.

5.2. Second-Stage Effects of Advertising Exposure on Drug Utilization

5.2.1. Baseline Estimates

Having shown that Part D had a substantial differential impact on advertising exposure for high elderly share markets, we next analyze how non-elderly drug utilization responded to this shock to advertising. First, we graph the trends in total prescriptions purchased by the non-elderly for above-median vs. below-median elderly share areas in Panel B of Figure 3. We continue to focus on the sample of advertised brand-name chronic drugs. Prior to Part D, drug utilization trends track each other very closely in high and low elderly share areas, but then diverge precisely in 2006 with a relative increase in utilization for non-elderly living in high

[32] Considering the mean difference between high and low elderly share areas, the continuous instrument estimate implies that moving from an average low to high elderly share area would lead to an increase of 0.25 (.04*6.358) views per quarter. This is similar to the estimate using the binary instrument in Panel B which is 0.35.

elderly share markets.[33] This graph mirrors the patterns in advertising exposure, and provides visual evidence of strong effects of advertising on utilization.

In Column 2 of Table 2, we estimate the reduced form difference-in-differences specification (Equation 3) using the total number of chronic prescriptions purchased by the non-elderly as the outcome variable. The effect of Part D on non-elderly drug utilization is positive and statistically significant at the 1% level for both the continuous and binary measures of elderly share. Drug utilization increased by 4.5 percent relative to the baseline mean.

We also assess the timing of the utilization effect as well as the common trends assumption, by estimating an event-study regression. The event-study replaces the $Share65_m \times Post_t$ variable in Equation 3 with a full set of quarter dummies interacted with the elderly share measure. Each coefficient estimate gives the difference in prescriptions purchased in high versus low elderly share areas relative to the omitted reference period: quarter 4 of 2005. These coefficients are reported in Table 3 for both the continuous and binary measures of elderly share. High and low elderly share areas had the same pre-trends in prescriptions purchased, as reflected in the statistically insignificant (and close to zero) coefficients prior to 2006. The coefficients then immediately become positive and statistically significant in quarter 1 of 2006 when Part D begins. The effect persists through the end of the study period. These results show that there was an immediate differential utilization response to Part D. Thus, any alternative explanation for the utilization effect would need to coincide precisely with the introduction of Part D.

In Column 3 of Table 2, we present 2SLS estimates for the effect of advertising exposure on prescriptions purchased. Comparing above and below median elderly share areas in Panel B,

[33] Again, the overall reduction in brand-name chronic drug prescriptions in 2006 is due to patent expirations for these drugs, as patients switched to generic versions. In results not shown, when we exclude the 4 major drugs that went off patent in 2006 (Pravachol, Wellbutrin, Zocor, and Zoloft), we find a flatter overall trend in utilization across the period and a similar divergence in trends across high vs. low elderly share in 2006.

we find that an additional ad viewed would lead to an increase of 0.014 prescriptions filled for a chronic condition among the entire sample of non-elderly individuals. In other words, if an ad were viewed by 71 individuals (1/0.014), it would result in one additional prescription being filled. Results are similar in panel A. Using the mean for prescriptions filled and ads viewed, the implied elasticity of demand with respect to advertising views for chronic drugs is 0.54.

5.2.2. Comparison of Magnitudes with Prior Literature

Our estimate cannot be directly compared to previous elasticity estimates in the literature because it measures the responsiveness of utilization to advertising *exposure* (or views), whereas most studies measure responsiveness to advertising *expenditures*. We cannot directly estimate an elasticity with respect to expenditures for comparison with prior studies since the Nielsen data does not contain information on advertising expenditures.[34] However, Sethuraman et al. (2011)—in a meta-analysis of advertising elasticities across consumer products—show that exposure elasticities are larger than expenditure elasticities on average, suggesting that firms are operating in a region where increases in advertising dollars lead to less than proportional increases in views. This is consistent with decreasing returns to advertising spending.[35] Specifically, Sethuraman et al. (2011) find that elasticities measured with respect to advertising

[34] Nielsen collects limited data on advertising expenditures at the local level. Expenditure data is not available for local commercials shown during network or syndicated programming, which comprise the majority of local commercials. Only commercials shown during "local television" programming (e.g. local news) have expenditure data. For this reason, we cannot use expenditure data in this study.

[35] In theory, the exposure elasticity could be higher or lower than the expenditure elasticity, depending on whether exposures have decreasing or increasing returns to advertising spending. Advertising could have increasing returns due to quantity discounting or decreasing returns due to saturation or competitive responses. For example, the cost per exposure may increase as spending increases, because scarce television time becomes saturated and firms must shift from buying ads for the most well targeted to less well targeted programming. Moreover, as firms spend more on advertising this could trigger stronger competitor advertising responses, which would also increase costs per exposure at the margin and lead to decreasing returns. Sethuraman et al. (2011) offer the following framework for comparing the relative size of the advertising exposure—or Gross Rating Point (GRP)—elasticity versus the advertising expenditure elasticity: "Let a 1% increase in advertising dollars increase GRPs by v% and sales by w%. Then, by definition, dollar advertising elasticity = w, and GRP advertising elasticity = w/v. It follows that, all else being equal, dollar elasticity is greater than GRP elasticity if $v > 1$, and GRP elasticity is greater than dollar elasticity if $v < 1$." In other words, we should expect that exposure elasticities are larger than the expenditure elasticities if there are decreasing returns to advertising dollars ($v<1$).

exposure are on average 2.3 times larger than elasticities measured with respect to advertising expenditures. If we apply this "conversion factor" to our estimate, this would produce an advertising expenditure elasticity of 0.23 (0.54/2.3), which is within the range of prior estimates in the DTCA literature.[36]

5.2.3. Robustness Tests

In this section, we conduct a series of robustness tests which show that our baseline estimates are not sensitive to pre-trends, sample restrictions or sample composition changes. These tests are presented in Table 4. Each cell represents a separate regression where the reported estimate is the coefficient on the instrument (either the continuous or binary version).

The first row in Table 4 repeats the baseline estimates. In the second row, we add ZIP code specific linear time trends to Equation 3. Since the results remain quite similar in magnitude, such trends do not appear to be exerting substantial influence on our results. This reinforces our event study analysis, which also showed no evidence of pre-existing differential trends. In the third row, we restrict our sample to 2004-2007 to exclude the Great Recession. Workers remaining in our sample during the recession may be observationally different than those in the pre-recession sample and this would be a concern if such composition changes are differentially occurring across high versus low elderly share markets. Our results are similar when we exclude the recession years verifying that changes in the composition of the sample were not differential by elderly share. In the fourth row, we include only the employers that were continuously in the claims data for all years. Differential (and systematic) composition

[36] See for example, Berndt et al., 1995; Rosenthal et al., 2003; Dave and Saffer, 2012; Sinkinson and Starc, 2015.

changes due to employer churn could bias our estimates.[37] The results are very similar for this subset of firms, although the precision is reduced slightly due to the smaller sample size.

In a final test for sample composition changes, we examine whether demographic characteristics of enrollees change around Part D differentially across high and low elderly share markets. Given the lack of demographic detail in the claims data, we assign each person the average characteristics of their three-digit ZIP code using the 2000 Census. In Appendix Figure B.3, we plot mean demographic characteristics across high and low elderly share markets.[38] While there are small composition changes throughout the study period, we do not observe any large *differential* changes in the demographic characteristics of the sample, and especially not around the introduction of Part D. Together, these tests show that sample composition changes and differential pre-trends cannot explain the observed patterns in drug utilization.

5.2.4. Tests for Alternative Explanations for Utilization Effects

The clear relationship between exposure to Part D and increases in both advertising views and prescription drug utilization by the non-elderly suggest large effects of advertising. However, there are three main alternative explanations which should be considered that may lead us to overstate the contribution of advertising. First, reductions in drug prices (due to changes in bargaining power, benefit design or other firm behaviors) could also lead to increased drug utilization by the non-elderly. Second, firms may increase promotional activities after Part D in ways besides DTCA including, most notably, promotion directed at physicians ("detailing"). Finally, Part D may impact physician practice styles which could spill over to non-elderly patients. If any of the above effects occur, then our estimates may reflect both advertising effects

[37] Out of the 41 firms that we observe in the claims data, 13 firms are observed in all seven years of the study period. These firms account for about 50 percent of drug claims. On average, we observe firms for five consecutive years.
[38] The average characteristics for each ZIP code are held constant at 2000 levels, so any observed changes in characteristics over the sample period come from shifts in the sample towards more or less disadvantaged ZIP codes.

(for which we observed large first-stage changes) and other unobserved spillover effects of Part D on the non-elderly. Understanding spillovers resulting from insurance expansions is of special policy interest, and it is additionally interesting to determine the mechanisms driving spillovers. Our evidence will show that advertising plays the dominant role. In this section, we consider possible alternative explanations in turn to assess their validity and quantify their contributions.

A. Changes in Prices?

We first examine whether pharmaceutical firms lowered drug prices more in areas with a higher elderly share after Part D, which could lead to a differential increase in drug utilization. Previous studies found that national retail prices declined after Part D due to the increased bargaining power of insurers (Duggan and Scott Morton, 2010; Lakdawalla and Yin, 2015). However, it is not known: whether these retail price reductions were passed along to patients in the form of lower out-of-pocket prices, which is what determines consumer drug demand; whether out-of-pocket price reductions for the elderly spilled over to the non-elderly; and whether out-of-pocket prices declined more in areas with a higher elderly share. We test for differential out-of-pocket price changes directly using our claims data. Figure 5 plots trends in average out-of-pocket prices for the non-elderly across high and low elderly share areas.[39] We find a slight time series *increase* in overall out-of-pocket costs[40] after Part D, but no differential changes after 2006 across geographic areas.[41] This suggests that the observed drug utilization patterns following Part D cannot be explained by out-of-pocket price changes.

[39] We compute the average out-of-pocket price for each advertised chronic brand-name drug by ZIP code at the level of the National Drug Code (NDC). Using the NDC ensures that features of the product remain constant over time.
[40] The sawtooth pattern in the figure results from non-linear insurance contracts, which generate higher cost-sharing at the beginning of the year and lower cost-sharing at year-end, once deductibles/stop-loss thresholds have been met.
[41] Since we observe prices only for drugs that are purchased, it is possible that the price trends reflect movements in the composition of drugs towards newer, more expensive, products. To address this, in Panel B, we restrict the sample to a balanced panel of NDCs observed in every quarter. We restrict the sample to 2004-2007 to maximize the number of NDCs that we can include in the balanced panel.

B. Changes in Detailing?

Second, we assess whether pharmaceutical detailing may have also increased differentially across areas after the introduction of Part D. Depending on whether detailing is a substitute or complement for DTCA, this could bias our findings towards or away from zero. There are reasons why we might not expect a sudden increase in detailing as we did with DTCA. Detailing may adjust more slowly, since additional detailing requires an increase in physicians' time allocated to sales calls and/or hiring sales representatives. In contrast, additional DTCA can be purchased almost instantaneously.[42]

While we are unable to directly observe detailing data at the DMA level, we conduct an indirect test for Part D's effect on detailing by exploiting within DMA variation in elderly shares. Direct-to-consumer advertising does not vary within a DMA, because local television station signals reach all households. Detailing, however, is more localized since pharmaceutical sales representatives can target individual physicians or practices. In other words, detailing efforts are not constrained by DMA boundaries and should respond to localized demand shocks in areas smaller than the DMA. If detailing responded to Part D, we would expect to observe a larger increase in detailing, and consequently, utilization, in localized areas (e.g. ZIP codes) with a higher share of elderly *within* a DMA. Thus, if utilization increases due to Part D operates partially through detailing, we would expect changes in utilization within the DMA to be correlated with local elderly shares.

To test this hypothesis, we estimate the reduced form Equation 3 with elderly shares computed at the three-digit ZIP code level, instead of the DMA level, and include DMA x quarter fixed effects so that identification originates only from variation in elderly shares *within*

[42] The fact that we observe an immediate utilization response after Part D suggests that direct-to-consumer advertising is the main driver of the effect, since detailing is more likely to adjust with a lag.

DMAs. Three-digit ZIP codes are the only sub-DMA level of variation we can observe in our data.[43] If within-DMA variation plays no role, then inclusion of the DMA x quarter fixed-effects should wipe out the estimated effects on utilization. This test is meaningful because within-DMA variation in elderly share is significant.[44] For example, in the Tampa-St. Petersburg (Sarasota) DMA, the three-digit ZIP code elderly share ranges from 11% to 27%.[45]

The results of this test are presented in Table 5. Column 1 reproduces the baseline reduced form results (computing elderly share at the DMA level) using only ZIP codes that can be uniquely matched to DMAs. The results are very similar to the main results in Table 2. Column 2 reproduces our results using elderly share computed at the three-digit ZIP code level instead of the DMA level. The effects of ZIP code-level elderly share on total prescriptions are of a roughly similar magnitude as the effects of DMA-level elderly share.[46] Since DMA and ZIP code elderly shares are correlated, the consistency of these results is not surprising. The main test is presented in Column 3, which adds DMA x quarter fixed effects. Here, the effect of the ZIP code-level elderly share goes to zero and becomes statistically insignificant.[47] This shows that utilization did not respond to Part D differentially by elderly share within DMAs, which suggests that detailing did not change after Part D or, at least, that detailing responses were unrelated to elderly share. More generally, this result also provides evidence against other

[43] Another measure of elderly share relevant to practices would be Hospital Service Areas (HSAs). However, we are unable to collapse the data to this level since HSAs are smaller than 3-digit ZIP codes (there are 3,436 HSAs in the U.S. compared to 910 3-digit ZIP codes). Hospital Referral Regions (HRRs), another alternative, are much larger than 3-digit ZIP codes and comparable in size to DMAs, so they would not provide within DMA variation. Incidentally, the 3-digit ZIP codes are comparable in size to Health Service Areas (as defined by the NCHS) which represent areas that are relatively self-contained with respect to hospital care. While it is difficult to pinpoint the exact geographic unit that would capture the elderly share of patients for a given practice, it is likely somewhere between Dartmouth HSAs and HRRs, so 3-digit ZIP codes represent a middle ground.

[44] On average, there are 12 three-digit zipcodes per DMA and a maximum of 40.

[45] If there were less variation at the sub-DMA level, we would expect standard errors to increase, but they do not.

[46] Column 2 is using a noisier measure of the relevant elderly share variable and, indeed, we find that the estimate is attenuated in Panel A. The Panel B instrument is dichotomous so classical measurement error results do not apply.

[47] The standard errors in Columns 2 and 3 are nearly the same such that the absence of an estimated effect in Column 3 is not due to increased noise or a relative lack of intra-DMA variation.

possible confounders of Part D that are correlated with elderly share at the sub-DMA level (e.g., changes in other promotional activities, physician behavior, pharmacy behavior, etc.).

C. Changes in Physician Practice Style?

Finally, we consider the possibility that there were other spillovers of Part D on the non-elderly, unrelated to advertising. For example, one leading possibility is changes to physician practice styles. Part D increased the volume of prescriptions written for the elderly, which may influence prescribing habits, leading physicians to write more prescriptions for their non-elderly patients as well.[48] The results in the section above suggested that such spillovers did not occur at a sub-DMA level. However, to test further for the possibility of other spillovers, we conduct a placebo test examining whether there were differential effects of Part D on non-elderly drug utilization for drug classes that *do not* advertise (e.g., diuretics). We would expect that other spillover effects from Part D (e.g., prescribing behavior changes) would affect utilization for all drug classes, whether or not they advertised. This test serves not only to rule out spillovers due to physician practice style, but more generally tests for any other unobserved Part D spillovers.

Figure 6 compares trends in non-elderly drug utilization across high and low elderly share markets for both advertised and non-advertised drug classes (we analyze each drug class separately in Appendix Figure B.4). For this test we draw from the full sample of drug classes, not only the five chronic conditions we analyzed previously. About half of all drug classes had zero advertising during the study period (typically related to the amount of generic penetration in the class).[49] We restrict the sample to the top 10 advertised and non-advertised drug classes among individuals ages 40-60 in order to ensure that these drugs are relevant for the non-elderly.

[48] For example, by prescribing more drugs to elderly patients, a physician may learn more about the drugs' therapeutic benefits, leading to more prescribing of successful treatments to all patients.

[49] For example, diuretics, which are nearly all generics, saw no advertising during the study period. On the other hand, anti-hyperlipdemia drugs, where only 26% of claims are for generics, had a positive amount of advertising.

As shown in Figure 6, there was a large differential increase in drug use for advertised drug classes after Part D in high elderly share areas vs. low elderly share areas, but only a slight and statistically insignificant increase for non-advertised drug classes. This is consistent with a causal role for advertising, since the effect is found only for advertised drug classes. Comparing the magnitudes in the analogous triple-difference regression in Panel B of Appendix Table B.4, we observe an increase of 0.012 prescriptions[50] for advertised drug classes (an 8.2% increase relative to the baseline mean) which is statistically significant at the 1% level. For non-advertised drug classes, we observe an increase of 0.001 prescriptions (1.3% increase) which is not statistically significant. While mean utilization for advertised classes is higher than for non-advertised classes, the proportional change in utilization relative to the mean is more than six times as large for advertised drugs (8.2% vs. 1.3% increase). Using log prescriptions as the outcome in column 2 produces similar results (6.9% vs 1.5% increase). When we estimate the model using the continuous instrument in Panel A—which reflects moving from 0 to 100 percent elderly share—the utilization effect for non-advertised classes becomes positive and significant but the proportional effect for advertised classes is still substantially larger (6.2% vs. 2.3%).[51]

We also examine the differential change across high and low elderly areas for each drug class separately in Appendix Figure B.4. The patterns appear strikingly different for advertised and non-advertised drug classes. We observe large and clear differential increases in high elderly share areas for nearly all advertised drug classes, which demonstrates that this effect is not driven by a single class but appears consistently in all advertised classes. Meanwhile, for

[50] This estimate represents the sum of the effect for non-advertised classes (0.001) and the additional effect specific to advertised classes (0.011).

[51] To interpret the estimates in Panel A, we consider the mean difference between high and low elderly share areas. The continuous instrument estimate implies that moving from an average low to high elderly share area would lead to an increase of 0.009 [0.04*(.181+.044)] prescriptions for advertised drug classes. This is a 6.2% (0.009/.146) increase relative to the mean. The percentage increase for non-advertised drug classes is computed similarly.

most non-advertised drug classes, we find no differential effect of Part D across high vs. low elderly share markets. For only 3 of the 10 non-advertised classes (diuretics, calcium channel blockers, and thyroid agents) do we observe any suggestive evidence of positive differential effects beginning after Part D.[52] While the substantially larger utilization effects observed for advertised drug classes relative to non-advertised classes is strong evidence that advertising is the predominant driver of this increase, the small positive effects for some non-advertised drug classes suggest that other mechanisms may also play a role.

Positive effects for non-advertised drug classes could partially reflect *indirect* effects of advertising if there are complementarities across advertised and non-advertised drug classes. Some advertised drugs may be natural complements with unadvertised drugs for a given condition. Moreover, visits to the doctor for an advertised drug could lead to the patient being diagnosed with other conditions which also require treatment. Alternatively, positive effects could be unrelated to advertising if they are due to other spillover effects of Part D on the non-elderly population such as changes to physician practice style or other unobserved Part D effects.

We quantify these alternative spillover effects using the results from the non-advertised drugs in Appendix Table B.4. This provides a useful way to identify other Part D spillover effects on the non-elderly (broadly defined), since these drug classes do not advertise, yet we expect larger spillover effects in areas with higher elderly share. If we assume, conservatively, that the entire utilization effect for non-advertised drug classes is due to Part D spillovers unrelated to advertising, then this implies that as much as 16% (using Panel B estimate) to 37% (Panel A) of the utilization effect for advertised drug classes could be due to other Part D

[52] The classes are sorted by baseline mean utilization so that we can compare advertised and non-advertised classes with similar means. The difference in means does not appear to be driving the different effects, since effects are smaller for classes that do not advertise even conditional on initial mean utilization.

spillovers.[53] This suggests a lower bound on our main elasticity estimate with respect to advertising views of 0.34 to 0.45 (or an elasticity of 0.14 to 0.19 when computed with respect to advertising expenditures).

In summary, we do not find a differential decrease in drug prices after Part D. We also find little evidence that detailing explains utilization patterns. Detailing or other promotion is generally conducted at a more localized level than a DMA and we find that elderly share has no effect on utilization outcomes at the sub-DMA level. This also suggests that any spillovers appear to be unique to the DMA-level. We further study non-advertised drugs to quantify possible spillovers and find that these alternative spillovers account for a small share of the advertising effect. We conclude that advertising is the predominant driver of utilization changes.

5.3. Potential Welfare Implications

Given the substantial effect of advertising on total drug utilization, we decompose the utilization effect to quantify the various causal pathways from advertising to utilization. These results have important welfare implications for both consumers and firms. First, we decompose the utilization effect into the extensive and intensive margins. Second, we examine the effects on drug adherence, a special case of the intensive margin effect. Third, we estimate whether there are positive spillovers of advertising on non-advertised drugs in the same drug class.

5.3.1. Extensive vs. Intensive Margin Effects

In Appendix Table B.5, we present 2SLS estimates for extensive and intensive measures of prescription drug use for chronic drugs. We estimate three margins of adjustment for drug utilization: extensive margin effects (any prescription drug use), intensive margin effects (number of prescriptions or days supplied conditional on use), and total effects combining both

[53] This is computed by noting that utilization increases for advertised drug classes by 8.2% vs. 1.3% for non-advertised drug classes using Panel B and 6.2% vs. 2.3% using Panel A.

margins. We find positive effects for all of the outcome variables. The coefficients are statistically significant at the 5% level in all but two specifications. We perform a decomposition exercise to compare the relative magnitude of intensive and extensive margin effects (the details of this decomposition are in Appendix A.1), finding that about 70 percent of the total advertising effect for prescriptions purchased is driven by extensive margin effects. Thus, a substantial proportion of the utilization effect appears to come from increased take-up.

5.3.2. Effects on Drug Adherence

We extend the above analysis of intensive margin effects by looking specifically at the effects on drug adherence. Advertising may increase adherence if it serves as a reminder to take medication, makes the condition more salient, or increases the perceived benefits of treatment. It may also reduce adherence if it enhances awareness of harmful side effects. Poor adherence to prescribed drugs reduces their effectiveness, leading to worse health and greater costs. An estimated 50% of patients with chronic diseases do not follow treatment regimens as prescribed (Viswanathan, et al., 2012). While it is difficult to interpret rising drug use due to advertising as "appropriate" use, increasing drug adherence has clearer positive welfare implications.

We present the results for drug adherence graphically in Figure 7. This figure is analogous to previous figures, but the outcome is now the proportion of non-elderly individuals with "high adherence" (defined as MPR≥80%). Similar results for the continuous measure of MPR are in Appendix Figure B.5. Adherence is mechanically very high in the first few quarters of the study period because we start following patients in the quarter of their first observed drug treatment and most individuals in these early quarters have just initiated treatment by

construction.[54] However, this mechanical relationship is uniform across geographic areas and should not impact our results. Additionally, we will show that excluding these early quarters from the analysis has little effect on the results. Once the adherence measure has stabilized in 2005, we find that the proportion of non-elderly with high adherence is nearly identical across high and low elderly share areas, but then immediately diverges in 2006. There is an absolute and relative increase in adherence in high elderly share areas and this effect is persistent.

To estimate the magnitudes, we present the corresponding regression results for the reduced form and 2SLS estimates in Table 6 (see Appendix Table B.7 for continuous measure of MPR). We present results separately for the full sample, excluding the recession, and excluding 2004 when adherence is mechanically high. The results are qualitatively similar across samples. In the full sample, Part D led to a 0.4 percentage point increase in the proportion of individuals with high adherence. Restricting the sample to 2005-07, the estimate increases to 1.2 percentage points. The 2SLS estimates are also positive and largely significant. Given an 8.1% increase in advertising exposure after Part D, these estimates imply an adherence elasticity with respect to advertising ranging from 0.09 to 0.25 depending on the sample. Using the high end estimate, the number of ads viewed would need to increase by 40% in order to increase adherence by 10%.

Next, we present results from an alternative measure of MPR in Appendix Table B.8. In our baseline results (Row 1), we computed the MPR between a person's first and last drug claim. However, discontinuation of treatment is also an important dimension of non-adherence. In Row 2, we assume that the MPR equals zero after the last observed drug claim.[55] With this measure,

[54] For example, in the first quarter, everyone in the sample has filled at least one prescription, so their adherence will be atypically high. In the second quarter, everyone has filled at least one prescription in that quarter or the previous quarter, and so forth. In later quarters, the sample composition becomes more balanced.

[55] This assumption is most appropriate for chronic conditions that require lifetime treatment. Depression is an exception because guidelines recommend that a patient receives treatment until the symptoms have improved (Donahue et al., 2004). Our baseline MPR is conservative as it does not assume that lifetime treatment is needed.

MPR reflects both compliance with an ongoing prescription and the rate at which medication is discontinued. The 2SLS results using this alternative measure of MPR are slightly larger than the baseline results (in both absolute and relative terms) in most samples. This is suggestive that advertising may also reduce the rate of treatment discontinuation.

We also estimate the adherence effect for only existing patients in Rows 3 and 4. In the previous results, the changes in adherence represent a combination of effects from both existing and new drug users. In particular, the increase in advertising after Part D caused more people to initiate drug treatment. These new entrants into the sample may have different underlying compliance behavior. To isolate the adherence responses of the existing patients from the new initiators, we replicate the previous results using only the sample of individuals who initiated drug treatment before Part D. When we exclude the new initiators, the results become larger for both measures of MPR. This suggests that the marginal person who initiates treatment because of advertising is on average less compliant. A back-of-the-envelope calculation suggests that those who initiate treatment due to advertising are about half as likely to have high adherence (MPR≥80%) relative to existing patients.[56] There are a few possible reasons for this. The marginal person might have a less severe condition or advertising may attract people who are less attached to treatment (e.g. someone impulsively trying a drug they saw on TV only to quickly discontinue its use). Thus, while increasing adherence among existing users may be welfare enhancing, the welfare effects of new initiation due to advertising are less clear. Some of the additional drug use due to advertising could represent wasteful spending since initiating a chronic treatment without adhering to it may not improve health.

[56] The total effect of advertising on adherence is 0.017, which is a weighted average of the effect for new initiators and existing patients. The adherence effect for existing patients is 0.022. The probability of drug take-up increased by 0.001 after Part D in high elderly share areas from a baseline of 0.06. Using this estimate, combined with the adherence effects, we estimate that the proportion of non-elderly individuals with high adherence after Part D is 0.632 for existing patients and 0.319 for new initiators.

5.4. Spillover Effects to Non-Advertised Drugs

Finally, we analyze whether there were spillover effects of advertising on non-advertised drugs within the same drug class to test for market expansion versus substitution effects.[57] Substitution effects occur when a person who would have taken a competitor drug switches to an advertised drug after viewing an ad for the drug. Market expansion effects occur when a person requests an advertised drug from her doctor, but the doctor then prescribes another therapeutically similar drug instead. Insurance formularies could also induce such positive spillovers. For example, if brand-name Lipitor is excluded from the formulary (or placed on a higher cost-sharing tier), while generic Zocor is covered, advertising for Lipitor could increase generic Zocor use. We test for these types of spillover effects by re-estimating Equation 3, replacing the outcome variable with the total prescriptions purchased for *non-advertised* drugs belonging to the same therapeutic drug classes as the advertised chronic drugs. We separately estimate the effects for non-advertised generic drugs and non-advertised brand drugs (many of the brand drugs do not advertise because they are off-patent). This analysis differs from the previous test in Figure 6 because we now want to understand how advertising in a class influences utilization for non-advertised drugs in that class. Thus, we compare products *within* a drug class based on whether or not they advertise (as opposed to comparing products *across* drug classes that have a positive amount of advertising versus classes that have zero advertising).

Figure 8 shows the trends in average prescriptions purchased across high and low elderly share markets for advertised chronic drugs (repeated from Figure 3), non-advertised chronic drugs (generics and brands separately) in the same classes as the advertised chronic drugs, and both types of chronic drugs combined to study the overall effects. For non-advertised generic

[57] While a brand's advertising may also have spillovers on the use of other advertised brands, we cannot identify this effect since Part D impacts all advertised drugs simultaneously. Thus, we focus on identifying market expansion and substitution effects for non-advertised versus advertised drugs, which is one component of the spillover effects.

drugs (in the same classes as advertised chronic drugs), we see both an absolute and relative increase in utilization in high elderly share markets immediately after Part D.[58] This provides strong evidence of a market expansion effect, since DTCA increases generic use and on net does not cause substitution away from lower-cost generics to higher-cost advertised drugs. We do not observe any differential change in non-advertised brand use after Part D. There are likely greater spillovers on non-advertised generics than brands because they are cheaper. Finally, we observe a large effect from combining advertised and non-advertised chronic drugs (Panel D) which is also consistent with market expansion. The regression analogs are in Table 7 and show that these utilization effects are all positive and statistically significant, except for non-advertised brand drugs.[59] Consistent with the previous advertising literature, we find large positive spillovers from advertising. We add to this by showing that spillover effects are concentrated among lower-cost generic drugs, which has important welfare implications for consumers and firms. From the consumer perspective, spillovers may be welfare enhancing as this suggests at least some role for informative, rather than market-stealing advertising. In contrast, had we found a complete shift from non-advertised to advertised drugs, this would have represented little welfare gain since advertised drugs may not be significantly superior to non-advertised drugs.

6. Conclusion

This paper provides a new natural experiment approach to estimating the impact of DTCA on drug utilization and sheds light on the causal mechanisms for the advertising effect. We find that non-elderly living in high elderly share areas were exposed to relatively more

[58] The secular increase in utilization, which differs from the declining trend we see for advertised drugs, reflects the fact that there is substitution from the advertised brand-name drugs to generics after brands lose patent protection.
[59] Proportional effects relative to the baseline mean for non-advertised generic drugs are also 5 times larger than for non-advertised brand drugs (15% vs. 3% increase in use).

pharmaceutical advertising after Part D. This increase in advertising led to substantial increases in chronic drugs purchased. Our results suggest an elasticity with respect to advertising views of 0.54. Although this estimate exceeds prior estimates from the literature, this can be reconciled by accounting for the different ways that advertising has been measured. We measure advertising in terms of actual views, which has been shown to produce larger elasticities (Sethuraman et al., 2011) compared to the more commonly used measures of advertising expenditures or number of ads. Adjusting for differences in measurement, our estimates imply an advertising expenditure elasticity of 0.23. We find limited evidence to suggest that this estimate is driven by changes in prices, detailing, or physician prescribing behavior differentially occurring in high elderly share areas. However, accounting for these other potential mechanisms suggests a conservative lower bound on the advertising expenditure elasticity ranging from 0.14 to 0.19.

While the literature on prescription drug demand has focused heavily on the importance of prices and insurance status in explaining utilization patterns, we generate estimates of the responsiveness of demand to a non-monetary factor and find economically important effects. Using the range of price elasticities in the literature (Goldman, Joyce, and Zheng, 2008) combined with our main results, our estimates imply that a 10 percent increase in advertising exposure produces the same increase in prescription drug utilization as a 9 to 27 percent reduction in out-of-pocket price.[60] Our estimates are also relevant to understanding the broader consequences of insurance expansions and the operation of such spillovers through advertising.

When we apply our advertising elasticity estimate to the national trend in DTCA expenditures, we estimate that about 31% of the rise in drug spending since 1997 (when the FDA

[60] Based on the review in Goldman, Joyce and Zheng (2007), estimates of the price elasticity of demand for prescription drugs range from -0.2 to -0.6. Using our estimated elasticity of demand with respect to advertising of 0.54, we compute the corresponding price elasticity equivalent to a 10% change in advertising exposure as: (0.54/.2)*10=27 or (0.54/.6)*10=9.

relaxed its advertising restrictions) can be attributed to DTCA.[61] While one must exercise caution in extrapolating our estimates to the national historical trend, our results are suggestive that DTCA is a significant, though not primary, contributor to the rapid rise in drug spending in the U.S. Innovation and pricing over this period have also played a role in driving spending.

We study the effects of a market-wide shock to advertising, which allows us to identify the net impact on drug use.[62] Much of the literature has focused on the firm-side and how advertising affects firm's own revenue. Our interest is in how public policy influences market-wide incentives for DTCA, and in the resulting implications for patients. To inform the debate over whether DTCA should be encouraged, limited, or banned, the aggregate effect of expanding advertising for all drugs is the relevant policy parameter. Other policies that stimulate DTCA might have different local average treatment effects (Imbens and Angrist, 1994). However, our policy experiment bears directly on policies expanding public insurance.

Evaluating the welfare consequences of the rise in drug spending requires an understanding of the benefits of DTCA. We find that a large share of the utilization response to advertising is driven by take-up of treatment. Given that the conditions we study are generally considered to be under-treated and under-diagnosed (e.g. Hirschfeld, et al., 1997; Majumdar et al., 1999), increased take-up is likely to lead to improved health, representing a welfare gain for consumers. However, we find that individuals who initiate therapy due to advertising have lower rates of treatment compliance, which could mitigate some of these health gains. For patients

[61] To recover this parameter, we begin by estimating the advertising elasticity for total drug spending (including spillover effects on non-advertised drugs) in Appendix Table B.9. Our results imply that a 10 percent increase in advertising views increases total drug spending by about 4 percent (using the more conservative binary instrument). We deflate this estimate by a factor of 2.3 to account for the relationship between advertising expenditures and advertising views (Sethuraman et al., 2011), since we only observe time series growth in advertising expenditures. Based on this estimate, we predict that drug spending would increase by 59% in response to the increase in national DTCA expenditures from 1997-2010. Comparing this to the actual increase in national drug spending (193%), DTCA accounts for about 31% of the growth in drug spending since the FDA relaxed restrictions in 1997.

[62] Since Part D affected advertising incentives for all drugs, it does not serve as an appropriate instrument to test for market stealing between one advertised brand name drug and another.

who are less attached to treatment regimens or for whom treatment is marginally less appropriate, increased spending may lead to little health improvement. On the other hand, improved adherence for existing patients has clearer welfare implications and we find strong results on this dimension. Furthermore, if advertising serves primarily to persuade, rather than to inform, we may observe distortions in use towards the newest, most expensive drugs, irrespective of their quality. Our evidence on spillover effects suggests that a significant share of the increase in utilization comes from non-advertised, lower-cost generic drugs. Our estimates provide a rich picture of the utilization responses to DTCA by examining numerous mechanisms explaining the overall increase and provide an important step in understanding advertising's welfare effects. Ultimately, an analysis of the health benefits as well as other perceived utility gains from the additional treatments induced by DTCA are needed to characterize the full welfare effects. This goes beyond the scope of the current analysis, given the limited measures of health available in our claims data, but represents a potentially important area for future research.

References

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

Andrade, S., et al. 2006. Methods for evaluation of medication adherence and persistence using automated databases. *Pharmacoepidemiology and Drug Safety.* 15(8):565-574.

Avery, R., Eisenberg, M. and K. Simon. 2012. The impact of direct-to-consumer television and magazine advertising on antidepressant use. *Journal of Health Economics.* 31:705-718.

Blume-Kohout, M. and N. Sood. 2013. Market size and innovation: Effects of Medicare Part D on pharmaceutical research and development. *Journal of Public Economics*. 97:327-336.

Bradford, W., et al. 2006. How direct-to-consumer television advertising for osteoarthritis drugs affect physicians' prescribing behavior. *Health Affairs.* 25(5):1371-1377.

Centers for Medicare and Medicaid Services. 2012. Chronic conditions among Medicare beneficiaries.

Dave, D. 2013. Effects of pharmaceutical promotion: A review and assessment. *NBER Working Paper 18830.*

Dave, D. and H. Saffer. 2012. Impact of direct-to-consumer advertising on pharmaceutical prices and demand. *Southern Economic Journal.* 79(1): 97-126.

Donohue, J., Berndt, E., Rosenthal, M., et al., 2004. Effects of pharmaceutical promotion on adherence to the treatment guidelines for depression. *Medical Care.* 42(12): 1176–1185.

Duggan, M. and Scott Morton, F. 2010. The impact of Medicare Part D on pharmaceutical prices and utilization. *American Economic Review*. 100(1):590-607.

Goldman, D., Joyce, G., and Zheng, Y. 2007. Prescription drug cost sharing: Associations with medication and medical utilization and spending and health. *JAMA*. 298(1):61-69.

Goldman, D., et al. 2004. Pharmacy benefits and the use of drugs by the chronically ill. *JAMA*. 291(19): 2344-2350.

Hess, L, et al. 2006. Measurement of adherence in pharmacy administrative databases: A proposal for standard definitions and preferred measures. *A. of Pharmacotherapy*. 40:1280-88.

Hirschfeld, R, et al. 1997. The National Depressive and Manic-Depressive Association consensus statement on the undertreatment of depression. *JAMA.* 277(4):333-340.

Holmer, A. 2002. Direct-to-consumer advertising—strengthening our health care system. *New England Journal of Medicine.* 346(7):526-528.

Iizuka, T. and G. Jin. 2005. The effect of prescription drug advertising on doctor visits. *Journal of Economics and Management Strategy*. 14(3): 701–727.

Imbens, G. and J. Angrist. 1994. Identification and Estimation of Local Average Treatment Effects. *Econometrica*. 62(2):467-475.

Joyce, G., Goldman, D., Karaca-Mandic, P., and Y. Zheng. 2007. Pharmacy benefit caps and the chronically ill. *Health Affairs.* 26(5): 1333-1344.

Kanazawa, M. and J. Funk. 2001. Racial discrimination in professional basketball: Evidence from Nielsen ratings. *Economic Inquiry.* 39(4): 599–608.

Kantar Media. 2011. Pharmaceutical Marketing. *Ad Age Insights White Paper*, October 17, 2011.

Kearney, M. and P. Levine. 2015. Media influences on social outcomes: The impact of MTV's *16 and Pregnant* on teen childbearing. *American Economic Review. 105(12):3597-3632.*

Ketcham, J. and K. Simon. 2008. Medicare Part D's effects on elderly drug costs and utilization. *American Journal of Managed Care*. 11:SP14-22.

Lakdawalla, D., Sood, N., and Q. Gu. 2013. Pharmaceutical advertising and Medicare Part D. *Journal of Health Economics.* 32:1356-1367.

Lakdawalla, D., and W. Yin. 2015. Insurers' negotiating leverage and the external effects of Medicare Part D. *Review of Economics and Statistics*. 97(2):314-331.

Lichtenberg, F. and Sun, S. 2007. The impact of Medicare Part D on prescription drug use by the elderly. *Health Affairs*. 26(6):1735-1744.

Majumdar, S., Gurwitz, J., and S. Soumerai. 1999. Undertreatment of hyperlipidemia in the secondary prevention of coronary artery disease. *Journal of General Internal Medicine*. 14(12):711-717.

Nielsen. 2014. The total audience report. December Issue.

Rosenthal, M., et al. 2003. Demand effects of recent changes in prescription drug promotions. *Frontiers in health policy research.* 6:1-26.

Saffer, H., Wakefield, M. and Y. Terry-McElrath. 2007. The effect of nicotine replacement therapy advertising on youth smoking. *NBER Working Paper 12964*.

Sethuraman, R., et al. 2011. How well does advertising work? Generalizations from meta-Analysis of brand advertising elasticities. *Journal of Marketing Research*. 48(3):457-471.

Shapiro, B. 2018. Positive spillovers and free riding in advertising of prescription pharmaceuticals: The case of antidepressants. *Journal of Political Economy*. 126(1):381-437.

Sinkinson, M. and A. Starc. 2015. Ask your doctor? Direct-to-consumer advertising of pharmaceuticals. *NBER Working Paper 21045*.

Stock, J., Wright, J., and M. Yogo. 2002. A survey of weak instruments and weak identification in GMM. *Journal of Business and Economic Statistics.* 20(4):518–529.

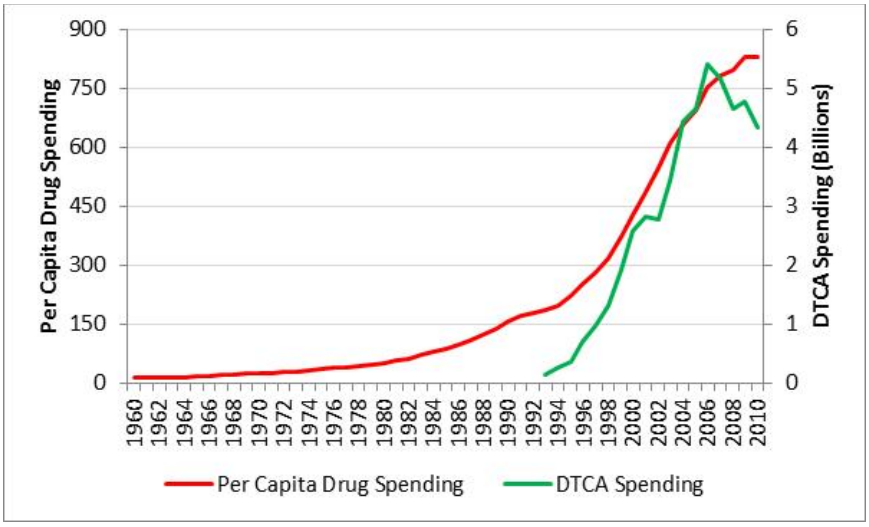
Viswanathan M, et al. 2012. Interventions to improve adherence to self-administered medications for chronic diseases in the United States: A systematic review. *Annals of Internal Medicine*. 157:785-795.

Wosinska, M. 2002. Just what the patient ordered? Direct-to-consumer advertising and the demand for pharmaceutical products. *HBS Marketing Research Papers No. 02-04*.

Wosinska, M. 2005. Direct-to-consumer advertising and drug therapy compliance. *Journal of Marketing Research.* 42(3): 323-332.

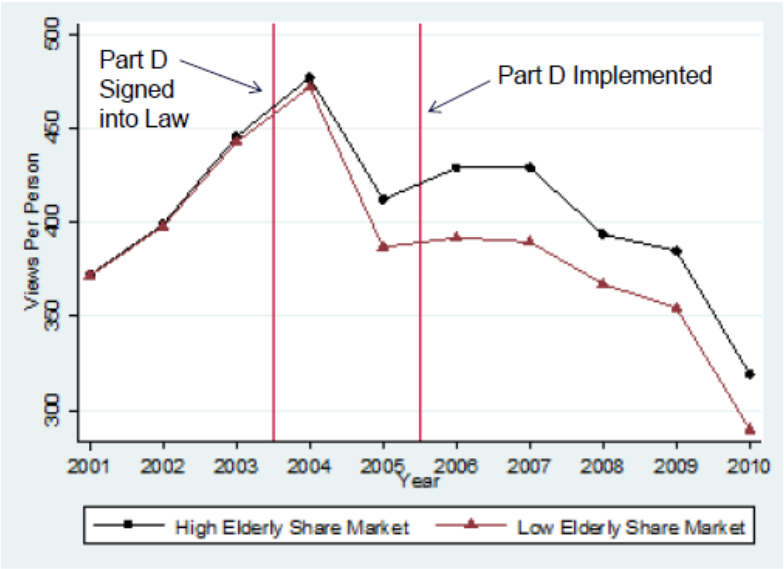
Yin, W. et al. 2008. The effect of the Medicare Part D prescription benefit on drug utilization and expenditures. *Annals of Internal Medicine.* 148(3):169-177.

Figure 1 –Direct-to-Consumer Advertising and Prescription Drug Spending, 1960-2010



Sources: Dave (2013), National Health Expenditure Accounts (2015). The data are presented in nominal values.

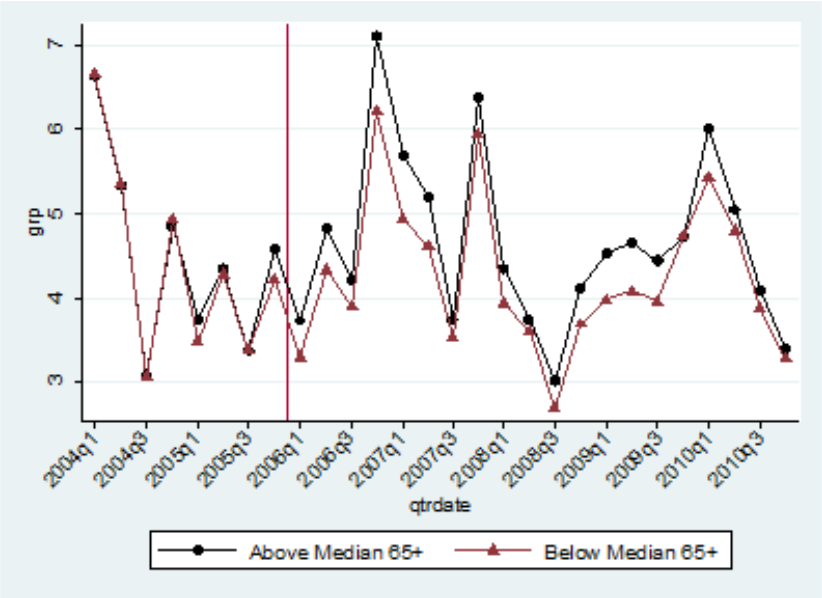
Figure 2 – Annual Views per Person of TV Ads for Top 200 Brand Name Drugs, for Non-Elderly



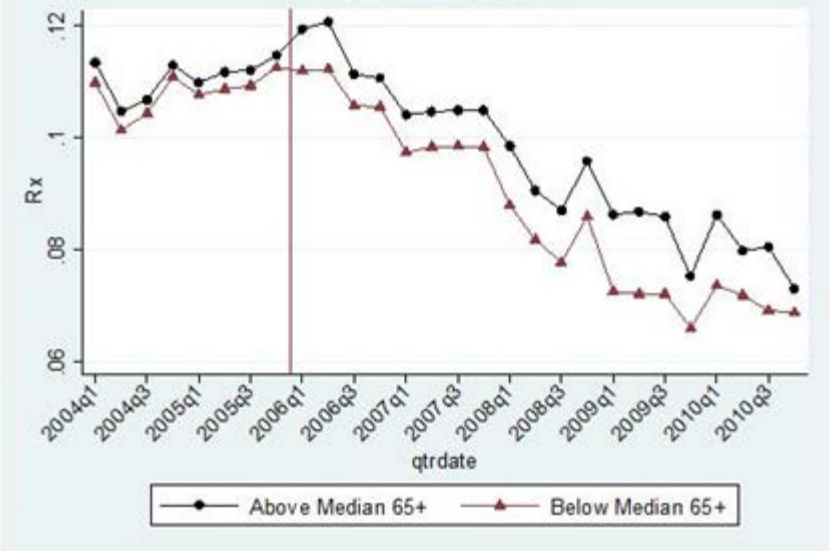
Notes: Sample means from Nielsen Ad*Views in above median elderly share markets relative to below median elderly share markets. The vertical lines represent the dates when Part D was signed into law (December 2003) and was implemented (January 2006). Means are plotted for a balanced panel of the top 200 advertised brand-name drugs. There is a secular downward trend in overall views per person due to patent expirations of several of these drugs over this time period (in particular, four of the top 200 drugs went off patent around 2006: Pravachol, Wellbutrin XL, Zocor, and Zoloft). The downward trend in views matches the pattern in national advertising expenditures shown in Figure 1. In Appendix Figure B.2, we exclude all drugs that went off-patent during the study period.

Figure 3 – Quarterly Views per Person of TV Ads and Mean Utilization of Chronic Drugs, for Non-Elderly

Panel A: Views Per Person for Chronic Drug Ads

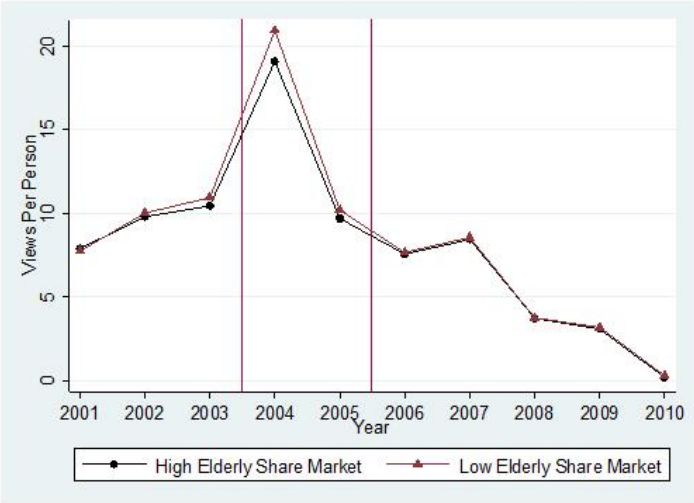


Panel B: Average Number of Prescriptions Purchased for Chronic Drugs



Notes: Sample means from Nielsen Ad*Views (views per capita for non-elderly) and claims (mean number of total prescriptions purchased for non-elderly) in above median elderly share markets relative to below median elderly share markets. Includes the 50 drugs that advertised during the study period for 5 chronic conditions: depressions, diabetes, hyperlipidemia, hypertension, and osteoporosis. The vertical line represents the implementation date of Medicare Part D.

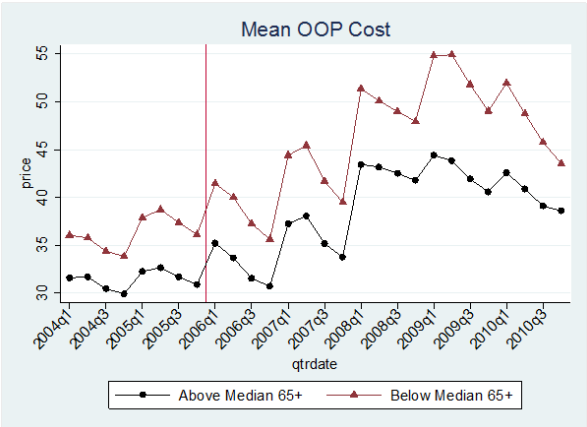
Figure 4 – Placebo Test: Annual Views per Person of TV Ads for Contraceptive Drugs, for Non-Elderly



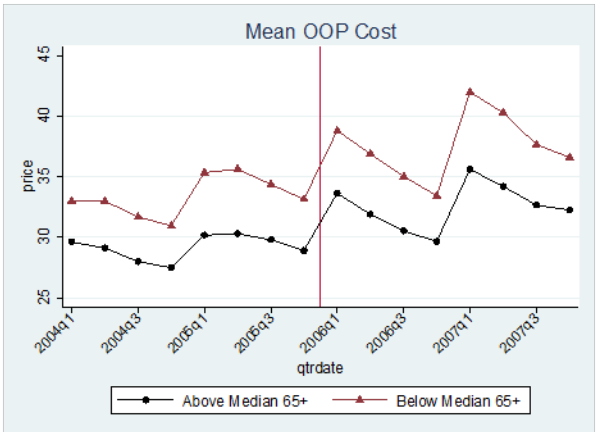
Notes: Sample means for contraceptive drugs from Nielsen Ad*Views in above median elderly share markets relative to below median elderly share markets. The vertical lines represent the dates when Part D was signed into law (December 2003) and was implemented (January 2006).

Figure 5 – Mean Out-of-Pocket Price for Chronic Drugs, for Non-Elderly

Panel A: All NDCs – Chronic Drugs

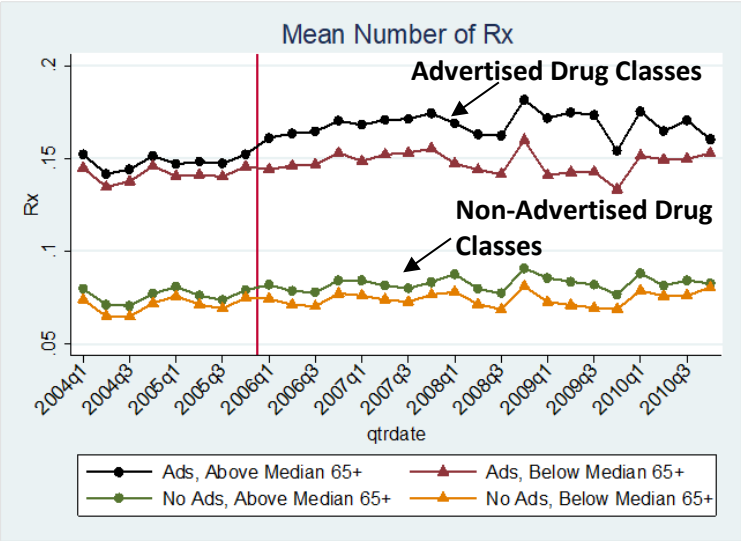


Panel B: Balanced Panel of NDCs (2004-07) – Chronic Drugs



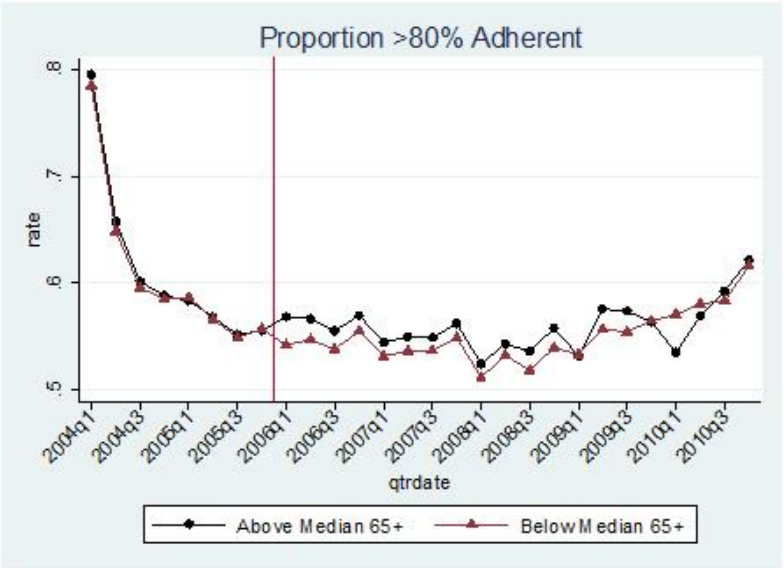
Notes: Sample means from claims (mean out-of-pocket price, ages 40-60) in above median elderly share markets relative to below median elderly share markets. Panel A includes all NDCs (drug products) associated with the 50 chronic drugs that advertised during the study period. Panel B repeats the exercise in Panel A using a balanced panel of NDCs from 2004-2007 (i.e. each NDC has a non-missing observation in each quarter). We exclude one observation that is an extreme outlier ($333,493 for Actos in Q1:2009 in low elderly share areas) and likely to be reporting error. The vertical line represents the implementation date of Medicare Part D.

Figure 6 – Mean Utilization for Advertised Drug Classes vs. Non-Advertised Drug Classes, for Non-Elderly



Notes: Sample means from claims (mean number of total prescriptions purchased, ages 40-60) in above median elderly share markets relative to below median elderly share markets. The top two lines (black and red) are for the top 10 advertised drug classes and the bottom two lines (green and orange) are for the top 10 non-advertised drug classes (see Appendix Figure B.4 for full list of drug classes included). The vertical line represents the implementation date of Medicare Part D. We use the first two digits of the GPI code (available from IMS Health) to identify major classes of drugs.

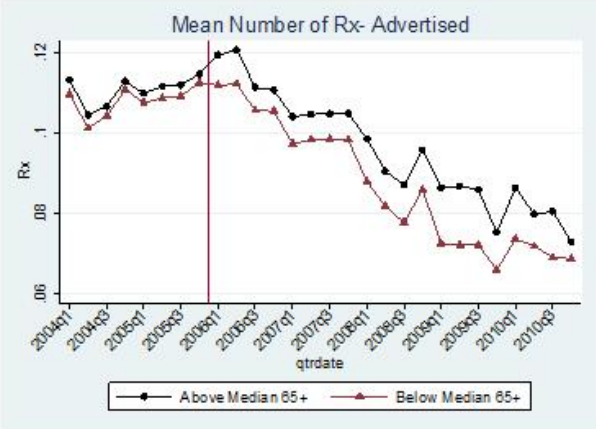
Figure 7 –Proportion with High Adherence of Chronic Drugs, for Non-Elderly



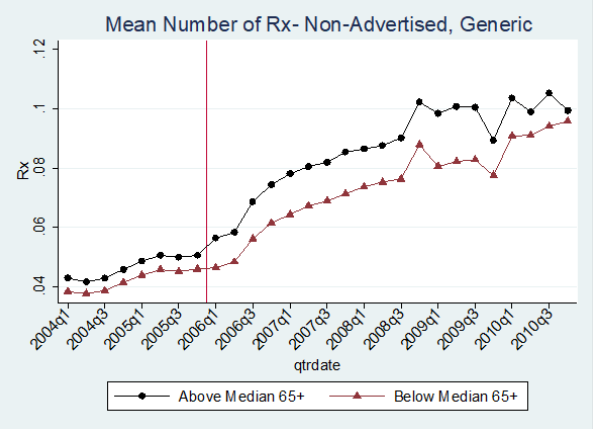
Notes: Sample means from claims (proportion of individuals with MPR≥80%, ages 40-60) in above median elderly share markets relative to below median elderly share markets. Includes the 50 drugs that advertised during the study period and the drugs that did not advertise for 5 chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis. The vertical line represents the implementation date of Medicare Part D.

Figure 8 – Quarterly Mean Utilization of Chronic Drugs: Spillover Effects

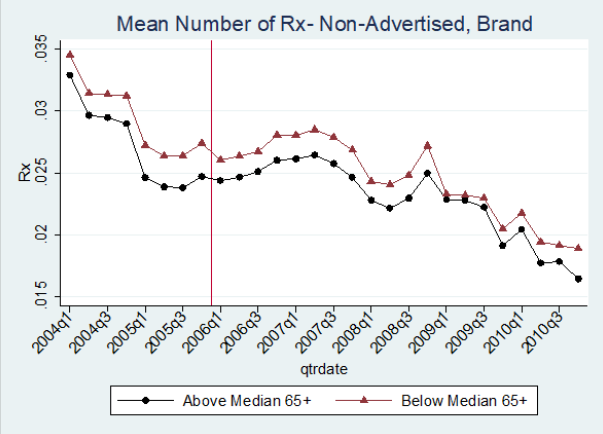
Panel A: Advertised Chronic Drugs



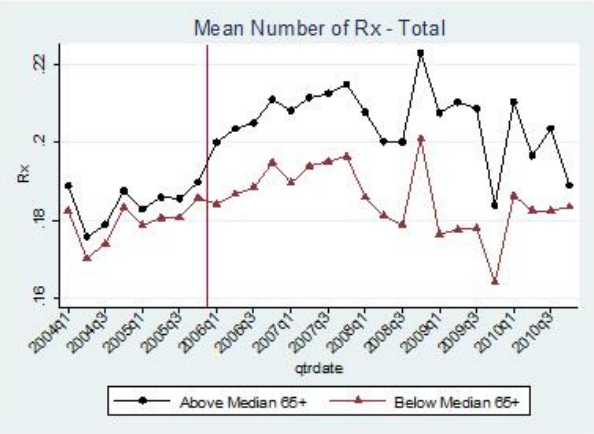
Panel B: Non-Advertised Chronic Drugs - Generic



Panel C: Non-Advertised Chronic Drugs – Brand



Panel D: Total Chronic Drugs



Notes: Sample means from claims (mean number of total prescriptions purchased, ages 40-60) in above median elderly share markets relative to below median elderly share markets. Panel A includes the 50 chronic drugs that advertised during the study period (repeated from Figure 3); Panel B includes generic drugs that did not advertise, but are in the same classes as the 50 advertised chronic drugs; Panel C includes brand drugs that did not advertise, but are in the same classes as the 50 advertised chronic drugs; Panel D includes both the advertised and non-advertised chronic drugs combined. The vertical line represents the implementation date of Medicare Part D.

Table 1 – Heterogeneity in Elderly Share Across Local TV Markets

TV Market	Share 65+	Pop 65+ (Census 2000)	Total Pop (Census 2000)	TV Market Ranking (Size)
Top 8 High Elderly Share Markets				
FT. MYERS-NAPLES	0.257	234,535	912,887	62
WEST PALM BEACH-FT. PIERCE	0.238	380,814	1,598,528	38
TAMPA-ST. PETE (SARASOTA)	0.213	787,553	3,702,269	14
WILKES BARRE-SCRANTON-HZTN	0.175	259,761	1,481,798	54
PITTSBURGH	0.173	503,077	2,901,329	23
ORLANDO-DAYTONA BCH-MELBRN	0.167	488,991	2,926,227	18
PADUCAH-CAPE GIRARD-HARSBG	0.158	156,329	987,215	81
SPRINGFIELD, MO	0.158	148,844	942,604	75
Top 8 Low Elderly Share Markets				
HOUSTON	0.082	410,910	5,020,575	10
SALT LAKE CITY	0.085	204,008	2,387,354	33
AUSTIN	0.085	116,640	1,371,385	40
ATLANTA	0.085	437,654	5,149,717	9
DALLAS-FT. WORTH	0.087	503,232	5,761,057	5
DENVER	0.093	320,372	3,451,529	17
WASHINGTON, DC (HAGRSTWN)	0.096	501,141	5,232,970	8
LOS ANGELES	0.098	1,578,642	16,144,245	2

Table 2 – Baseline Regressions for Total Utilization of Chronic Drugs, for Non-Elderly

	First Stage	Reduced Form	2SLS
Dependent Variable:	Views per Person (Non-Elderly)	# of Prescriptions	# of Prescriptions
	(1)	(2)	(3)
A. Instrument=Share65+*Post			
Share65+*Post	6.358***	0.107***	
	(1.116)	(0.023)	
Views per Person (Non-Elderly)			0.017***
			(0.004)
F-statistic	32.69		
B. Instrument=High Elderly Share*Post			
High Elderly Share*Post	0.348***	0.005***	
	(0.063)	(0.001)	
Views per Person (Non-Elderly)			0.014***
			(0.005)
F-statistic	30.86		
Mean of Dep. Var. (pre- Part D)	4.28	0.11	0.11
Zipcode x Condition x Quarter Obs	107,345	107,345	107,345

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the 3-digit ZIP code level; all specifications include quarter fixed effects, 3-digit ZIP code fixed effects, condition fixed effects. Includes the 50 drugs that advertised during the study period for 5 chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis. Data is from 2004-2010.

Table 3 – Timing of the Impact on Total Utilization of Chronic Drugs, for Non-Elderly

Dependent Variable:	# of Prescriptions (1)		# of Prescriptions (2)
Share65+ * 2004:Q1	0.051	HighShare * 2004:Q1	0.002
	(0.051)		(0.003)
Share65+ * 2004:Q2	0.066	HighShare* 2004:Q2	0.002
	(0.043)		(0.002)
Share65+ * 2004:Q3	0.046	HighShare * 2004:Q3	0.001
	(0.043)		(0.002)
Share65+ * 2004:Q4	0.035	HighShare * 2004:Q4	0.001
	(0.043)		(0.002)
Share65+ * 2005:Q1	-0.022**	HighShare * 2005:Q1	0.000
	(0.010)		(0.001)
Share65+ * 2005:Q2	0.002	HighShare* 2005:Q2	0.001
	(0.008)		(0.001)
Share65+ * 2005:Q3	0.000	HighShare * 2005:Q3	0.001
	(0.006)		0.000
Share65+ * 2006:Q1	0.133***	**HighShare * 2006:Q1**	0.006***
	(0.030)		(0.001)
Share65+ * 2006:Q2	0.140***	**HighShare * 2006:Q2**	0.007***
	(0.028)		(0.001)
Share65+ * 2006:Q3	0.093***	**HighShare * 2006:Q3**	0.004***
	(0.034)		(0.001)
Share65+ * 2006:Q4	0.083**	**HighShare * 2006:Q4**	0.004**
	(0.036)		(0.002)
Share65+ * 2007:Q1	0.133***	**HighShare* 2007:Q1**	0.006***
	(0.037)		(0.002)
Share65+ * 2007:Q2	0.131***	**HighShare* 2007:Q2**	0.005***
	(0.037)		(0.002)
Share65+ * 2007:Q3	0.135***	**HighShare* 2007:Q3**	0.005***
	(0.034)		(0.002)
Share65+ * 2007:Q4	0.135***	**HighShare* 2007:Q4**	0.005***
	(0.037)		(0.002)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the 3-digit ZIP code level; all specifications include quarter fixed effects, 3-digit ZIP code fixed effects, condition fixed effects. All Instrument x quarter interactions are included in the regression, however the 2008-2010 coefficients are not presented in this table to conserve space. Includes the 50 drugs that advertised during the study period for 5 chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis.

Table 4 – Total Utilization of Chronic Drugs – Alternative Specifications

	Reduced Form		2SLS	
Dependent Variable: # of Prescriptions	Instrument= Share65+*Post	Instrument= High Elderly Share*Post	Instrument= Share65+*Post	Instrument= High Elderly Share*Post
	(1)	(2)	(3)	(4)
1. Baseline Specification	**0.107*** **	**0.005*** **	**0.017*** **	**0.014*** **
	(0.023)	**(0.001)**	**(0.004)**	**(0.005)**
2. Adding zipcode-specific linear trends	0.102***	0.005***	0.010***	0.008***
	(0.021)	(0.001)	(0.003)	(0.002)
3. Excluding 2008-2010	0.097***	0.004***	0.011***	0.008***
	(0.018)	(0.001)	(0.003)	(0.003)
4. Including only continuously enrolled firms	0.072***	0.004**	0.012**	0.015*
	(0.027)	(0.002)	(0.006)	(0.008)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the 3-digit ZIP code level; all specifications include quarter fixed effects, 3-digit ZIP code fixed effects, condition fixed effects. Each cell represents the coefficient on Instrument x Post from a separate regression. The specifications are as follows: 1) same as Table 2, 2) adds 3-digit ZIP code specific linear trends, 3) excludes the years 2008-2010, 4) includes only firms that were continuously in the claims sample from 2004-2010. Includes the 50 drugs that advertised during the study period for 5 chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis.

Table 5 – Detailing Test: Within-DMA Total Utilization of Chronic Drugs

Dependent Variable:	# of Prescriptions		
	Baseline	ZIP3 level	DMA x Qtr FE
	(1)	(2)	(3)
A. Instrument=Share65+*Post			
Share65+*Post (DMA level)	0.111***		
	(0.033)		
Share65+*Post (ZIP3 level)		0.087***	0.015
		(0.027)	(0.026)
B. Instrument=High Elderly Share*Post			
High Elderly Share*Post (DMA level)	0.003**		
	(0.002)		
High Elderly Share*Post (ZIP3 level)		0.006***	0.002
		(0.002)	(0.002)
Mean of Dep. Var. (pre- Part D)	0.10	0.10	0.10
Zipcode x Condition x Quarter Obs	67,495	67,495	67,495

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the 3-digit ZIP code level; all specifications include qtr fixed effects, 3-digit ZIP code fixed effects, condition fixed effects. Col 1: same as Table 2, but for sample of ZIP codes that are uniquely matched to one DMA, elderly share computed at the DMA-level; Col 2: elderly share computed at 3-digit ZIP code level; Col 3: adds DMA x quarter fixed effects, elderly share computed at 3-digit ZIP code level. Includes the 50 drugs that advertised during the study period for 5 chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis.

Table 6 – Adherence of Chronic Drugs

	Reduced Form			2SLS		
Dependent Variable: I(High Adherence)	Full Sample	2004-2007	2005-2007	Full Sample	2004-2007	2005-2007
	(1)	(2)	(3)	(4)	(5)	(6)
A. Instrument=Share65+*Post						
Post*Share65+	0.184***	0.234***	0.404***			
	(0.057)	(0.056)	(0.114)			
Views per Person (Non-Elderly)				0.017**	0.017***	0.033***
				(0.007)	(0.005)	(0.013)
B. Instrument=High Elderly Share*Post						
High Elderly Share*Post	0.004*	0.008***	0.012***			
	(0.003)	(0.003)	(0.004)			
Views per Person (Non-Elderly)				0.008	0.011***	0.021**
				(0.005)	(0.004)	(0.008)
Mean of Dep. Var (pre- Part D)	0.61	0.61	0.56			
Zipcode x Condition x Quarter Obs	102,477	59,252	44,519	102,477	59,252	44,519

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the 3-digit ZIP code level; all specifications include quarter fixed effects, 3-digit ZIP code fixed effects, condition fixed effects. The outcome variable is the proportion of individuals with MPR>=80%. Includes the 50 drugs that advertised during the study period and the drugs that did not advertise for 5 chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis.

Table 7 – Spillover Effects on Non-Advertised Chronic Drugs

	Reduced Form				2SLS			
Dependent Variable: # of Prescriptions	Advertised Drugs	Non-Advertised Drugs: Generic	Non-Advertised Drugs: Brand	Total	Advertised Drugs	Non-Advertised Drugs: Generic	Non-Advertised Drugs: Brand	Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Instrument=Share65+*Post								
Post*Share65+	0.107***	0.100***	0.025***	0.233***				
	(0.023)	(0.027)	(0.007)	(0.038)				
Views per Person (Non-Elderly)					0.017***	0.016***	0.004***	0.037***
					(0.004)	(0.005)	(0.002)	(0.008)
B. Instrument=High Elderly Share*Post								
High Elderly Share*Post	0.005***	0.006***	0.001	0.011***				
	(0.001)	(0.002)	0.000	(0.002)				
Views per Person (Non-Elderly)					0.014***	0.016***	0.002	0.032***
					(0.005)	(0.005)	(0.002)	(0.008)
Mean of Dep. Var (pre- Part D)	0.11	0.04	0.03	0.18	0.11	0.04	0.03	0.18
Zipcode x Condition x Quarter Obs	107,345	107,345	107,345	107,345	107,345	107,345	107,345	107,345

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the 3-digit ZIP code level; all specifications include quarter fixed effects, 3-digit ZIP code fixed effects, condition fixed effects. Includes the 50 chronic drugs that advertised during the study period and the drugs in the same classes that did not advertise. Non-advertised drugs are separated into generic and brand products. Data is from 2004-2010.

FOR ONLINE PUBLICATION

Appendix A

A.1 Decomposition of Extensive and Intensive Margin Effects

The increase in total drug utilization we observe due to advertising is driven both by increased take-up of treatment (extensive margin) as well as increased use among existing drug users (intensive margin). In this section we decompose the overall effect of advertising into the extensive and intensive margins. We re-estimate the main 2SLS regression for total prescriptions shutting down the extensive margin effect (i.e. we hold the take-up rate constant at pre-Part D levels). This allows us to estimate the proportion of the total effect that is due to intensive margin changes. The remaining proportion of the total effect is then due to extensive margin changes. We estimate:

$$\text{(A1)} \quad AnyUse_{mct,<65} = \sigma_m + \tau_c + \epsilon_{mct}$$

Where $AnyUse_{mct,<65}$ is the proportion of non-elderly individuals with any use of prescription drugs for condition c in market m and quarter t. We estimate this equation for the pre-Part D period from 2004-2005. We then use the estimated parameters to predict $\widehat{AnyUse}_{mct,<65}$ for the entire sample from 2004-2010. Since $\widehat{AnyUse}_{mct,<65}$ varies only by condition and market, the proportion that takes-up prescription drugs (i.e. extensive margin) is held constant over time.

Next we construct a counterfactual measure of total prescriptions purchased which holds the extensive margin constant: $\hat{Y}_{mct,<65} = \widehat{AnyUse}_{mct,<65} * Y_{mct,<65}$, where $Y_{mct,<65}$ is the average number of prescriptions purchased conditional on use. We use this constructed outcome variable to estimate the 2SLS model as before. The 2SLS results are presented in Columns 3 and 4 of Appendix Table B.6. The estimates using the counterfactual outcome, representing the intensive margin, are less than one-third the size of the baseline total effect (Columns 1 and 2). Using the preferred continuous instrument specification, this implies that extensive margin changes explain 71% to 73% of the total utilization effect. A straightforward back-of-the-envelope calculation using the pre-Part D take-up rate and estimated intensive margin effect from Appendix Table B.5 produces similar estimates of the extensive margin effect.[63]

[63] Using the continuous instrument, the change in prescriptions purchased is 0.017 for one additional ad viewed. The change in prescriptions purchased along the intensive margin is predicted to be the fraction of the sample that

A.2 Construction of Adherence Measures

Our measure of adherence is the medication possession ratio (MPR). The MPR is calculated as the number of days with drug on-hand (i.e. days supplied) divided by the number of days in the quarter. We adjust the numerator of the MPR to account for claims with overlapping days supplied. For example, it is typical to refill a prescription before finishing the days supplied for the initial prescription. If overlapping claims have the same active ingredient,[64] we assume that the person finishes the days supplied in the first claim before starting the days supplied in the second claim. For overlapping claims with different active ingredient names (for the same condition), we assume that patients start using the days supplied for the second claim on the fill date and discard remaining days supplied for the first claim. This case likely represents a drug switch. Since advertising may lead to more drug switching, it is especially important to account for this case to avoid overstating the effect of advertising on adherence. Days in the hospital were assumed to be fully compliant and patients resumed their prescriptions after they were discharged.

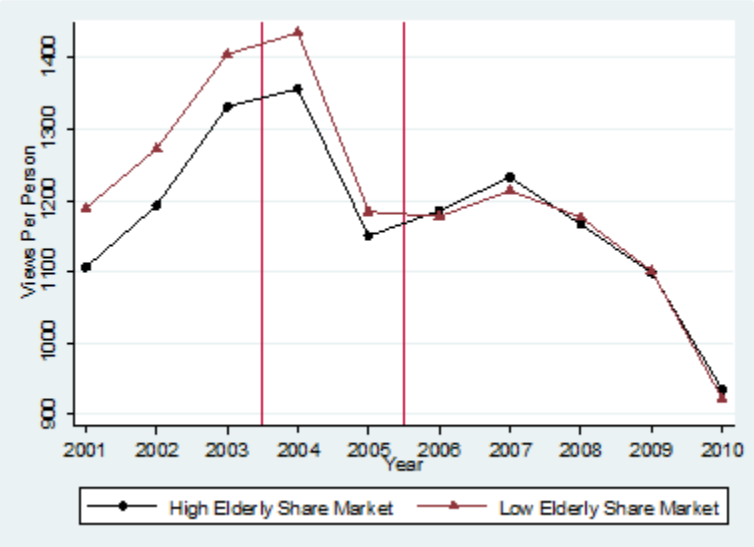
After constructing the quarterly MPR for each individual by condition, we also create a binary indicator for individuals who had MPR $\geq$80%, which is considered high adherence and is the threshold most commonly reported in the pharmaceutical literature (Andrade, et al., 2006). As before, we collapse the data by three-digit ZIP code, condition, and quarter, computing the mean MPR and the proportion of individuals with MPR $\geq$80% in each cell.

used chronic drugs prior to Part D (0.063) x the estimated change in prescriptions purchased among users (0.057). Subtracting this from the total effect, we get the predicted extensive margin effect: 0.013 (or 76% of the total effect).

[64] Combination drugs are viewed as a unique combination of two or more active ingredients.

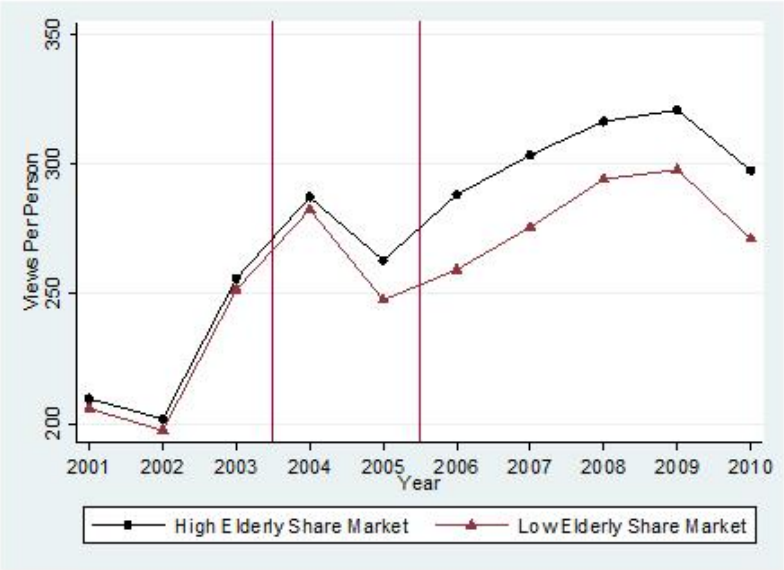
Appendix B

Appendix Figure B.1 – Annual Views per Person of Ads for Top 200 Brand Name Drugs, for Elderly 65+



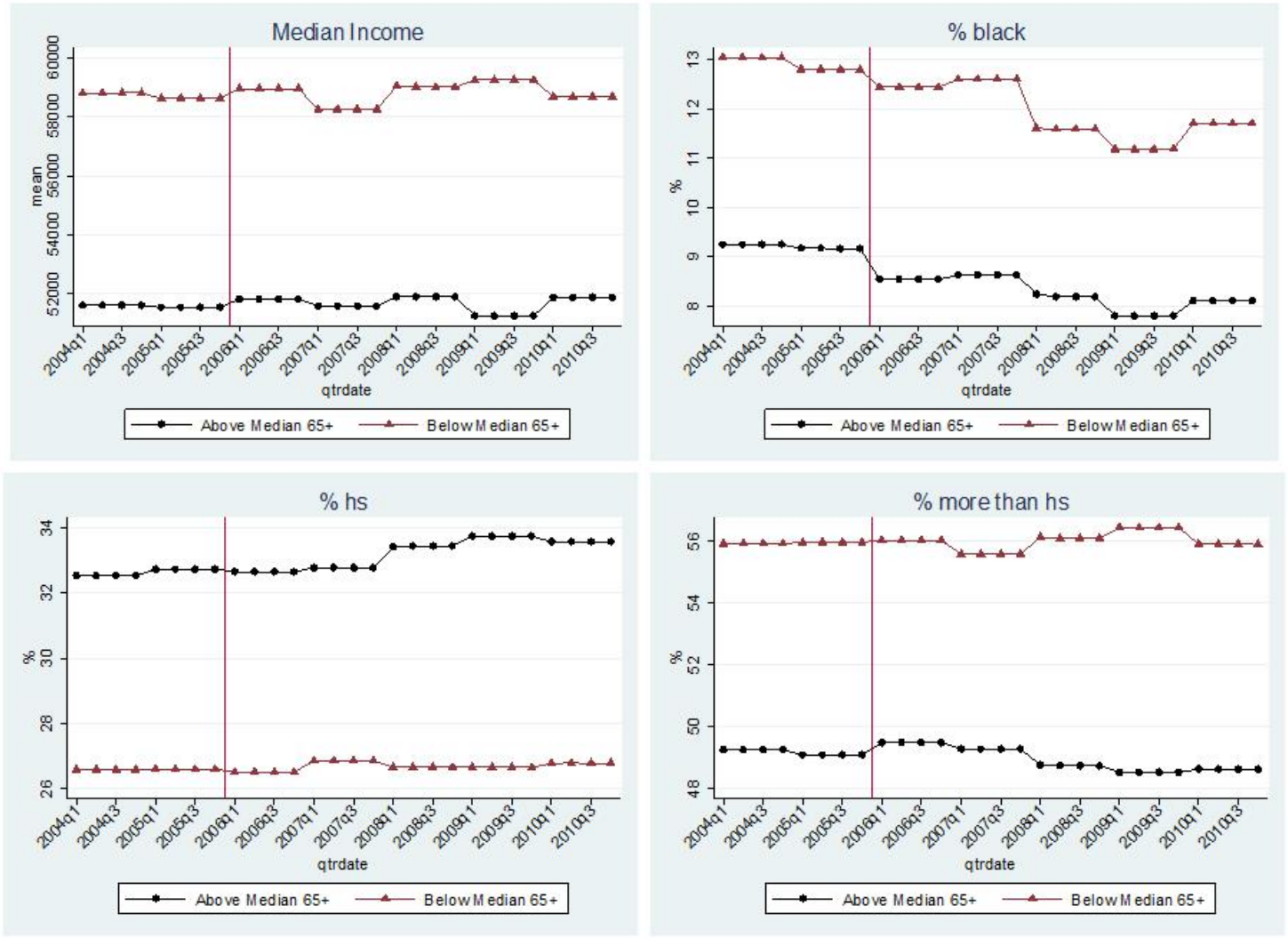
Notes: Sample means from Nielsen Ad*Views in above median elderly share markets relative to below median elderly share markets. The vertical lines represent the dates when Part D was signed into law (December 2003) and was implemented (January 2006). Means are plotted for a balanced panel of the top 200 advertised brand-name drugs. There is a secular downward trend in overall views per person due to patent expirations of several of these drugs over this time period (in particular, four of the top 200 drugs went off patent around 2006: Pravachol, Wellbutrin XL, Zocor, and Zoloft). The downward trend in views matches the pattern in national advertising expenditures shown in Figure 1.

Appendix Figure B.2 – Annual Views per Person of Ads for Top Brand Name Drugs: Excluding Drugs that went Off-patent from 2001-2010, for Non-Elderly



Notes: Sample means from Nielsen Ad*Views in above median elderly share markets relative to below median elderly share markets. The vertical lines represent the dates when Part D was signed into law (December 2003) and was implemented (January 2006). Means are plotted for a balanced panel of the top advertised brand-name drugs. We exclude all drugs that went off-patent during the study period.

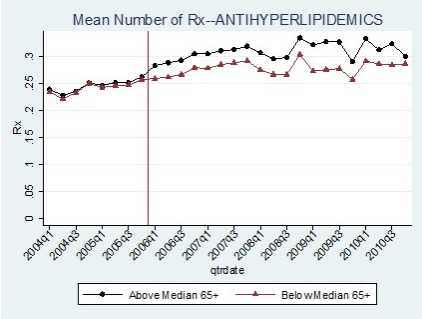
Appendix Figure B.3 – Trends in Composition of Claims Data Sample

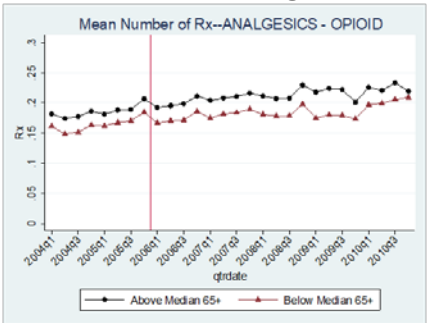


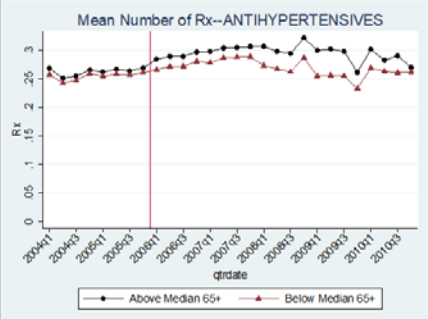
Notes: Sample means of Census 2000 characteristics linked to individuals in claims sample by 3-digit ZIP code.

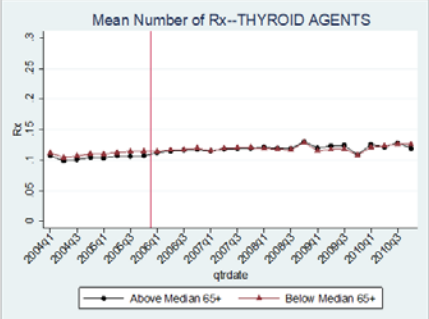
Appendix Figure B.4 - Effects for Advertised vs. Non-Advertised Drug Classes, by Class

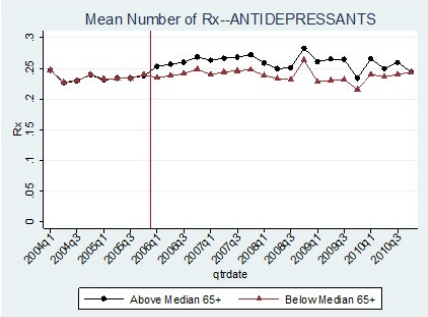
Advertised Drug Classes | **Non-Advertised Drug Classes**

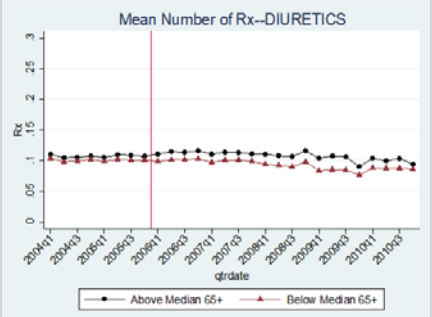


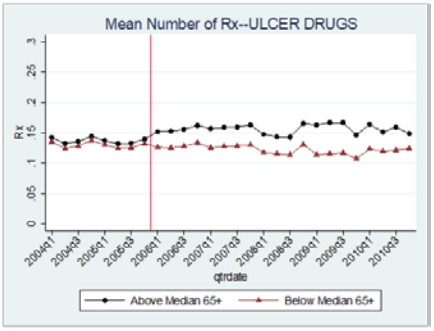


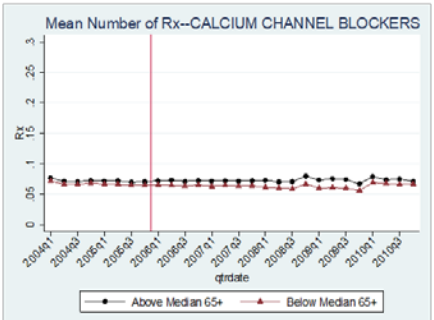


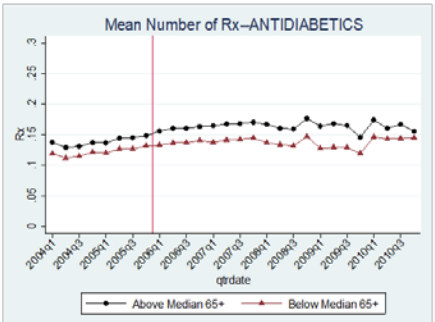


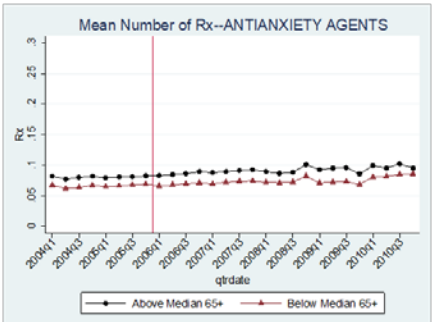




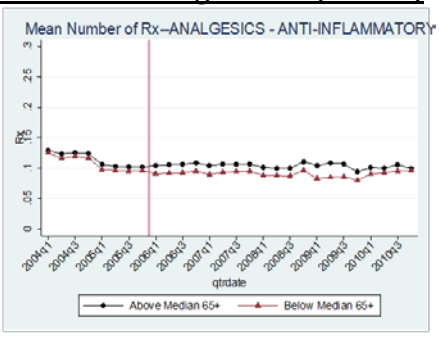


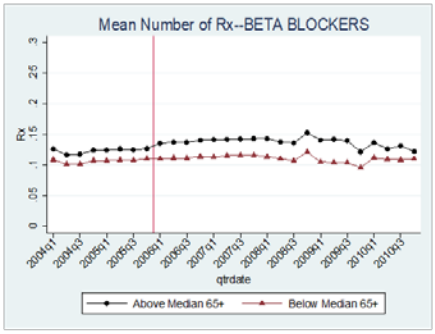


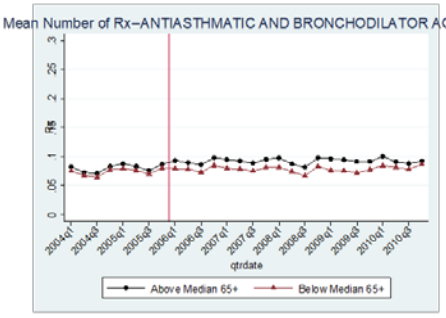


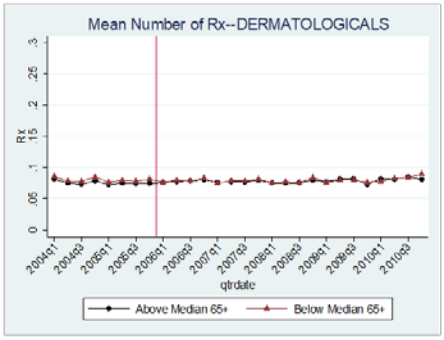


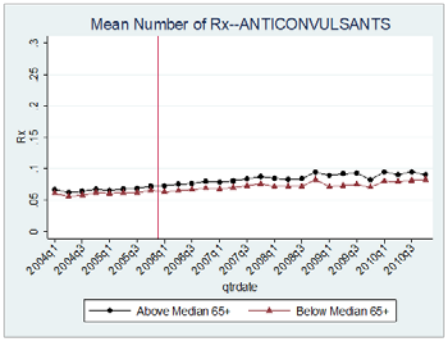
Advertised Drug Classes (Cont'd)



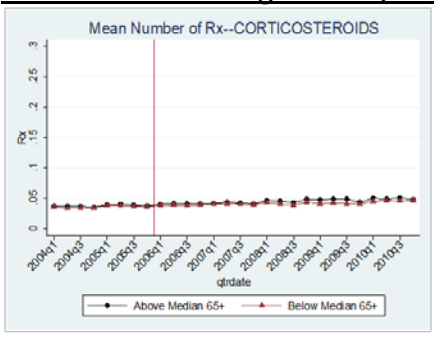


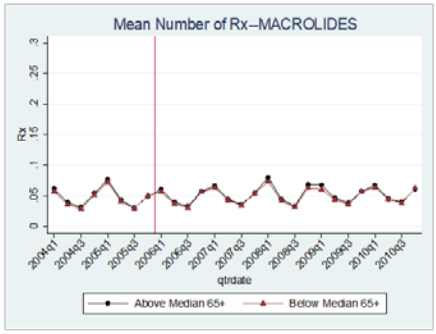


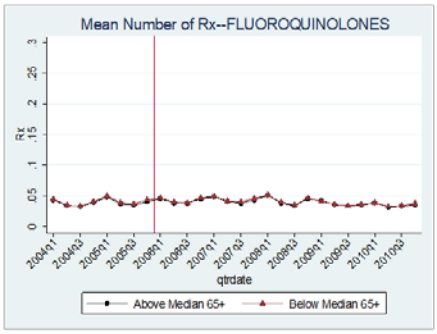


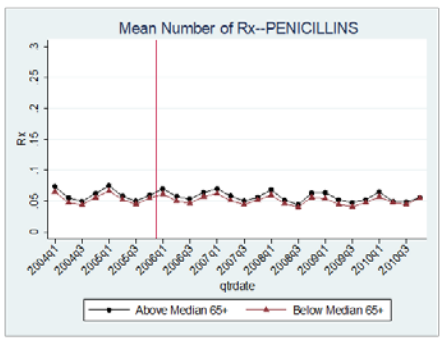


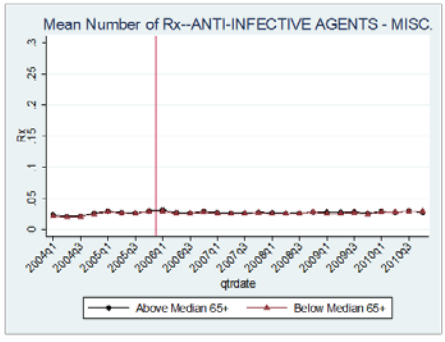
Non-Advertised Drug Classes (Cont'd)



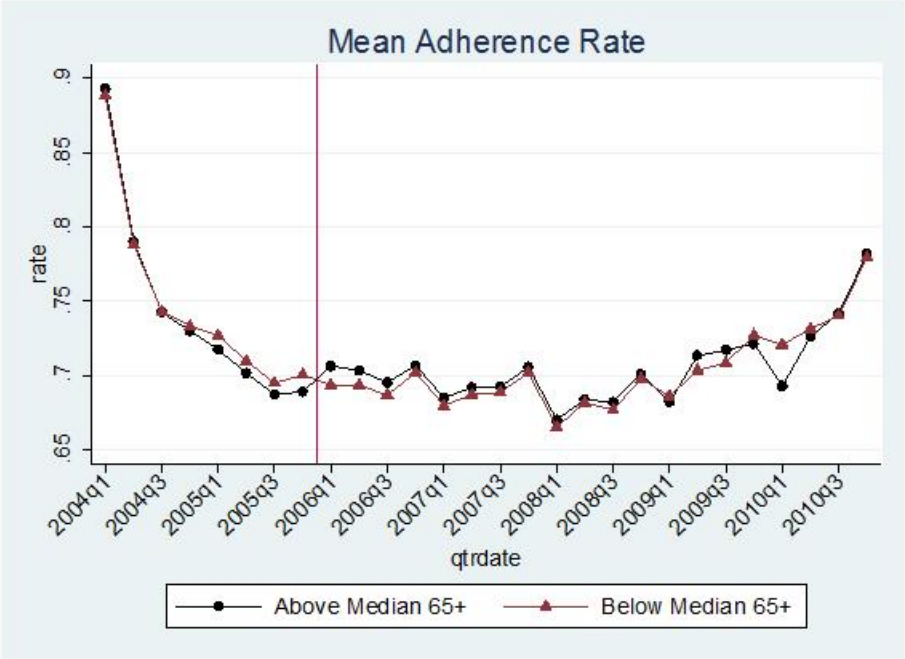








Appendix Figure B.5 – Adherence of Chronic Drugs: Medication Possession Ratio



Notes: Sample means from claims (mean MPR, ages 40-60) in above median elderly share markets relative to below median elderly share markets. Includes the 50 drugs that advertised during the study period and the drugs that did not advertise for 5 chronic conditions: depressions, diabetes, hyperlipidemia, hypertension, and osteoporosis. The vertical line represents the implementation date of Medicare Part D.

Appendix Table B.1—Top Advertised Chronic Drugs, 2001-2010

Condition	Brand-Name Drug
DEPRESSION	CYMBALTA
DEPRESSION	EFFEXOR
DEPRESSION	PAXIL
DEPRESSION	PRISTIQ
DEPRESSION	PROZAC
DEPRESSION	SARAFEM
DEPRESSION	WELLBUTRIN
DEPRESSION	ZOLOFT
DIABETES	ACTOS
DIABETES	AVANDIA
DIABETES	BYETTA
DIABETES	EXUBERA
DIABETES	HUMALOG
DIABETES	JANUVIA
DIABETES	LANTUS
DIABETES	LEVEMIR
DIABETES	METAGLIP
DIABETES	ONGLYZA
DIABETES	NOVOLIN
DIABETES	NOVOLOG
HYPERLIPIDEMIA	ALTOCOR
HYPERLIPIDEMIA	BIDIL
HYPERLIPIDEMIA	CADUET
HYPERLIPIDEMIA	CRESTOR
HYPERLIPIDEMIA	LESCOL
HYPERLIPIDEMIA	LIPITOR
HYPERLIPIDEMIA	LOVAZA
HYPERLIPIDEMIA	NIASPAN
HYPERLIPIDEMIA	PRAVACHOL
HYPERLIPIDEMIA	TRILIPIX
HYPERLIPIDEMIA	VYTORIN
HYPERLIPIDEMIA	WELCHOL
HYPERLIPIDEMIA	ZETIA
HYPERLIPIDEMIA	ZOCOR
HYPERTENSION	ALTACE
HYPERTENSION	AVAPRO
HYPERTENSION	COREG
HYPERTENSION	DIOVAN
HYPERTENSION	INNOPRAN
HYPERTENSION	TEKTURNA
HYPERTENSION	TOPROL
OSTEOPOROSIS	ACTIVELLA
OSTEOPOROSIS	ACTONEL
OSTEOPOROSIS	BONIVA
OSTEOPOROSIS	EVISTA
OSTEOPOROSIS	FORTEO
OSTEOPOROSIS	FOSAMAX
OSTEOPOROSIS	PREMARIN
OSTEOPOROSIS	PREMPRO
OSTEOPOROSIS	RECLAST

Appendix Table B.2 – Sample Means of Nielsen Advertising Variables by Elderly Share

	2005		*2007*		***2005-07 Change***	
Variable (Mean)	**Low Elderly Share**	**High Elderly Share**	**Low Elderly Share**	**High Elderly Share**	**Low Elderly Share**	**High Elderly Share**
Proportion 65+ (2000)	0.110	0.146	0.110	0.146	-	-
Population 65+ (2000)	333,864	256,288	333,864	256,288	-	-
Total Population (2000)	3,070,123	1,748,112	3,070,123	1,748,112	-	-
Views per Person (ages 2-64)	387	413	390	429	3	17
Views per Person (ages 65+)	1,184	1,150	1,214	1,233	30	82
Year x Market observations	50	50	50	50	50	50

Notes: Means are computed across DMAs by year for the top 200 advertised brand-name drugs. Views per Person (rating points) are from the Nielsen data. Elderly share and population counts are from the 2000 Census.

Appendix Table B.3— Effect of Part D on Views Per Person for Top 200 Drugs

Dependent Variable: Views Per Person	Views per Person (Non-Elderly)	Views per Person (Elderly)
	(1)	(2)
A. Instrument=Share65+*Post		
Post*Share65+	64.379	263.830*
	(50.69)	(138.34)
B. Instrument=High Elderly Share*Post		
High Elderly Share*Post	6.233***	18.055***
	(1.63)	(5.04)
DMA x Quarter Obs	3,991	3,991

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the DMA level; all specifications include quarter fixed effects and DMA fixed effects. Data is from 2001-2010.

Appendix Table B.4 – Effects for Advertised Drug Classes vs. Non-Advertised Drug Classes

Dependent Variable:	# of Prescriptions	Log(# of Prescriptions)
A. Instrument=Share65+*Post		
Post*Share65+*Advertise	0.181***	0.761***
	(0.025)	(0.130)
Post*Share65+	0.044***	0.679***
	(0.012)	(0.183)
B. Instrument=High Elderly Share*Post		
Post*High Elderly Share*Advertise	0.011***	0.054***
	(0.002)	(0.008)
Post*High Elderly Share	0.001	0.015
	(0.001)	(0.009)
Mean of Dep. Var. (pre-Part D): Advertise=1	0.146	
Mean of Dep. Var. (pre-Part D): Advertise=0	0.075	
Zipcode x Drug Class x Quarter Obs	429,380	408,165

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the 3-digit ZIP code level; all specifications include quarter fixed effects, 3-digit ZIP code fixed effects, an Advertise indicator (equals 1 when the drug class has any positive amount of advertising during the study period, zero otherwise), Post x Advertise, and Advertise x Share 65+ (or Advertise x High Elderly Share). These variables have been omitted from the table to conserve space. Sample includes the top 10 advertised drugs classes and top 10 non-advertised drug classes (see Appendix Figure B.4 for the full list of drug classes). Note that the estimated effect for non-advertised classes is Post*HighElderlyShare and the effect for advertised classes is the linear combination of Post*HighElderlyShare + Post*HighElderly Share*Advertise (Panel A is defined similarly). For example, in Panel B, the differential effect on utilization for non-advertised drug classes is 0.001, while advertised classes is 0.012 [0.001+0.011]. Data is from 2004-2010.

Appendix Table B.5 – Total Utilization of Chronic Drugs, 2SLS—

Extensive and Intensive Margins

Dependent Variable:	# of Prescriptions		Days Supply		Any Use	
	Full Sample	2004-2007	Full Sample	2004-2007	Full Sample	2004-2007
	(1)	(2)	(3)	(4)	(5)	(6)
A. Instrument=Share65+*Post						
Views per Person (Non-Elderly)	0.017***	0.011***	0.750***	0.560***	0.006**	0.004***
	(0.004)	(0.003)	(0.217)	(0.131)	(0.002)	(0.001)
B. Instrument=High Elderly Share*Post						
Views per Person (Non-Elderly)	0.014***	0.008***	0.480**	0.400***	0.003	0.003**
	(0.005)	(0.003)	(0.223)	(0.127)	(0.002)	(0.001)
Mean of Dep. Var (pre- Part D)	0.11		5.68		0.06	
Zipcode x Condition x Quarter Obs	107,345	61,440	107,345	61,440	107,345	61,440

Dependent Variable:	# of Prescriptions Conditional on Use		Days Supply Conditional on Use	
	Full Sample	2004-2007	Full Sample	2004-2007
	(7)	(8)	(9)	(10)
A. Instrument=Share65+*Post				
Views per Person (Non-Elderly)	0.057***	0.035***	2.151***	1.428***
	(0.017)	(0.012)	(0.533)	(0.406)
B. Instrument=High Elderly Share*Post				
Views per Person (Non-Elderly)	0.068***	0.028*	1.861***	1.366***
	(0.026)	(0.016)	(0.681)	(0.523)
Mean of Dep. Var (pre- Part D)	1.81		90.87	
Zipcode x Condition x Quarter Obs	100,427	58,624	100,427	58,624

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the 3-digit ZIP code level; all specifications include quarter fixed effects, 3-digit ZIP code fixed effects, condition fixed effects. We estimate each specification separately for the full sample and the pre-recession years 2004-2007. The total effects (which are presented in Cols 1-4) include zeros for those who do not purchase any chronic drugs. Includes the 50 drugs that advertised during the study period for 5 chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis.

Appendix Table B.6— Decomposition of Extensive and Intensive Margin Effects, 2SLS

Dependent Variable:	# of Prescriptions		Counterfactual # of Prescriptions		% of Total Effect is Extensive Margin	
			Holding Extensive Margin Constant		*1-(3)/(1)*	*1-(4)/(2)*
	Full Sample	2004-2007	Full Sample	2004-2007	Full Sample	2004-2007
	(1)	(2)	(3)	(4)	(5)	(6)
A. Instrument=Share65+*Post						
Views per Person (Non-Elderly)	0.017***	0.011***	0.005***	0.003***	71%	73%
	(0.004)	(0.003)	(0.001)	(0.001)		
B. Instrument=High Elderly Share*Post						
Views per Person (Non-Elderly)	0.014***	0.008***	0.006***	0.003*	57%	63%
	(0.005)	(0.003)	(0.002)	(0.001)		

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the 3-digit ZIP code level; all specifications include quarter fixed effects, 3-digit ZIP code fixed effects, condition fixed effects. Columns 1 and 2 repeat the main baseline results for total number of prescriptions purchased; Columns 3 and 4 show the effect on total prescriptions purchased coming from intensive margin changes (i.e. assuming that there are no changes in the extensive margin) as described in Appendix A; Columns 5 and 6 compute the percentage of the effect on total prescriptions purchased due to extensive margin effects. Includes the 50 drugs that advertised during the study period for 5 chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis.

Appendix Table B.7— Adherence of Chronic Drugs – Mean Medication Possession Ratio

		Reduced Form			2SLS		
Dependent Variable:	**Medication Possession Ratio**	Full Sample	2004-2007	2005-2007	Full Sample	2004-2007	2005-2007
		(1)	(2)	(3)	(4)	(5)	(6)
A. Instrument=Share65+*Post							
Post*Share65+		0.195***	0.219***	0.414***			
		(0.067)	(0.073)	(0.140)			
Views per Person (Non-Elderly)					0.018**	0.016**	0.034**
					(0.008)	(0.007)	(0.015)
B. Instrument=High Elderly Share*Post							
High Elderly Share*Post		0.005*	0.007**	0.012***			
		(0.003)	(0.003)	(0.004)			
Views per Person (Non-Elderly)					0.009*	0.009**	0.020**
					(0.005)	(0.004)	(0.009)
Mean of Dep. Var (pre- Part D)		0.75	0.75	0.71			
Zipcode x Condition x Quarter Obs		102,477	59,252	44,519	102,477	59,252	44,519

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the 3-digit ZIP code level; all specifications include quarter fixed effects, 3-digit ZIP code fixed effects, condition fixed effects. The outcome variable is the medication possession ratio (MPR). Includes the 50 drugs that advertised during the study period and the drugs that did not advertise for 5 chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis.

Appendix Table B.8 – Adherence of Chronic Drugs: Alternative Specifications, 2SLS

	Instrument= Share65+*Post			Instrument= High Elderly Share*Post		
Dependent Variable: I(High Adherence)	Full Sample	2004-2007	2005-2007	Full Sample	2004-2007	2005-2007
	(1)	(2)	(3)	(4)	(5)	(6)
A. All Individuals ages 40-60						
1. Baseline Specification	**0.017****	**0.017*****	**0.033*****	**0.008**	**0.011*****	**0.021****
	(0.007)	**(0.005)**	**(0.013)**	**(0.005)**	**(0.004)**	**(0.008)**
2. Alternative MPR	0.016*	0.021***	0.037***	0.006	0.016***	0.026***
(Including Discontinuation)	(0.008)	(0.006)	(0.013)	(0.007)	(0.005)	(0.009)
B. Excluding Individuals who Initiated Treatment after Part D						
3. Baseline Specification	0.022***	0.020***	0.036***	0.014***	0.013***	0.023***
	(0.006)	(0.005)	(0.012)	(0.004)	(0.004)	(0.008)
4. Alternative MPR	0.030***	0.025***	0.041***	0.023***	0.019***	0.031***
(Including Discontinuation)	(0.008)	(0.005)	(0.013)	(0.006)	(0.005)	(0.009)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the 3-digit ZIP code level; all specifications include quarter fixed effects, 3-digit ZIP code fixed effects, condition fixed effects. The outcome variable is the proportion of individuals with MPR>=80%. Each cell represents a separate regression with the coefficient on "views per person (non-elderly)" reported. Includes the 50 drugs that advertised during the study period and the drugs that did not advertise for 5 chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis.

Appendix Table B.9 – Effects on Total Chronic Drug Spending

	Reduced Form			2SLS		
Dependent Variable: Total Expenditures	Advertised Drugs	Non-Advertised Drugs	Total	Advertised Drugs	Non-Advertised Drugs	Total
	(1)	(2)	(3)	(4)	(5)	(6)
A. Instrument=Share65+*Post						
Post*Share65+	12.488***	5.878***	18.367***			
	(3.399)	(2.033)	(3.801)			
Views per Person (Non-Elderly)				1.964***	0.925**	2.889***
				(0.537)	(0.424)	(0.779)
B. Instrument=High Elderly Share*Post						
High Elderly Share*Post	0.532***	0.092	0.624**			
	(0.205)	(0.121)	(0.248)			
Views per Person (Non-Elderly)				1.526***	0.265	1.790**
				(0.576)	(0.350)	(0.716)
Mean of Dep. Var (pre- Part D)	14.61	4.75	19.36			
Zipcode x Condition x Quarter Obs	107,345	107,345	107,345	107,345	107,345	107,345

Notes: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors at the 3-digit ZIP code level; all specifications include quarter fixed effects, 3-digit ZIP code fixed effects, condition fixed effects. Includes the 50 drugs that advertised during the study period and the drugs that did not advertise for 5 chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis. Data is from 2004-2010.