PRELIMINARY DRAFT, PLEASE DO NOT CITE

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

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ABSTRACT

Direct-to-consumer advertising (DTCA) of prescription drugs has increased dramatically in recent years leading to much debate about its value to patients. In this paper, we examine how DTCA influences drug utilization along the extensive and intensive margins, using data on advertising for local media markets from Nielsen and data on drug utilization from pharmacy claims of large private employers. We exploit a large and plausibly exogenous shock to DTCA driven by the introduction of Medicare Part D in 2006 which led to large relative increases in DTCA in geographic areas with a high concentration of Medicare beneficiaries compared to areas with a low concentration. We examine the effects of this sudden differential increase in advertising on the non-elderly population under age 65 in order to isolate the effects of advertising on drug utilization from the direct effects of Part D. We find substantial differential increases in drug utilization that mirror the increases in DTCA after Part D. These effects are driven both by increased take-up of treatment and improved drug adherence. Our results imply significant spillovers from Medicare Part D onto the under 65 population and an important role for non-price factors in influencing prescription drug consumption behavior.

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1. Introduction

Spending on direct-to-consumer advertising (DTCA) of prescription drugs in the U.S. has increased dramatically in the last two decades from $150 million in 1993 to over $4 billion in 2010 (Dave, 2013; Dave and Saffer, 2012).[1] Most of this advertising occurs on television, where pharmaceuticals represented the third highest category of advertising expenditures in 2014 (behind automotive and fast food restaurant advertising).[2] The Nielsen Corporation estimates that an average of 80 pharmaceutical ads are aired every hour.[3] Given that adults ages 50-64 and 65+ (populations with high rates of prescription drug use) watch an average of 39 and 47 hours of live television per week, respectively (Nielsen, 2014), the pervasiveness of pharmaceutical advertising could potentially have large effects on prescription drug consumption behavior. Indeed, the rise in advertising has coincided with a sharp increase in spending on prescription drugs (see Figure 1). However, the causal direction of this relationship could go in both directions, given that this time period saw the introduction of a large number of new blockbuster drug products which could induce greater advertising. Additionally, the coincidence of other confounding factors has made it difficult to isolate the independent effect of DTCA. While much has been written about the various causal pathways through which price and cost-sharing affect drug utilization, less attention has been paid to studying how non-price factors like advertising influence prescription drug consumption decisions.

The rise in advertising has generated much debate about its effects on patient welfare. In fact, most countries ban this type of advertising. On the one hand, DTCA may educate patients about available treatments, encourage individuals to seek care for underdiagnosed conditions, and improve communication between patients and physicians. Advertisements may also serve to remind patients to take their existing medications and influence their perception of the benefits of treatment, promoting better drug adherence (Holmer, 2002; Donohue et al., 2004; Wosinska, 2005). However, DTCA may also lead to unnecessary treatments and increased drug spending.

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[1] This rise in advertising was precipitated by a change to FDA regulations in 1997 which relaxed restrictions on television and radio advertising. 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. Before 1997, most advertising was in print and it was very limited.

[2] See Nielsen Corporation "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

In this paper, we examine the causal pathways through which DTCA influences drug utilization, with a particular focus on drugs that treat five chronic conditions that account for a large share of advertising spending:[4] depression, diabetes, hyperlipidemia, hypertension, and osteoporosis. This paper makes two main contributions. First, we exploit a major policy change as a natural experiment to identify the effects of DTCA on drug utilization. Most previous studies of DTCA have had to rely on cross-sectional or time-series variation in advertising expenditures to identify the effect on drug utilization or adherence. However, a limitation of this approach is that demand factors could 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. Second, we use this empirical framework to estimate the effects of DTCA not only on overall drug utilization but also separately on the intensive and extensive margins, with particular attention to the effects on patient adherence to prescriptions. We tease apart the contributions of these component effects to the total relationship between advertising and utilization.

We provide one of the first quasi-experimental studies on the effects of DTCA on drug use by exploiting a large and plausibly exogenous shock to DTCA driven by the introduction of Medicare Part D in 2006. Previous work investigating the impact of Part D on advertising spending (Lakdawalla, Sood, and Gu, 2013) showed that Medicare Part D led to large relative increases in DTCA for drugs that are differentially used by Medicare beneficiaries. In this paper, we use an instrumental variable strategy which 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. Both the levels and trends in advertising exposure across high and low elderly share areas were nearly identical prior to Part D.

Advertising cannot be perfectly targeted to the elderly and, consequently, we also observe a differential increase in advertising exposure for the non-elderly. We exploit the sudden

[4] Among the 25 most advertised brand-name drugs, these 5 conditions account for half of total advertising expenditures (Kantar Media, 2011).

differential increase in advertising exposure for non-elderly that live in elderly-dominated areas to estimate the effects of advertising on drug utilization. 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. Our focus on the non-elderly allows us to isolate the effects of advertising on drug utilization from the direct effects of Part D.

We use data from two unique sources to examine how relative changes in DTCA across geographic areas impacts drug utilization. We measure pharmaceutical advertising using data on Nielsen ratings in local media markets which we observe separately for the non-elderly (under 65) and the elderly (65+). While most of the DTCA literature uses advertising expenditures or the volume of ads to quantify advertising, ratings are a more direct measure of actual advertising exposure.[5] 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, 2014; Kanazawa and Funk, 2001). We obtain measures of drug utilization using administrative pharmacy and medical claims from a database of over 40 large national employers covering about 18 million person-years.

We find that drug utilization is highly responsive to advertising exposure. Following Part D, there was a 6 percent increase in the average number of prescriptions purchased by the non-elderly in areas with high elderly share, relative to areas with low elderly share. Event study results show that this differential utilization effect coincided precisely with the implementation of Part D in 2006 and persisted through the end of our study period in 2010. 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 trends would have continued to be the same in the absence of Part D. Our results imply that a 10 percent increase in advertising views leads to a 5.4 percent increase in total prescriptions filled for advertised chronic drugs. We also find significant positive differential effects for other utilization outcomes along both the intensive and extensive margins including total prescriptions and days supplied conditional on use, and the probability of any prescription drug use. As one important intensive

[5] 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.

margin measure, we find strong evidence that additional drug advertising promotes medication adherence, finding that a 10 percent increase in advertising increases adherence to a drug therapy by 1 to 2.5 percent.

The utilization results are robust to trends and alternative specifications of the instrument. Furthermore, we find that the relative increase in utilization in high elderly share areas cannot be explained by differential changes in the sample composition of the claims data due to firm or employee churn, reductions in drug prices, increased detailing efforts, or other non-advertising spillovers of Part D on the non-elderly such as changes in physician prescribing behavior. The empirical tests we perform to address each of these possible alternative explanations strongly suggest that the observed utilization patterns are driven by advertising.

Finally, we also assess whether the increase in advertising led simply to substitution from non-advertised to advertised drugs or whether it generated a net increase in drug utilization for the drug classes. We find evidence of a large net increase in drug utilization, suggesting substantial positive spillover effects on the use of non-advertised drugs within the same drug classes. 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 drug demand to a non-monetary factor and find economically important effects. Using the range of price elasticities in the literature (Goldman, Joyce, and Zhang, 2008) combined with our main results, our estimates imply that a 10 percent increase in advertising exposure generates a change in prescription drug utilization equivalent to a 9 to 27 percent reduction in out-of-pocket price.

Another contribution of our study is to quantify spillover effects of Part D on the non-elderly population. Numerous studies have examined the effects of Part D on the elderly, but few studies have considered the effects on the non-elderly. One mechanism through which Part D may have an effect on the non-elderly is through advertising. By increasing insurance coverage for one population, we find that Part D had the effect of generating additional demand for individuals outside of the Medicare program. These demand increases were themselves large and economically important.

The rest of the paper proceeds as follows. Section 2 presents background on Part D and the mechanisms for its effect on advertising, as well as a review of the related DTCA literature.

Section 3 describes the data sources. Section 4 outlines the empirical framework. Section 5 presents the results and section 6 concludes.

2. Background and Related Literature

2.1. Why Should Medicare Part D Increase Advertising Exposure?

Medicare is a federal program that provides health insurance to the elderly, ages 65 and over, and qualifying non-elderly disabled individuals. On January 1, 2006, Medicare expanded to include coverage of outpatient prescription drugs through the introduction of Part D. Part D was enacted as a provision of the Medicare Modernization Act (MMA), which was signed into law in December of 2003, and represented one of the largest expansions of the Medicare program since its inception. Part D substantially increased the proportion of elderly with drug insurance and as a result lowered average out-of-pocket drug costs for Medicare beneficiaries. Previous research has shown that this price reduction increased drug utilization among the 65+ population (e.g. Ketcham and Simon, 2008; Yin et al., 2008; Lichtenberg and Sun, 2007).

The widespread changes brought about by Part D may have significantly altered the incentives faced by pharmaceutical firms to advertise.[6] A long line of research has shown that more profitable markets generate greater returns to capturing new consumers, and in turn stimulate more intense advertising effort. Since the returns to advertising are higher when there are more insured consumers in the market (insured consumers face lower out-of-pocket costs)— and Part D considerably expanded drug-insurance coverage among the elderly— we would expect advertising to increase after the introduction of Part D. The theoretical framework for this prediction and associated literature are presented in previous work (Lakdawalla, Sood, and Gu, 2013).

In particular, economic theory implies that drug advertising would increase more in geographic areas with a higher share of elderly individuals (relative to areas with a low share of elderly) which experienced a greater expansion in insurance coverage. Consistent with this idea, previous research (Lakdawalla, Sood, and Gu, 2013) found that Part D led to a large relative increase in DTCA for drugs differentially used by Medicare beneficiaries. That paper, which focused primarily on the effects of Part D on advertising, also suggested scope for utilization

[6] Studies have found other supply-side responses to Part D such as increasing investments in R&D for therapeutic drug classes that predominately treat the elderly (Blume-Kohout and Sood, 2013).

effects of advertising using the Medical Expenditure Panel Survey (MEPS). We build on this previous work, by exploiting a new strategy based on geographic variation in elderly shares as well as claims data to fully identify and characterize the causal effects of advertising on drug utilization. The geographic variation also allows us to control for drug-specific shocks, which is of particular importance during our study period given a wave of patent expirations and black box warnings.

Since advertising cannot be perfectly targeted to the elderly, there are likely spillover effects to the non-elderly. In particular, we would predict that non-elderly individuals living in areas with a high concentration of elderly would likely be exposed to a larger increase in DTCA following Part D relative to individuals living in areas with a lower concentration. We show that this prediction is borne out in the data and use this source of variation to estimate the relationship between DTCA and drug utilization for the non-elderly.

2.2. Previous Literature on Advertising Effects

Our paper contributes to a large literature on the impacts of DTCA on drug utilization (see Dave, 2013 for a recent survey). The majority of studies in this literature find positive demand effects of advertising. Advertising has a dual nature. Advertising may grow the entire market for all firms ("market expansion") or it may steal market share away from competitors ("market stealing"). Studies consistently find evidence of significant market expansion effects from advertising (e.g. Rosenthal et al., 2003; Iizuka and Jin, 2005; Bradford et al., 2006; Shapiro, 2015). However, there is mixed evidence about whether market stealing occurs, such that a brand's advertising increases demand for its own product. 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.

Evidence from consumer and physician surveys supports the view that advertising increases the likelihood that a patient initiates a request for a specific drug treatment and that physicians fulfill these requests (Hollon, 2005). In one randomized controlled trial, actors are sent to doctors' offices presenting symptoms of depression. Those who asked for a specific drug treatment or general treatment for depression related to an ad they saw on television were significantly more likely to be prescribed an anti-depressant relative to those who did not request treatment (Kravitz et al., 2005). The magnitude of the effects ranged from 53-76% for those requesting treatment relative to 31% for those not requesting treatment.

While a large literature investigates the impacts of pharmaceutical advertising, a persistent challenge has been in identifying a source of variation in advertising that is orthogonal to demand factors.[7] Our study offers four main innovations.

First, we provide one of the first natural experiment studies on the effects of DTCA on drug utilization using the introduction of Part D, which introduces exogenous geographic variation in advertising that is unrelated to individual demand and health status for the non-elderly. To our knowledge, the only other study that provides evidence from a natural experiment is a working paper by Sinkinson and Starc (2015), which exploits changes in advertising due to political election cycles (which temporarily displace DTCA), to examine the effects of own and rival advertising on firm revenue. The estimated elasticities in our study tend to be much larger. This may be partially explained by the differences in identification strategies, with Sinkinson and Starc (2015) exploiting temporary reductions in advertising and our study exploiting a permanent increase. Given the long-lasting effects of advertising, we might expect smaller effects from decreasing advertising intensity.

Second, we use data which measures actual exposure to advertising rather than advertising expenditures or the number of ads. Ultimately, an individual consumer's behavior depends on the number and type of ads they see, but spending is only one factor that affects what consumers watch. Exposure to advertising is the product of a host of factors including the number of ads, the quality of the programming where the ads are shown, the time of day (e.g. primetime vs. late night) or day of the week the ads are shown, and how often individuals watch television. We measure exposure directly, rather than relying on proxies such as spending or number of ads aired. While nearly all DTCA studies use advertising expenditures or volume to quantify advertising, one exception is Avery, Eisenberg, and Simon (2012) which uses survey data from Kantar/TNS Media Intelligence on individual-level exposure to ads for anti-depressants. One limitation of this data, however, is that drug utilization is self-reported and limited to only a binary variable of whether or not a person has taken an anti-depressant in the last 12 months.

[7] Studies that attempt to address this 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.

Our utilization data are constructed using administrative pharmacy claims data and provide comparatively rich measures such as total prescriptions and days supplied.

Third, we estimate the effects of advertising on take-up of treatment and medication adherence, and evaluate how these component effects come together to define the overall relationship between advertising and drug utilization. Since much of the pharmaceutical advertising literature has focused on total utilization effects, little is known about the mechanisms that underlie the relationship between drug utilization and advertising. Specifically, there is little empirical evidence on the effects of advertising on drug adherence and the few existing studies find very small or null effects (Donohue et al. 2006; Wosinska, 2005). Understanding the components of the drug utilization effect is needed to begin to assess whether the increase in use induced by DTCA is welfare enhancing.

Finally, we estimate the effects of DTCA for a large number of brand-name drugs across several conditions. Prior studies often focus on a single drug class or a small subset of brand-name drugs. Given that FDA policy tends to relate to all types of prescription drugs uniformly, our estimates are likely more generalizable for such policy considerations.

3. Data Sources

3.1. Advertising Data

The data on viewership of pharmaceutical ads in local media markets come from the Nielsen Corporation Ad*Views™ database from 2001-2010. 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) which span the entire United States. Each DMA is comprised of one or more counties in which the home market television station holds a dominance of total hours viewed.[8] 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 these markets. We use data on local ads since there is scope for targeting different ads to different markets. Local ads can be shown during network programming (e.g. NBC), syndicated programming, or local television

[8] For example, the Los Angeles DMA contains 8 counties in the surrounding area which were selected because of their relatively homogeneous television programming.

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 from 2001-2010, which account for more than 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 aggregated by brand-name prescription drug, DMA, quarter, and for two demographic groups: ages 2-64 and ages 65+. Specifically, we observe:

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

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 market (DMA) m, in age-group a, and in quarter t, multiplied by 100. We divide rating points by 100 in order to interpret this measure as average views per person for the quarter. We refer to this scaled measure as "rating points" throughout the paper. Rating points for a brand can increase if the number of commercials increases, the commercials become better targeted (e.g. primetime vs. late night), and/or more individuals in the market watch 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 are typically used as measures of advertising in the DTCA literature.[9]

While in recent years, a variety of alternative methods for watching television programming have been introduced—such as time shifted viewing (e.g. DVR) and internet viewing—traditional live television still remains the dominant medium. In the third quarter of 2014, adults

[9] Nielsen collects very 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 do not use expenditure data in this study.

ages 50-64 watched on average 43.2 hours of television 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). 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. Nonetheless, Nielsen does account for most time-shifted viewing in its rating points by including views of all recorded programming watched within seven days of its initial release.

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.[10] 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 about all outpatient prescription drug purchases including the drug name, National Drug Code (NDC), days supplied (e.g. 30 days, 60 days, etc.), and payments. We link the claims data by NDC with data from IMS Health to obtain consistently defined drug names and therapeutic drug classes for each prescription. Limited demographic information is provided on the claims, 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.[11] 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.

We use the three-digit ZIP code to match the claims data with the Nielsen advertising data. Each person in the claims data is assigned to a local advertising market (DMA) based on their

[10] Data from this company prior to 2004 is not defined in a consistent way with data from 2004 onwards, thus we cannot use it in our analysis.

[11] 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.

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 only 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[12] average of advertising exposure (rating points) across all of the possible DMAs where they could reside. About 30 percent of the individuals in the claims data receive this probabilistic measure of advertising exposure.[13] Consequently, we use the three-digit ZIP code as the effective advertising market rather than the DMA, since advertising exposure is constant within three-digit ZIP codes for all individuals in the sample.

We initially focus on two variables: total number of prescriptions purchased and total days supplied. We aggregate these measures to quarterly totals for each person by drug. 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 were advertised during our study period and are contained in the Nielsen top 200 (see list of drugs in Appendix Table 1). We collapse the data to the three-digit ZIP code level by condition, to conduct our analyses at the level of variation in advertising exposure. Since Part D affected advertising 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. This results in 107,345 ZIP code-by-condition-by-quarter observations. In computing mean prescriptions purchased and mean days supplied within a ZIP code and condition, zeros are included for individuals who were enrolled in a health insurance plan but did not purchase any drugs for the condition.[14] Separate means are computed for advertised and

[12] Population weights for the 5-digit ZIP code level come from the 2000 Decennial Census. In the Census, population estimates are aggregated by ZIP Code Tabulation Areas (ZCTAs) and we use a 5-digit ZIP code to ZCTA crosswalk to obtain the 5-digit ZIP code population estimates.

[13] We will also show that we estimate similar effects when we select on individuals that we can precisely assign to a single DMA.

[14] In other words, in the individual-level data (before collapsing), each person gets 5 observations for each of the conditions in each quarter whether or not they were diagnosed with the condition. If they do not use a drug for that condition, the observation is zero. We do not condition on having a diagnosis of the condition as advertising might affect the rate of diagnosis.

non-advertised drugs[15] within each of the five chronic conditions. We focus primarily on advertised drugs and use non-advertised drugs in select specifications.

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 quarter of the individual's first drug claim through the quarter of their last drug claim for that condition. We consider adherence as receiving continuous treatment for a condition, rather than for a specific brand since this is the more relevant dimension from a policy and welfare perspective.[16] Adherence is measured quarterly and separately for each condition as the medication possession ratio (MPR), which is a widely used method for measuring medication compliance with claims data (Peterson, et al., 2007; Hess, et al., 2006). Specifically, 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 to avoid double counting covered days. For example, it is typical to refill a prescription before finishing the days supplied for the initial prescription. The extra days supplied during the overlap period does not indicate better drug adherence. We address this issue based on the drug's active ingredient name.[17] If overlapping claims have the same active ingredient, we assume that the person finishes the days supplied in the first claim before starting the days supplied in the second claim. A refill of an existing medication or a switch from a brand name to generic product would fall under this category. 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 throw away the remaining days supplied for the first claim. This case likely represents a drug switch that resulted from an unsatisfactory response to the initial medication. Therefore, we assume that the first claim ended when the second claim was filled. Since advertising may lead to more drug switching, it is especially important to account for this case in order to avoid overstating the effect of advertising on adherence. Finally, days in the hospital were assumed to be fully compliant and patients resumed their prescriptions after they were discharged.

[15] Non-advertised drugs (typically off-patent brands or generics) are drugs that belong to the same therapeutic drug classes as the 50 advertised chronic brand-name drugs, but do not advertise during our study period.
[16] Specifically, we combine utilization for advertised drugs with the non-advertised drugs in the same therapeutic classes as the advertised drugs.
[17] Combination drugs are viewed as a unique combination of two or more active ingredients.

After constructing the quarterly MPR for each individual by condition, we also create a binary indicator for individuals who had MPR ≥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 ≥80% in each cell.

3.3. Population Data

Finally, we compute the share of the population that is 65 and over (i.e. eligible for Medicare) in each local advertising market (DMA) using the 2000 Census. From the advertiser's perspective, the DMA is the relevant market. For individuals who cannot be matched to a single DMA, they are assigned the population-weighted average of the elderly share across all possible DMAs where they could reside. There is substantial heterogeneity in the share of the population that is 65+ across markets, ranging from 8% in the Houston DMA to 26% in Fort Myers-Naples DMA (see Table 1).

3.4. Descriptive Statistics

In Table 2, we present sample means for the advertising variables by elderly share for 2005 and 2007, before and after Part D. For each year, we split the 100 DMAs into above-median elderly share markets and below-median elderly share markets. Average views per person of pharmaceutical ads are much greater for elderly viewers (ages 65+) relative to non-elderly viewers (ages 2-64). 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 non-elderly viewers. This difference is likely driven by the targeting of ads to programming that elderly viewers watch, as well as the fact that older viewers watch more hours of television per year. Comparing the change in views per person from 2005 to 2007 across market types, we observe a three to five times larger increase in ads viewed in high elderly share markets for elderly and non-elderly viewers following Part D.

Table 2 also reveals differences in the average population size across high and low elderly share markets. High elderly share markets tend to be less populated than low elderly share markets. This may be partially due to retiree preferences for less urban areas. This result suggests that it will be important to include market fixed effects in all of our analyses.

4. Empirical Strategy

This study uses the introduction of Medicare Part D on January 1, 2006 as an exogenous shock to DTCA. We expect advertising to increase after the introduction of Part D more in geographic areas with a higher share of elderly individuals relative to areas with a low share of elderly. Our instrumental variable strategy exploits this differential advertising shock. First, we use a difference-in-difference model to estimate changes in DTCA exposure before and after Part D for the non-elderly across areas with a high elderly share relative to areas with a low elderly share. This first-stage equation is estimated as follows:

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

Where $DTCA_{mct,<65}$ is the average views per person (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. $Share65_m$ is the share of population 65+ in market m in 2000, and $Post_t$ is an indicator that equals 1 if the year is 2006-2010 (post-Part D). 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 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. Since geographic areas with a high concentration of elderly are potentially different from areas with a low concentration, all of our analyses condition on market fixed effects, which account non-parametrically for cross-sectional differences in elderly share. We also include time fixed effects to account for secular time trends and condition fixed effects 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 within areas.

Next, we estimate a reduced form equation to compare changes in drug utilization for 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:

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

Where $Y_{mct,<65}$ is mean total prescriptions or days supply purchased by non-elderly individuals in market m in quarter t for advertised drugs that treat condition c. We also use this reduced form model to estimate effects on other measures of drug utilization including prescriptions purchased and days supplied conditional on use and drug adherence. Standard errors are clustered by three-digit ZIP code. We scale the reduced form effect by the first stage to obtain the 2SLS estimate, defined by $\frac{\hat{\theta}}{\hat{\beta}}$. This allows us to estimate the effect of advertising on prescriptions purchased.

5. Results

Our analysis proceeds in three steps. We first provide evidence that our instrument predicts changes in advertising exposure, a necessary condition for identifying the impact of advertising on drug utilization. Second, we estimate the causal impact of advertising exposure on total drug utilization for the non-elderly using two-stage least squares. 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.

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

5.1.1. Overall Sample of Drugs

We begin by showing that the share of the population that is 65+ in an area is strongly predictive of differential changes in advertising exposure after Part D. We first show this graphically. Figure 2 plots mean annual views per person (rating points) of ads for the top 200 brand-name pharmaceuticals from 2001-2010 for two groups of DMAs: one with above median elderly share and the other with below median share. Panel A plots views per person for the non-elderly (under 65) and Panel B plots it for the elderly (65+).

Prior to 2006, both the levels and trends in advertising exposure are nearly identical for the non-elderly across geographic areas. However, after Part D was implemented in 2006, advertising exposure starts to increase 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.[18]

Since we are following a balanced panel of 200 brand-name drugs, there is a secular downward trend in overall advertising over this time period due to the "aging" of these drugs. Several of our drugs lost patent protection over this period.[19] Since off-patent drugs typically do not advertise (Dave, 2013), patent expirations reduce aggregate advertising expenditures. Given the similar pre-trends in advertising exposure across markets, 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.

In Appendix Table 2, we estimate the magnitude of these changes in advertising exposure using a difference-in-difference model similar to Equation 2 at the DMA level. This corresponds to the graphical evidence shown in Figure 2. Comparing non-elderly individuals in areas with high elderly share to their peers in low elderly share areas, we find that Part D generated an additional 25 ads viewed per year, or about one additional ad every other week. This represents a 6 percent increase from the mean advertising exposure level.[20] As a point of comparison, we also estimate the change in advertising exposure for elderly viewers (ages 65+). For the elderly, the effect of Part D on the number of ads viewed is much larger, as expected, since Medicare beneficiaries are likely the intended target audience for these ads. We find that Part D generated an additional 72 ads viewed per year, or an additional ad every 5 days, for elderly viewers in high elderly share markets relative to their peers in low elderly share markets (see Column 2 of Appendix Table 2). This represents a 6.3 percent increase relative to the mean for this group.

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

[18] The patterns in advertising exposure are similar for elderly viewers, as seen in Panel B of Figure 2. 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.

[19] Notably, there were 4 major patent expirations that occurred around 2006 for four of the top 200 drugs: Pravachol, Wellbutrin, Zocor, and Zoloft.

[20] Using the coefficient from the binary instrument in Appendix Table 2 and the annual mean for views per person in high elderly share markets in 2005 reported in Table 2, we calculate the percentage changes as (6.233*4)/413=0.06.

substantial spillover effects on the non-elderly in these areas. This result is consistent with the hypothesis that Part D increased the returns to advertising more in areas with higher elderly share. This positive relationship between elderly share and changes in advertising is a necessary condition for identifying the impact of advertising exposure on drug utilization.

5.1.2. Chronic Drugs

While the above results verify a strong relationship between the instrument and advertising exposure for all drugs in our sample, 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 and account for a large share of advertising, as described in Section 3.2. First, we replicate the graphical evidence from above for the chronic drugs sample. In Panel A of Figure 3, we plot mean views per person of ads for the selected brand-name chronic drugs. The data are plotted at the quarterly level and for 2004-2010, which corresponds to the quarterly claims data. Although the quarterly data are somewhat noisier, the patterns are the same as they were for 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. In fact, we see that advertising exposure for the non-elderly is greater in high elderly share areas compared to low elderly share areas in every quarter after Part D. We assume that the trends in advertising exposure across areas would have continued to be nearly identical in the absence of Part D.

Motivated by the graphical evidence, we estimate the analogous difference-in-differences regression model shown in Equation 2. This specification represents the first-stage in our research design. Consistent with the full sample of drugs, we find a strong relationship between the introduction of Part D and differential changes in advertising of chronic drugs across geographic areas. Panel A of Table 3 presents the first-stage results using the "Post" variable interacted with Share 65+ as the instrument, while Panel B interacts "Post" with a binary indicator for above-median elderly share (mirroring the graphical evidence).

Using the continuous instrument in Panel A, the results show that a geographic area with a one percentage point higher elderly share experienced an increase in quarterly advertising

exposure of 0.06 views per person after Part D and that this effect is statistically significant at the 1% level. Panel B compares above-median to below-median elderly share areas and shows markedly similar results.[21] Comparing high to low elderly share areas, ads viewed for chronic brand-name drugs increased by 8.1 percent relative to the baseline mean. Additionally, 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) and confirm the power of the instruments.

5.1.3. Validity of the Instrument

We argue that Part D accounts for the differential change in advertising exposure across areas beginning in 2006. As evidence that there are no other differential shocks to advertising incentives occurring around 2006, we implement a simple placebo test for our research design 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, we find no differential effect of Part D on advertising exposure for the non-elderly across high versus low elderly share markets, as shown in Figure 4. The levels and trends of advertising exposure for contraceptives across areas are virtually identical before and after Part D. This finding is consistent with Lakdawalla, Sood, and Gu, (2013), who find larger relative increases in national advertising expenditures for drugs with a higher Medicare market share following Part D. Furthermore, as we showed above, 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. We provide further evidence that the corresponding utilization effects that we estimate are not driven by other factors in Section 5.2.

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

5.2.1. Baseline Estimates

[21] 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 (4*0.06358) views per quarter. This is similar to the estimate using the binary instrument in Panel B which is 0.35.

Having shown that Part D had a substantial differential impact on advertising exposure for high elderly share markets, we next analyze how drug utilization responded to this shock to advertising. First, we graph the trends in total prescriptions purchased by the non-elderly across above-median and below-median elderly share areas in Panel B of Figure 3. We continue to focus on the sample of 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 elderly share markets.[22] This graph mirrors the patterns in advertising exposure, and provides visual evidence of strong effects of advertising on utilization.

Next, we estimate the reduced form difference-in-differences specification in 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. Column 2 of Table 3 shows that the number of chronic prescriptions filled increased by 4.5 percent after Part D in high elderly share markets relative to low elderly share markets.

We also assess the timing of the utilization effect as well as the common trends assumption, by estimating an event-study regression where the outcome variable is the number of chronic prescriptions purchased. The event-study replaces the $Post_t$ indicator 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 elderly share versus low elderly share areas relative to the omitted reference period: quarter 4 of 2005 (the quarter before Part D begins). These coefficients are reported in Table 4 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 and remains relatively constant. These patterns hold for both versions of the instrument. Since these results show that there was an immediate differential utilization response to Part D across areas,

[22] 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) from the analysis sample, 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.

any alternative explanation for the utilization effect would need to coincide precisely with the timing of Part D.

In Column 3 of Table 3, we present instrumental variable estimates for the effect of advertising exposure on total prescriptions filled for brand-name chronic drugs. Panel A shows the 2SLS estimate using the continuous elderly share instrument, while Panel B shows results for the binary instrument. The results suggest that an additional ad viewed would lead to an increase of 0.014 to 0.017 prescriptions filled for a chronic condition among the entire sample of non-elderly individuals ages 40-60. In other words, we estimate that if an ad were viewed by 59 to 71 individuals[23], it would result in one additional prescription being filled. Using the mean for prescriptions filled and ads viewed, the implied elasticity of demand with respect to advertising for chronic drugs is 0.54. This estimate may not be directly comparable to previous elasticity estimates in the literature, because it measures the responsiveness to actual advertising exposure, whereas most studies measure responsiveness to advertising expenditures. We might expect that the expenditure elasticities would be smaller if there were diminishing returns to advertising. In this case, additional increases in advertising dollars would lead to less than proportional increases in views.

5.2.2. Robustness Tests

Our baseline estimates are not sensitive to trends and sample restrictions, which we will show in this section through a series of robustness tests. First, we include interactions of ZIP code fixed effects and a linear time trend as an additional test for differential pre-trends across areas. Second, we restrict our sample to pre-recession years from 2004-2007. Third, we include only the firms that were continuously in the sample for all years. Fourth, we test for changes in the demographic characteristics of enrollees across high and low elderly share areas.

The results of these robustness tests are presented in Table 5. Each cell represents a separate regression where the reported estimate is the coefficient on the instrument (either the continuous or binary version). We report the reduced form and 2SLS estimates separately. The first row in Table 5 repeats the baseline estimates. In the second row, we add ZIP code specific linear trends to the model in Equation 3. This specification allows for systematically different trends in drug utilization across higher and lower elderly share markets in the absence of Part D.

[23] The estimates are for the continuous and binary instruments, respectively (1/0.017=59 and 1/0.014=71).

Since the results remain quite similar in magnitude and are highly significant, such trends appear not to be exerting substantial influence on our results which is consistent with our figures and event study analysis which showed little evidence of pre-existing trends.

We also test for whether the composition of the claims sample changed before and after Part D differentially across areas with high and low elderly shares. Differential composition changes that are correlated with drug utilization would bias our estimates. We implement three tests for sample composition changes. First, we consider changes in the composition of the sample due to the 2008 Great Recession. We observe a decline in the number of firms in our sample and the average number of employees in each firm beginning in 2008, which suggests that firms are laying off workers, discontinuing health insurance benefits, and/or workers are reducing their take-up of insurance. Workers remaining in our sample during the recession may be observationally different than those in the pre-recession sample. However, this is only a concern to the extent that these composition changes are differentially occurring across high versus low elderly share markets. Row 3 of Table 5 shows the reduced form and 2SLS estimates excluding the recession years 2008-2010. The results are broadly robust to this exclusion verifying that any changes in the composition of the sample were not differential by elderly share.

Second, we evaluate the effects of firm churn in the claims data more generally. Out of the 41 firms that we observe in the claims data, 13 firms are observed (i.e. were clients of the health benefits consulting firm) 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 (typically) consecutive years. In row 4 of Table 5, we re-estimate the drug utilization results using only the firms that were continuously in the sample in all years. The results are very similar to the baseline estimates, though the precision of the estimates is reduced slightly due to the smaller sample size.

Third, we investigate changes in the composition of the sample due to firm and employee churn more directly, by examining whether individuals' characteristics change around Part D differentially across high and low elderly share markets. Given the lack of detailed information about demographic characteristics in the claims data, we assign each person the average

characteristics of their three-digit ZIP code of residence using the 2000 Decennial Census.[24] In Figure 5, we plot average demographic characteristics for the entire non-elderly sample across high and low elderly share markets from 2004-2010. We look at changes in median income, percent black, percent with high school education, and percent with more than high school education. 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.[25] While there are small composition changes throughout the time 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 three tests strongly suggest that composition changes in the claims data are not driving the observed differential changes in drug utilization.

5.2.3. Alternative Explanations for Utilization Effects

In this section, we assess the significance of possible alternative explanations for the observed trends in drug use for the non-elderly. We test whether Part D led to: 1) differential reductions in drug prices across high and low elderly share areas; 2) differential changes in physician prescribing behavior for non-elderly patients; and 3) increased detailing efforts that were differentially targeted across DMAs. As shown below, we do not find any evidence to support these alternative hypotheses.

We first examine whether pharmaceutical firms lowered drug prices more in areas with a higher elderly share after Part D, which would lead to a differential increase in drug utilization. Previous studies found that national retail prices declined after Part D for drugs that are most commonly used by Medicare beneficiaries (Duggan and Scott Morton, 2010) and that the increased enrollment in private drug insurance plans allowed insurers to negotiate lower retail prices (Lakdawalla and Yin, 2014). However, it is not known: whether these retail price reductions were passed along to patients in the form of lower copays, which is ultimately 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

[24] We obtain census characteristics at the ZIP Code Tabulation Area (ZCTA) level. Average characteristics at the 3-digit ZIP code level are the population-weighted average across the ZCTAs within the 3-digit ZIP code.
[25] Given the sample restriction that we only include individuals with full-year insurance coverage, the average characteristics are constant within a year.

higher elderly share. Our main specification (Equation 3) presumes that any price effects did not disproportionately affect high elderly share areas, and we can test this assumption explicitly in our data.

Using the claims data, Figure 6 plots trends in average out-of-pocket prices for the non-elderly across high and low elderly share areas. We compute the average out-of-pocket price for each drug in each ZIP code and quarter at the level of the National Drug Code (NDC).[26] Using the NDC ensures that the features of the product remain constant over time. In Panel A, we show mean out-of-pocket prices for the NDCs associated with the 50 advertised chronic brand-name drugs. It appears that there is a slight overall *increase* in out-of-pocket prices after Part D, though there is no differential effect across geographic areas around the implementation date.[27] Since we observe out-of-pocket prices only for drugs that are purchased, it is possible that the price trends reflect movements in the composition of drugs purchased towards newer, more expensive, products. To address this, in Panel B, we restrict the sample to a balanced panel of NDCs that are observed in every quarter.[28] Again, we observe an increasing trend in out-of-pocket prices over time and, importantly, no apparent differential trends across high and low elderly share areas after Part D. This confirms that the drug utilization patterns cannot be explained by price changes.

Second, we consider the possibility that there were other spillovers of Part D on the non-elderly, unrelated to advertising, such as changes to physician prescribing behavior. Part D increased the volume of prescriptions written for the elderly. This may have influenced prescribing habits, leading physicians to write more prescriptions for their non-elderly patients as well.[29] If this occurred, we would observe Part D spillovers on utilization for the non-elderly population, but they would be driven by physician behavior, not by advertising. To test for this possibility, we compare drug utilization by the non-elderly across high and low elderly share

[26] The NDC is a unique eleven-digit identification number assigned by the FDA to every drug product in the United States. The digits correspond to the manufacturer ID, strength, dosage, and formulation of the product, and the package size. Each brand-name drug is typically associated with multiple NDCs.

[27] 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 the end of the year, once deductibles and stop-loss thresholds have been met.

[28] We also restrict the sample to 2004-2007 to maximize the number of NDCs that we can include in the balanced panel.

[29] 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. Physicians might also develop prescribing habits based on the increased volume of elderly prescribing which spills over to other patients.

markets for drug classes that advertised during the study period relative to drug classes that did not advertise during the study period. If increased utilization by the non-elderly were driven by spillovers unrelated to advertising, we would expect to see increases in utilization for all drug classes (whether or not they advertised).

Figure 7 compares non-elderly drug utilization before and after Part D across high and low elderly share markets for both advertised and non-advertised drug classes. For this test we draw from the full sample of drug classes, not just from those classes that treat the five chronic conditions we analyzed previously. We identify 43 drug classes that had a positive amount of advertising[30] during the study period, and the remaining 52 drug classes did not advertise.[31] In the figure and regressions, we restrict the sample to the top 10 most widely used advertised drug classes and non-advertised drug classes among individuals ages 40-60 in order to ensure that the drugs classes are relevant for the non-elderly population (see Appendix Table 3 for the list of the 20 included drug classes).

We find a large relative increase in the use of advertised drugs in high elderly share markets immediately following Part D, but we observe only a very slight increase in the use of non-advertised drugs. Using a triple-difference regression which is analogous to the graph (see Table 6, Panel B), we find that the utilization effect for *non-advertised* drugs is in fact close to zero and statistically insignificant. Meanwhile, the effect for *advertised* drugs is large and statistically significant at the 1 percent level. Using the continuous instrument for the elderly share in Panel A of Table 6, we find a small positive effect of Part D on utilization of non-advertised drugs, but the effect for advertised drugs is more than five times as large. Even the proportional change relative to the mean is much smaller for non-advertised drugs. The substantially larger effects of Part D on utilization for advertised drugs compared to non-advertised drugs, suggests that the observed increase in utilization is driven by advertising, rather than other types of spillover effects, such as physician prescribing behavior, which would lead to increases in the use of advertised and non-advertised drugs alike.

[30] We use the first two digits of the GPI code (available from IMS Health) to identify major classes of drugs. The advertised drug classes are those associated with the 200 advertised brand-name drugs included in our Nielsen sample. Since these 200 drugs represent 96% of local advertising spending, this represents a virtual census of advertised drug classes.

[31] Advertising is related to the amount of generic penetration in the drug class. For example, among anti-hyperlipdemics, a widely advertised class of drugs, 26 percent of the claims in our sample are for generics. On the other hand, diuretics, which have been available for decades and have almost a 100 percent share of generic claims, saw no advertising during the study period.

Finally, we assess whether pharmaceutical "detailing" (promotional activity directed to physicians) may have increased differentially across areas after the introduction of Part D. Since Part D increased the returns from advertising to both consumers and physicians, it is possible that there was also an increase in detailing efforts in DMAs with a high concentration of elderly. Depending on whether detailing is a substitute or complement for direct-to-consumer advertising, this could bias our findings towards or away from zero. A previous study showed that detailing and direct-to-consumer advertising are not geographically correlated. Shapiro (2015) found, in the context of anti-depressants, that DMA-level direct-to-consumer advertising was uncorrelated with detailing in 2001-2003. Moreover, he found that the large and sudden rise in direct-to-consumer advertising following the 1997 change in FDA regulations did not lead to a trend break in detailing at the national level. We further validate these findings in our setting empirically.

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 in the DMA by design. Detailing, however, is more localized since individual physicians or practices can be targeted for visits by pharmaceutical sales representatives. In other words, detailing efforts are not constrained by DMA boundaries and should respond to more local demand shocks. If detailing were responsive 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 shares of elderly.

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 share within DMAs. 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. For example, in the Tampa-St. Petersburg (Sarasota) DMA, the three-digit ZIP code elderly share ranges from 11% to 27%.

The results of this test are presented in Table 7. Restricting the sample to ZIP codes that can be uniquely matched to DMAs,[32] column 1 reproduces the baseline reduced form results (which compute elderly share at the DMA level) using only these ZIP codes. The results are very similar to the main results in Table 3. In Column 2, the elderly share is computed at the three-digit ZIP code 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.[33] 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 for both instruments. This shows that utilization did not respond to Part D differentially by elderly share within DMAs, which is suggestive evidence that detailing did not change after Part D or, at a minimum, that detailing responses were unrelated to elderly share.

As one possible explanation for this result, it is plausible that detailing is more "sticky" than direct-to-consumer advertising because an increase in detailing requires an increase in physicians' time allocated to sales calls, hiring additional sales representatives, and/or displacing promotions for other pharmaceutical products. On the other hand, additional direct-to-consumer ads can be purchased almost instantaneously.[34] While we cannot eliminate the concerns about detailing entirely, we find it reassuring that detailing changes after Part D appear to be unrelated to elderly share.

5.3. Potential Welfare Implications

Given the substantial effect of advertising on total drug utilization, we decompose the overall utilization effect to quantify the various causal pathways from advertising to utilization. These results have important welfare implications from both the consumer and firm perspectives. We conduct three analyses. First, we decompose the total utilization effect into the extensive and intensive margins to understand advertising's role in inducing take-up of drugs versus greater use

[32] Recall that some three-digit ZIP codes overlap multiple DMAs and were assigned probabilistic measures of advertising exposure in the main results.
[33] 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.
[34] The fact that we observe an immediate utilization response after Part D also suggests that direct-to-consumer advertising is the main driver of the effect, since detailing would be expected to adjust with a lag.

among existing users. Second, we examine the effects of advertising 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 Table 8, we present 2SLS estimates for extensive and intensive measures of prescription drug use for chronic drugs. We estimate each specification separately for the full sample and the pre-recession years 2004-2007. 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 margins. Columns 1-4 estimate total effects. Columns 1 and 2 repeat the baseline estimates from Table 5 of total prescriptions purchased (including zeros for those who do not purchase any chronic drugs). In Columns 3 and 4, the dependent variable is days supplied of the prescription (e.g. 30 days, 60 days, etc.), including zeros. Days supplied provides a more standardized measure of the units of a prescription across different types of drugs. In Columns 5 and 6, we estimate extensive margin effects as the probability of any use of a chronic drug. Finally, we also estimate intensive margin effects in Columns 7-10: total prescriptions purchased and days supplied, conditional on use. We find positive effects of advertising for all of the outcome variables. The coefficients are statistically significant at the 1% or 5% level in all but two specifications. The positive intensive margin effects suggest an effect of advertising exposure on drug adherence, which we explore more explicitly below. Comparing the relative magnitude of intensive and extensive margin effects, a back-of-the-envelope calculation implies that about 71 percent of the total advertising effect for prescriptions purchased is driven by extensive margin effects.[35] Thus, a substantial proportion of the utilization effect of advertising appears to come from promoting take-up among new users. Given that the five conditions we study are generally considered to be under-treated and under-diagnosed, increased take-up may represent a welfare gain. However, an analysis of the health benefits as well as other perceived utility gains

[35] Using the binary instrument, the total change in prescriptions purchased is 0.014 for one additional ad viewed. We decompose this into the intensive and extensive margin effects. The change in prescriptions purchased along the intensive margin is predicted to be the fraction of the sample that used chronic drugs prior to Part D (0.06) x the estimated change in prescriptions purchased among users (0.068). Subtracting this from the total effect, we get the predicted extensive margin effect which is the fraction of the sample that are new users x the change in prescriptions purchased among new users.

from these additional treatments would be needed to characterize the full welfare effects. This goes beyond the scope of this analysis, given the limited measures of health available in our claims data, but represents a potentially important area for future research.

5.3.2. Effects on Drug Adherence

We extend the above analysis of intensive margin effects by looking specifically at the effects of advertising on drug adherence. Poor adherence to prescribed drug regimens for chronic conditions reduces their effectiveness, leading to worse health outcomes (summarized in DiMatteo, et al., 2002) and greater healthcare costs on the order of $100 to $289 billion annually. Noncompliance is common with an estimated 50 percent of patients with chronic diseases not following treatment regimens as prescribed (Viswanathan, et al., 2012). While it is difficult, using claims data, to definitively interpret rising drug utilization due to advertising as appropriate use or overuse, increasing drug adherence has clearer positive welfare implications because it has been shown to improve health.

Advertising may increase adherence if it serves as a reminder to take medication, makes the chronic condition more salient (especially for asymptotic diseases such as hyperlipidemia), or increases the perceived benefits of treatment. It may also reduce adherence if it enhances awareness of harmful side effects.

We first present the results for drug adherence graphically in Figure 8. This figure is analogous to the previous figures showing the trend in overall drug utilization across high and low elderly share areas, using as the outcome 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 1. Adherence is mechanically very high in the first few quarters of the study period, since 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.[36] This mechanical relationship in the data is uniform across geographic areas, as is visible in Figure 8, and should not impact our results. Additionally, we will show that excluding the early part of our study period from the analysis has little effect on the results.

[36] 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. As we move from left to right, the sample composition becomes more balanced in terms of time since treatment initiation.

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 prior to Part D, 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 magnitude of this effect we present the corresponding regression results for the reduced form and 2SLS estimates in Panel A of Table 9. We present results separately for the full sample period (2004-2010), excluding the recession years (2004-2007), and excluding the first year where adherence is mechanically high (2005-2007). The results are qualitatively similar across samples. In the full sample, we find that comparing high elderly share areas to low elderly share areas, Part D led to a 0.4 percentage point increase in the proportion of individuals with high adherence (or about a 1 percent increase relative to the 2005 mean). When restricting the sample to 2005-2007, the estimate increases to 1.2 percentage points. Only the latter estimate is statistically significant at conventional levels. The 2SLS estimates are also positive and mostly 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 restrictions. At the high end, the number of ads viewed would need to increase by 40 percent in order to increase adherence by 10 percent. In the full sample period, the elasticity for adherence is roughly one-sixth the size of the elasticity for total utilization. Using the continuous MPR as the outcome variable instead of the proportion with high adherence produces very similar estimates (see Appendix Table 4).

The changes in adherence represent a combination of behaviors from both existing and new drug users. In particular, the increase in advertising after Part D may have caused more people to initiate drug treatment. These new entrants into the sample may have had different underlying compliance behavior (i.e. higher or lower adherence). To isolate the adherence responses of the existing patients from the new initiators, in Table 9 Panel B, we replicate the previous table using only the sample of individuals who initiated drug treatments in 2004 or 2005, before the introduction of Part D. When we exclude the new initiators, the results increase slightly. While the differences are small, this suggests that the marginal person who initiates treatment because of advertising is on average less compliant. 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 something new they

saw on television 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. If advertising is capturing individuals for whom treatment is marginally less appropriate and less beneficial, or if new initiators simply comply less with prescribed treatments, then this could represent wasteful drug spending since initiating chronic treatments without adhering to them does not improve health.

5.4. Spillover Effects to Non-Advertised Drugs

Finally, we analyze whether there were spillover effects of advertising on non-advertised drugs. Previous research on the effects of advertising distinguish between market stealing effects, in which a brand's advertising increases demand for its own product, and market expansion effects, in which advertising by a specific brand increases total demand for the entire class of drugs. Since Part D affected advertising for all drugs, it does not serve as an appropriate instrument to test for market stealing between one advertised brand name drug and another. While shifts in market share may have occurred among drugs after Part D, we observe only the net effect on the overall demand for advertised drugs within a condition. However, we can use the variation from Part D to test for spillovers of advertising on non-advertised drugs, which is a component of the overall market expansion effect. Positive spillover effects could occur if a person viewing a television ad for a brand name drug requests this drug from her doctor, but the doctor then prescribes another therapeutically similar drug. Insurance formularies that cover only certain drugs or offer preferential cost-sharing for certain drugs could also induce this type of switching behavior. We test for spillover effects by re-estimating Equation 3, replacing the outcome variable with the total prescriptions purchased for *non-advertised* drugs that belong to the same therapeutic drug classes as the 50 advertised chronic drugs.

First, we show the results graphically in Figure 9 comparing the trends in average prescriptions purchased across high and low elderly share markets for advertised drugs (repeated from Figure 3), non-advertised drugs, and both types of drugs combined. For non-advertised drugs, we see nearly identical trends across markets prior to Part D and then both an absolute and relative increase in utilization in high elderly share markets immediately after the introduction of Part D. This provides strong evidence of a market expansion effect. The secular increase in both trends, which differs from the declining utilization we see for advertised drugs, reflects the fact

that the non-advertised drugs are typically generics or off-patent brands and that there is substitution from the brand-name drugs to generics after brands lose patent protection. We also observe a large differential effect of Part D on total utilization (combining both types of drugs). Thus, the effect cannot be driven purely by substitution from non-advertised drugs to advertised drugs. The regression analogs in Table 10 show that these effects are all positive and statistically significant. Consistent with the previous advertising literature, we find large positive spillovers from advertising. This has welfare implications for both consumers and firms. From the consumer perspective, the spillovers may be welfare enhancing as this suggests a more informative, rather than brand-specific, role for 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. From the firm's perspective, the free-riding of rival firms prevents the firm from capturing the full returns from advertising leading to lower advertising efforts, suggesting a welfare loss.

6. Conclusion

This paper provides some of the first quasi-experimental evidence of the impact of direct-to-consumer advertising on drug utilization, as well as the causal mechanisms for the advertising effect, by exploiting variation in advertising driven by the introduction of Medicare Part D. We compare changes in drug utilization for the non-elderly before and after Part D in markets with high versus low elderly share.

The results of this study show that advertising exposure for the non-elderly increased differentially in high elderly share markets immediately following the implementation of Part D. This pattern is also mimicked by our drug utilization outcomes along both the extensive and intensive margins. While drug utilization pre-trends tracked each other closely prior to Part D, we find a differential increase for the non-elderly following Part D. Decomposing the total utilization effect, we find that the effects are driven both by increased take-up and drug adherence. Using a back-of-the-envelope calculation, increased take-up accounts for about 71% of the total utilization effect.

The utilization results are robust to trends and alternative specifications of the instrument. Also, we find that the results are not sensitive to changes in the composition of the sample due to

firm and employee churn in the claims data. We find no evidence to suggest that the utilization patterns are driven by changes in prices, physician prescribing behavior, or detailing that is differentially occurring in high elderly share areas. We also find large spillover effects of advertising on utilization of non-advertised drugs, leading to overall market expansion effects.

Overall, we find substantial responsiveness of prescription drug demand to a non-price factor. In a review article, Goldman, Joyce and Zheng (2007) find that estimates of the price elasticity of demand for prescription drugs range from -0.2 to -0.6. Using this range of estimates, our results 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.[37] The substantial spillover effects of Part D on the non-elderly population may also warrant consideration by policymakers. These unintended behavioral responses to the policy by individuals outside of the Medicare program may have considerable welfare consequences.

[37] 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.

References

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 Pharmaceuticals 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.

Shapiro, B. 2015. Positive Spillovers and Free Riding in Advertising of Prescription Pharmaceuticals: The Case of Antidepressants.

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.

DiMatteo, M., et al. 2002. Patient adherence and medical treatment outcomes: a meta-analysis. *Medical Care.* 40(9): 794-811.

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. *Journal of the American Medical Association*. 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. *Annals of Pharmacotherapy*. 40:1280-1288.

Hollon, M. 2005. Direct-to-consumer advertising: A haphazard approach to health promotion, *Journal of the American Medical Association*, *293*(16), 2030-2033.

Holmer, A.F. 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.

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

Kanazawa, Mark. T. and Jonas P. 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. 2014. Media influences on social outcomes: The impact of MTV's *16 and Pregnant* on teen childbearing. *NBER Working Paper #19795.*

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

Kravitz, R., et al. 2005. Influence of patients' requests for direct-to-consumer advertised antidepressants: A randomized controlled trial," *Journal of the American Medical Association*, 293(16), 1995-2002.

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

Lakdawalla, D., and Yin, W. 2014. Insurers' Negotiating Leverage and the External Effects of Medicare Part D. *Review of Economics and Statistics*.

Lichtenberg, F. and Sun, S. 2007. The Impact of Medicare Part D on Prescription Drug Use by the Elderly. *Health Affairs*.

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

Peterson, A., et al. 2007. A Checklist for Medication Compliance and Persistence Studies Using Retrospective Databases. *Value in Health*, 10: 3–12.

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

Saffer, Henry, Melanie Wakefield and Yvonne Terry-McElrath (2007). "The effect of nicotine replacement therapy advertising on youth smoking." NBER Working Paper 12964.

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.

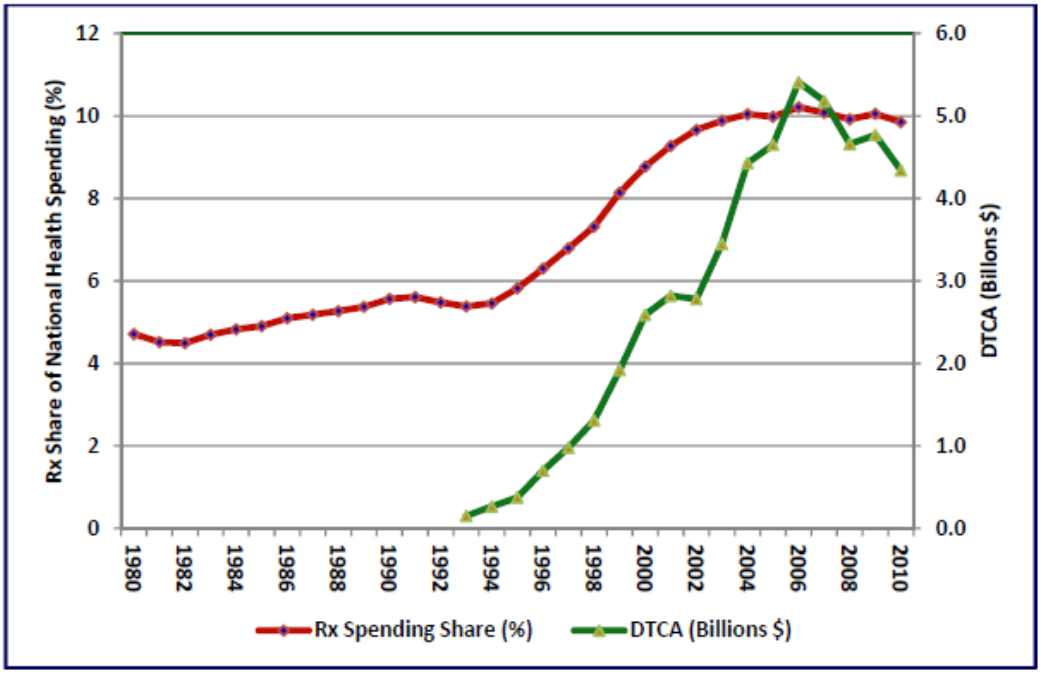
Viswanathan M, et al. 2012. Interventions to Improve Adherence to Self-administered Medications for Chronic Diseases in the United States: A Systematic Review. *Annals of Internal Medicine*. 157:785-795.

Wosinska, M. 2002. Just what the patient ordered? Direct-to-consumer advertising and the demand for pharmaceutical products. *Harvard Business School 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.

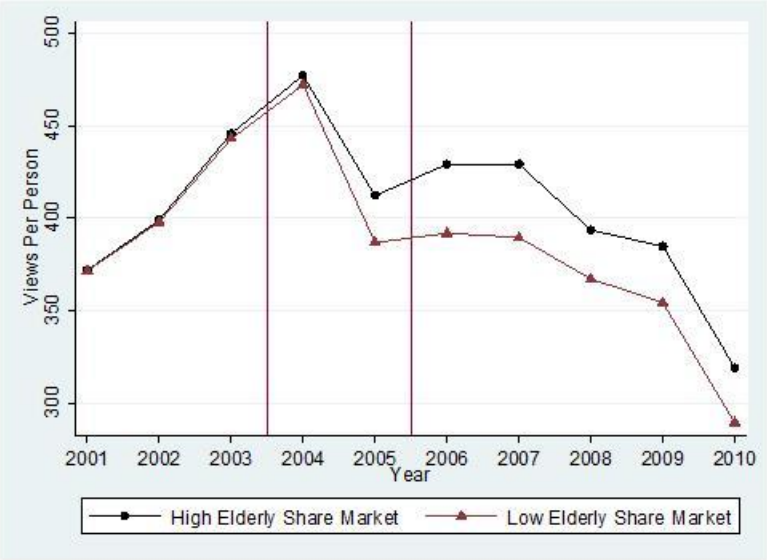
Figure 1 –Direct-to-Consumer Advertising and the Pharmaceutical Share of Total Healthcare Spending, 1980-2010



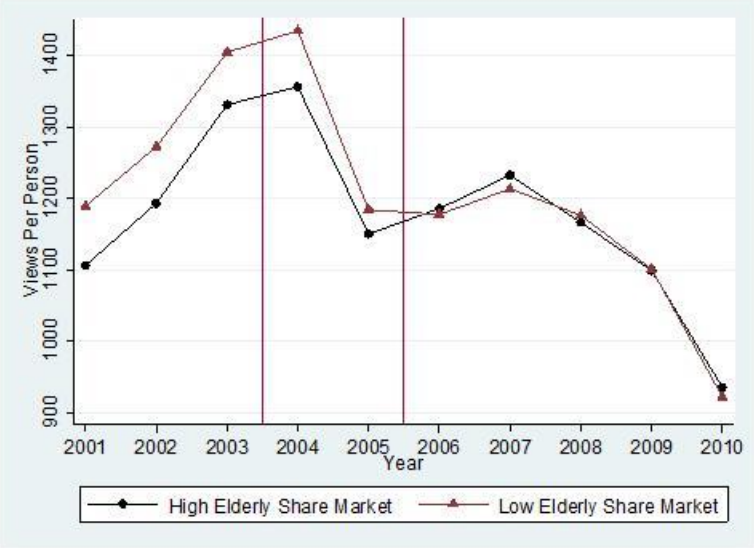
Source: From Dave (2013).

Figure 2 – Annual Views per Person of TV Ads for Top 200 Drugs

Panel A: Non-Elderly, Ages 2-64



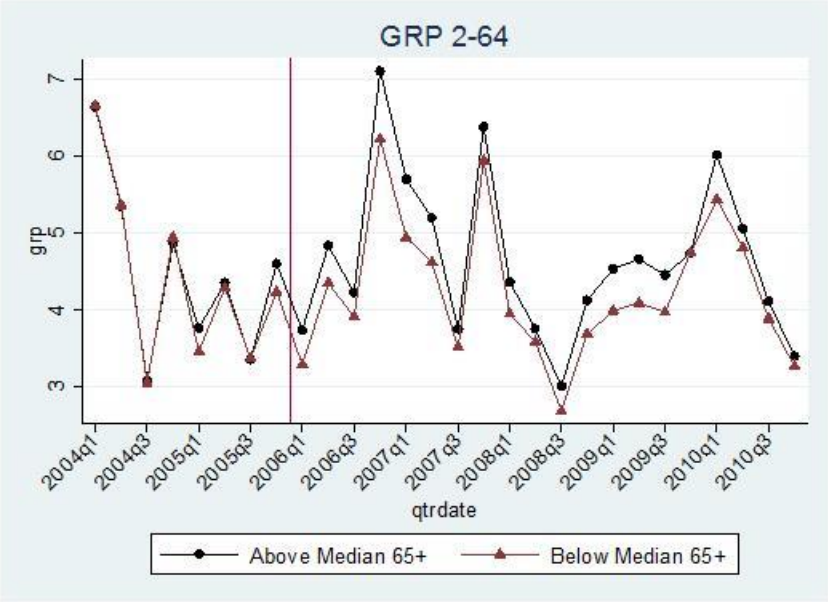
Panel B: Elderly, Ages 65+



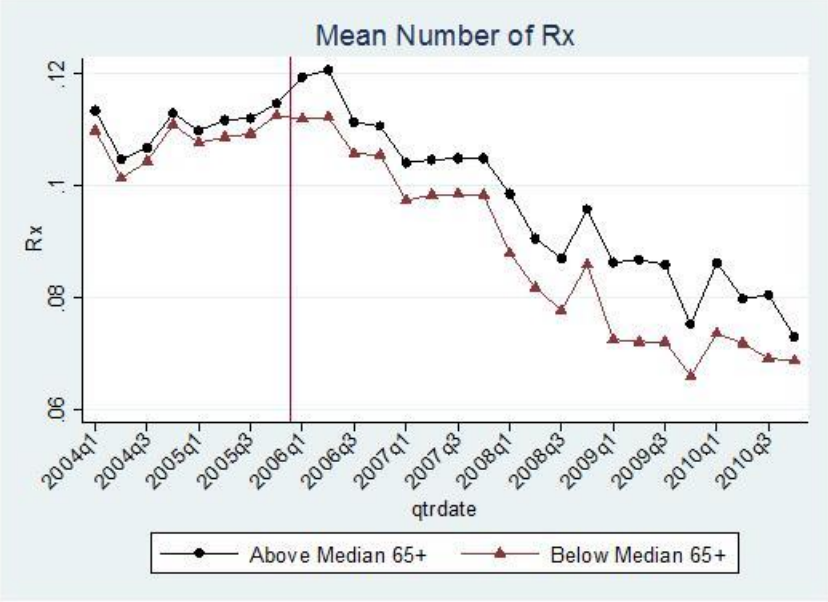
Notes: Sample means from Nielsen Ad*Views in above median elderly share markets relative to low elderly share markets. The vertical lines represent the dates when Part D was signed into law (December 2003) and was implemented (January 2006).

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

Panel A: Views Per Person for Chronic Drugs

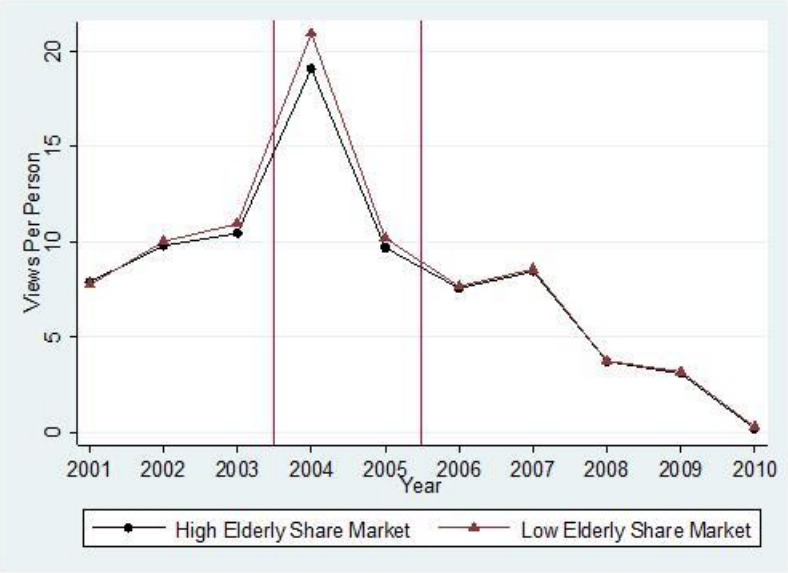


Panel B: Average Number of Prescriptions Purchased for Chronic Drugs



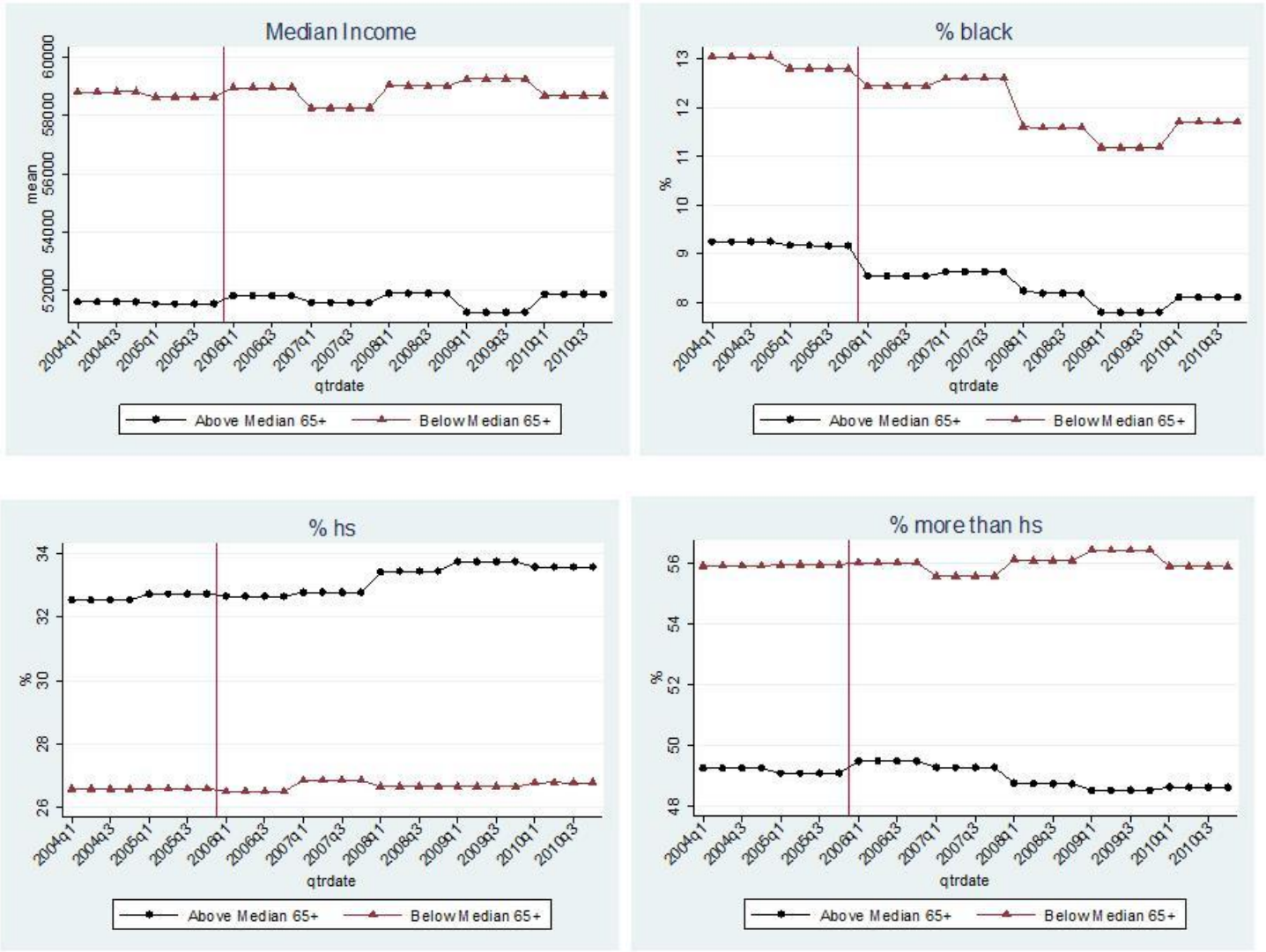
Notes: Sample means from Nielsen Ad*Views (views per capita, ages 2-64) and claims (mean number of total prescriptions purchased, ages 40-60) in above median elderly share markets relative to low elderly share markets. Includes the 50 drugs that advertised during the study period for 5 chronic conditions: 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, Non-Elderly



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

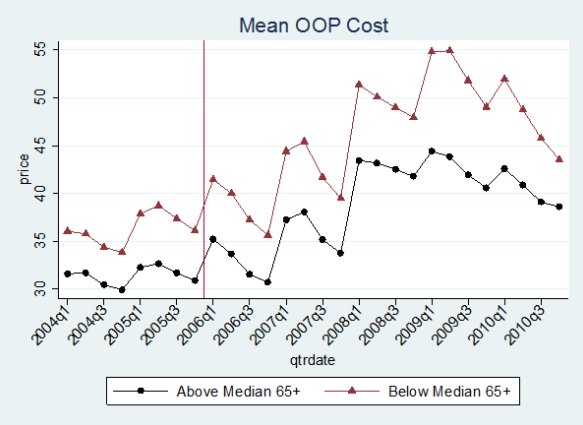
Figure 5 – Trends in Composition of Claims Data Sample



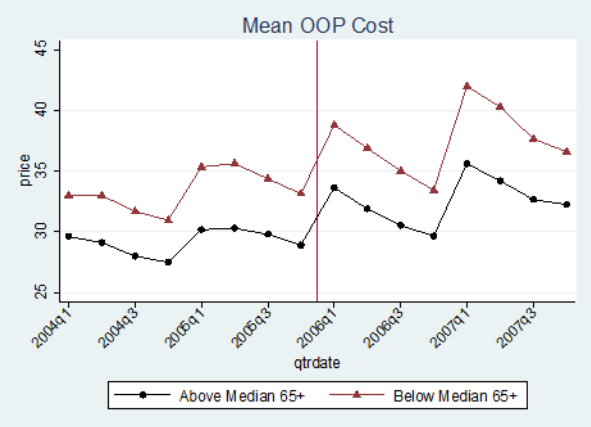
Notes: Sample means of Census 2000 characteristics linked to individuals in claims sample by 3-digit ZIP code.

Figure 6 – Mean Out-of-Pocket Price for Chronic Drugs, Non-Elderly

Panel A: All NDCs – Chronic Drugs

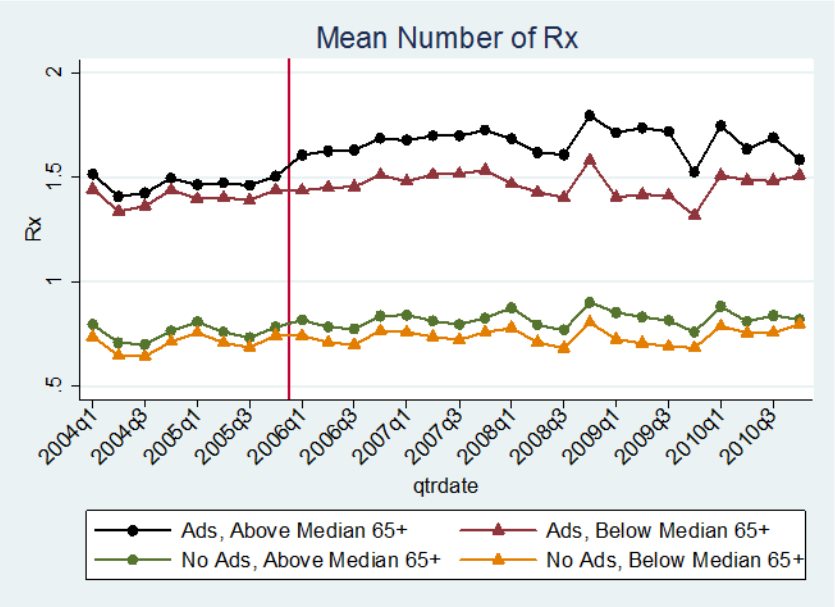


Panel B: Balanced Panel of NDCs (2004-2007) – Chronic Drugs



Notes: Sample means from claims (mean out-of-pocket price, ages 40-60) in above median elderly share markets relative to low 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 7 – Mean Utilization for Advertised Drug Classes vs. Non-Advertised Drug Classes, Non-Elderly



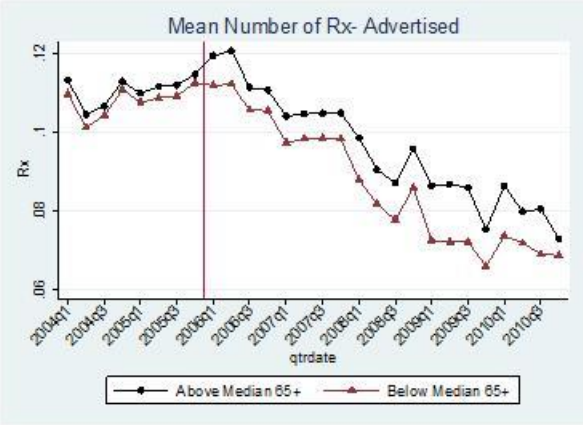
Notes: Sample means from claims (mean number of total prescriptions purchased, ages 40-60) in above median elderly share markets relative to low elderly share markets. The top two lines (black and red) are for the top 10 advertised drug classes and the bottom two lines (green and orange) are for the top 10 non-advertised drug classes (see Appendix Table 3 for full list of drug classes included). The vertical line represents the implementation date of Medicare Part D.

Figure 8 –Proportion with High Adherence of Chronic Drugs, Non-Elderly

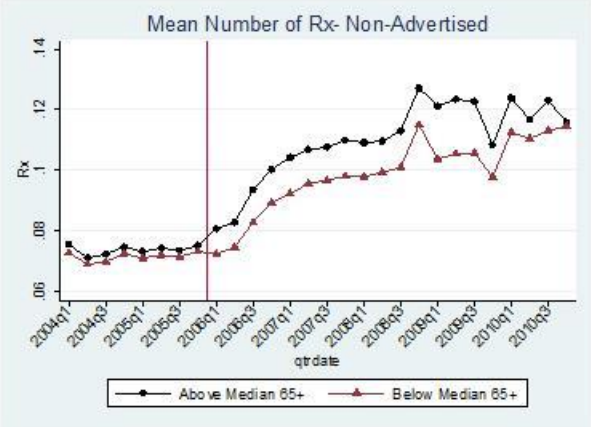
Notes: Sample means from claims (proportion of individuals with MPR>=80%, ages 40-60) in above median elderly share markets relative to low elderly share markets. Includes the 50 drugs that advertised during the study period and the drugs that did not advertise for 5 chronic conditions: depression, diabetes,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

Figure 9 – Quarterly Views per Person of TV Ads of Chronic Drugs: Spillover Effects

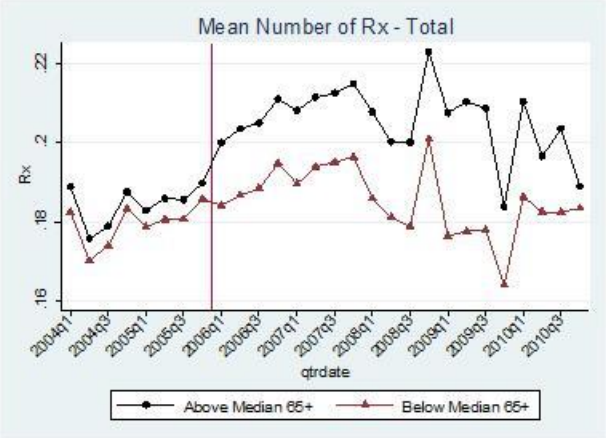
Panel A: Advertised Chronic Drugs



Panel B: Non-Advertised Chronic Drugs



Panel C: 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 low elderly share markets. Panel A includes the 50 chronic drugs that advertised during the study period (repeated from Figure 3), Panel B includes drugs in the same classes that did not advertise, Panel C includes both advertised and non-advertised drugs. 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

Notes: TV markets are defined by Nielsen Designated Market Areas (DMAs). Elderly share and population counts are from the 2000 Census.

Table 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.

Table 3 – Baseline Regression Results for Total Utilization of Chronic Drugs

	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 4 – Timing of the Impact on Total Utilization of Chronic Drugs

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 5 – Total Utilization of Chronic Drugs – Alternative Specifications

	Reduced Form		2SLS	
	Instrument= Share65+*Post	Instrument= High Elderly Share*Post	Instrument= Share65+*Post	Instrument= High Elderly Share*Post
Dependent Variable: # of Prescriptions				
	(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 3, 2) adds 3-digit ZIP code specific linear trends, 3) excludes the years 2008-2010, 4) includes only individuals employed by 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 6 – Effects for Advertised Drug Classes vs. Non-Advertised Drug Classes

Dependent Variable:	# of Prescriptions
A. Instrument=Share65+*Post	
Post*Share65+*Advertise	1.787***
	(0.247)
Post*Share65+	0.432***
	(0.120)
B. Instrument=High Elderly Share*Post	
Post*High Elderly Share*Advertise	0.105***
	(0.018)
Post*High Elderly Share	0.009
	(0.008)
Zipcode x Advertised Class x Quarter Obs	42,938

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, Advertise indicator, Post x Advertise, Advertise x Share 65+ (or Advertise x High Elderly Share). Sample includes the top 10 advertised drugs classes and top 10 non-advertised drug classes (see Appendix Table 3 for the full list of drug classes included). Each Zipcode x Quarter has two observations: one for mean utilization of advertised drugs, one for mean utilization of non-advertised drugs. Data is from 2004-2010.

Table 7 – 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 quarter fixed effects, 3-digit ZIP code fixed effects, condition fixed effects. The specifications are as follows. Column 1: same as Table 3, but for sample of ZIP codes that are uniquely matched to one DMA; elderly share is computed at the DMA-level, Column 2: elderly share is computed at 3-digit ZIP code level, Column 3: adds DMA x quarter fixed effects; elderly share is 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 8 – Total Utilization of Chronic Drugs, 2SLS – Alternative Outcomes

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. Includes the 50 drugs that advertised during the study period for 5 chronic conditions: depression, diabetes, hyperlipidemia, hypertension, and osteoporosis.

Table 9 – Adherence of Chronic Drugs

Panel A: All individuals with chronic drug claims

	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

Panel B: Excluding individuals who initiated treatment after Part D

	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+	0.256***	0.268***	0.437***			
	(0.043)	(0.048)	(0.104)			
Views per Person (Non-Elderly)				0.022***	0.020***	0.036***
				(0.006)	(0.005)	(0.012)
B. Instrument=High Elderly Share*Post						
High Elderly Share*Post	0.008***	0.009***	0.013***			
	(0.003)	(0.003)	(0.004)			
Views per Person (Non-Elderly)				0.014***	0.013***	0.023***
				(0.004)	(0.004)	(0.008)
Mean of Dep. Var (pre- Part D)	0.61	0.61	0.57			
Zipcode x Condition x Quarter Obs	96,628	58,533	43,800	96,628	58,533	43,800

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.

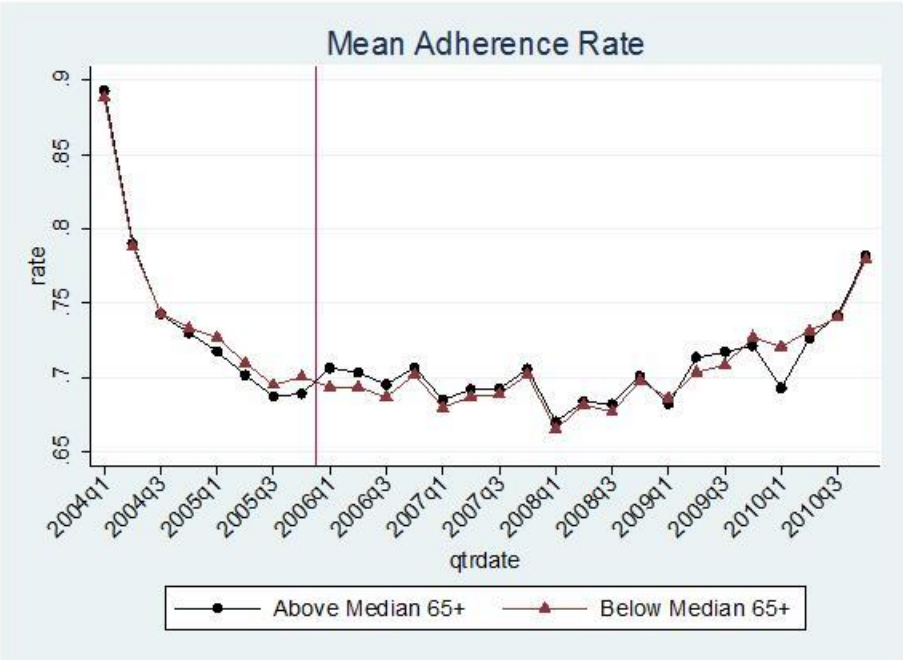
Table 10 – Spillover Effects for Non-Advertised Chronic Drugs

	Reduced Form			2SLS		
Dependent Variable: # of Prescriptions	Advertised Drugs	Non-Advertised Drugs	Total	Advertised Drugs	Non-Advertised Drugs	Total
	(1)	(2)	(3)	(4)	(5)	(6)
A. Instrument=Share65+*Post						
Post*Share65+	0.107***	0.125***	0.233***			
	(0.023)	(0.028)	(0.038)			
Views per Person (Non-Elderly)				0.017***	0.020***	0.037***
				(0.004)	(0.005)	(0.008)
B. Instrument=High Elderly Share*Post						
High Elderly Share*Post	0.005***	0.006***	0.011***			
	(0.001)	(0.002)	(0.002)			
Views per Person (Non-Elderly)				0.014***	0.018***	0.032***
				(0.005)	(0.005)	(0.008)
Mean of Dep. Var (pre- Part D)	0.11	0.07	0.18	0.11	0.07	0.18
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.

Appendix

Appendix Figure 1 – 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 low 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 1—Top Advertised Chronic Drugs

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 2— 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 3— Top 10 Advertised Classes and Non-Advertised Classes

Advertised Drug Classes -- Top 10 in Terms of Utilization by Ages 40-60

ANTIHYPERLIPIDEMICS
ANTIHYPERTENSIVES
ANTIDEPRESSANTS
ANTIDIABETICS
ULCER DRUGS
BETA BLOCKERS
ANALGESICS - ANTI-INFLAMMATORY
ANTIASTHMATIC AND BRONCHODILATOR AGENTS
DERMATOLOGICALS
ANTICONVULSANTS

Non-Advertised Drug Classes -- Top 10 in Terms of Utilization by Ages 40-60

ANALGESICS - OPIOID
THYROID AGENTS
DIURETICS
ANTIANXIETY AGENTS
CALCIUM CHANNEL BLOCKERS
PENICILLINS
MACROLIDES
CORTICOSTEROIDS
FLUOROQUINOLONES
ANTI-INFECTIVE AGENTS - MISC.

Appendix Table 4— 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.