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ABSTRACT

There is much debate about the effects of pharmaceutical direct to consumer advertising (DTCA) on health care use. In this paper, we inform this debate by examining the effects of DTCA on office visits, as well as treatment courses resulting from those visits, for five common chronic conditions (hypertension, hyperlipidemia, diabetes, depression, and osteoporosis). In particular, we examine whether office visits result in use of drug therapy and/or continued office visits over time. We test these questions by combining data on pharmaceutical advertising from Nielsen with claims data from 40 large national employers, covering 18 million person-years. We analyze a non-elderly population by exploiting plausibly exogenous variation in advertising exposure across areas due to the implementation of Medicare prescription drug coverage which led to larger increases in advertising in areas with high elderly share of population compared to low elderly share areas. We find that advertising increases the number of office visits for the non-elderly for the advertised condition. We also find substantial spillovers -- a large share of the increased office visits from advertising are associated with use of non-advertised generic drugs or do not result in use of any drugs. Finally, we find that the increase in office visits due to DTCA is associated with continued engagement with a physician through multiple consecutive follow up visits over time.

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1. INTRODUCTION

Direct-to-consumer advertising (DTCA) of pharmaceutical products is currently legal in only two countries – the United States and New Zealand – and consumers in the U.S. are exposed to high and increasing levels of DTCA. Spending on DTCA for prescription drugs has increased 10-fold over the span of two decades, rising from $555 million in 1996 to over $5.63 billion as of 2015 (Kantar Media 2016). The rapid increase in DTCA has been coincident with growth in expenditures on prescription drugs, which grew from $121 billion in 2000 to $297 billion in 2014 (CMS 2016). Policymakers and interest groups have engaged in rigorous debate surrounding the appropriateness of DTCA amidst growing concerns about high drug prices and the potential role of marketing in inflating costs (Dusetzina et al. 2019). In 2015, the American Medical Association (AMA) called for a ban on all DTCA (AMA 2015), and, in 2019, the Trump administration proposed new regulations requiring manufacturers to disclose prices in their advertisements (CMS 2019), though, they were overturned before implementation.

The debate on the effects of DTCA on health care use and health can be summarized as follows. Critics argue that DTCA may encourage substitution from cheaper generics to more expensive brand name drugs, or that it could result in over-screening for conditions without medical justification, leading to overspending. It has also been argued that DTCA may pose a harm to patients as it could lead to over-treatment, inappropriate prescribing behavior, or use of drugs that are not clinically indicated (Mintzes, 2012). On the other hand, proponents argue that DTCA has the potential to positively impact patients' health by providing information about diseases and available treatments, improving adherence to drug therapy, and engaging new patients with the healthcare system, potentially helping them receive care at an earlier stage (Mintzes, 2012). The existing literature suggests that much of the effect of DTCA on drug use is

at the extensive margin—i.e., drug initiation—which implies an increase in the number of office visits. In addition to initiating drug therapy, these new office visits may have value in the form of initiating non-pharmacological therapy or identifying health problems unrelated to the principal reason for the visit. However, they may also represent wasteful utilization if the visit was not medically necessary and does not result in any treatment. Little research has been done on the precise nature of the office visits induced by DTCA, which represents an unquantified cost or benefit.

While the prior literature has shown impacts of DTCA on drug use, the effects of DTCA on health care use, health, and welfare are less clear. For example, an extensive literature has shown that increases in DTCA lead to increased product sales (Alpert et al. 2019; Shapiro 2018; Sinkerson et al. 2018; Eisenberg et al. 2017; Dave et al. 2012; Avery et al. 2012; Iizuka et al. 2005), and a broader literature has confirmed the empirical effects of advertising more broadly (see Bagwell 2007). Some prior studies have also examined the effects of DTCA on initiation and adherence to drug therapy (Alpert et al. 2019; Shapiro 2018; Sinkerson et al. 2018). While other studies have examined prescriber behavior as a result of DTCA (Becker and Midoun 2016), to the best of our knowledge, only one prior study has examined the effect of DTCA on office visits (Iizuka & Jin 2005). The authors found an association between increases in DTCA and an increase in office visits – specifically ones that result in a prescription. However, the authors did not decompose the type of office visits resulting in a prescription into generic or branded drugs, nor did it measure follow-up visits. Furthermore, the authors acknowledge that the lack of a quasi-experimental design in their study makes a causal interpretation of their results suggestive.

In this study, we fill this gap in the literature by examining the effects of DTCA on office visits, the drugs prescribed at those visits, and the continuity of follow up visits using a quasi-experimental identification strategy. We begin by estimating the effect of DTCA on both the volume and the probability of having a doctor visit for one of five common and commonly advertised chronic conditions – hypertension, hyperlipidemia, diabetes, depression, and osteoporosis. We then focus on the types of doctor visits being induced by DTCA, and work to decompose the effect into doctor visits that result in a branded prescription, a generic prescription, or no prescription, with the latter representing a potential externality of DTCA. Finally, we explore whether DTCA leads to consecutive office visits which would indicate sustained engagement with the healthcare system. We do this by tracking the long-term, individual trajectories of healthcare use that are plausibly induced by DTCA by examining what treatment patterns emerge in the two, three, and four years after increased DTCA exposure.

We match individual-level enrollment and claims data from Ingenix (2004-2010) to data on pharmaceutical advertising data from Nielsen (2004-2010). We focus our analysis on advertising for five common and heavily advertised conditions: hypertension, hyperlipidemia, diabetes, osteoporosis, and depression. Taken together, drugs for these five conditions represent over half of all prescription drug advertising spending during our study period (Alpert et al. 2019).

The main empirical challenge in this paper is the endogeneity of advertising exposure. Firms are likely to target their advertisements towards consumers who suffer from conditions the drugs treat, leading a simple correlational analysis to have a systematic bias. To minimize the threat to validity from this targeting bias, we exploit a shock to advertising expenditures that occurred after the implementation of Medicare Part D on January 1, 2006. The introduction of

prescription drug coverage for Medicare enrollees significantly shifted demand for drugs in the U.S., and pharmaceutical manufacturers responded by increasing advertising expenditures (Lakdawalla et al. 2013). Following the identification strategy introduced in Alpert et al. (2019), we exploit the fact that DTCA differentially increased in geographic areas with a larger elderly population that is more likely to be receiving the Part D benefit.[12] We use this variation in advertising to examine the behavior of the *non-elderly* population living in these same areas. The non-elderly received a shock to advertising after Part D but are not directly affected by Part D since they are age-ineligible to enroll in Medicare.

We start by estimating the effects of DTCA on the number of office visits resulting in a diagnosis for one of our five chronic conditions for all patients in our sample. Next, we estimate person-level models on a subsample of individuals who had not had an office visit for one of the chronic conditions in the year prior to the implementation of Medicare Part D. We examine the effect of DTCA in this population on increased office visits, office visits with a post-visit advertised or non-advertised branded drug prescription, office visits with a post-visit generic drug prescription, and office visits with no post-visit prescription. This last group represents the previously unstudied externality of DTCA---the effect of DTCA on demand for non-pharmacological related office visits.

Our last analysis focuses on the persistence of care received by a patient. If DTCA is creating short bursts of increased demand with no subsequent drug adherence or follow-up office

[12] As discussed in Lakdawalla, Sood, and Gu, (2013), Medicare Part D increased the return to advertising through two mechanisms. First, prior studies suggest that more profitable markets generate greater returns to capturing new consumers, and in turn stimulate more intense advertising effort. Thus, the returns to advertising are higher when there are more insured consumers in the market, because insured consumers face lower out-of-pocket costs that induce greater spending. Second, insurance coverage might alter the responsiveness of consumers to advertising. Intuitively, an undecided consumer might be more likely to try a new drug after seeing an advertisement if the cost of trying the drug is lower.

visits, these visits may be indicative of wasteful spending. On the other hand, if advertising results in an initial office visit that then has several consecutive follow-ups, then DTCA could be engaging patients who had previously unmet medical needs with the healthcare system, which could be welfare enhancing. To analyze these trajectories, we estimate similar person-level models where we examine the effect of DTCA on the probability of having at least one annual office visit, an office visit and a drug prescription (either generic or branded), and an office visit but no drug prescription for two, three, and four consecutive years after their initial visit.

Overall, we find statistically significant effects of increased advertising on office visits. We find that 2.8 more non-elderly people per 1,000 had an office visit for one of the chronic conditions in high elderly share zip codes after exposure to increased advertising. Our two-stage least squares analysis finds that one additional ad view per person leads to 9.8 more non-elderly people per 1,000 having an office visit. We also find substantial spillover effects. A large share of the increased office visits from DTCA do not result in use of brand drugs (prescription or generic drugs). Finally, we find that the increase in office visits due to DTCA is associated with multiple consecutive follow-up visits which is indicative of sustained engagement with the healthcare system though this effect depreciates over time.

The remainder of this paper proceeds as follows: Section 2 describes the regulatory history of DTCA in the United States and discusses relevant literature; Section 3 outlines our data, methods, and identification strategy; Section 4 discusses the results of our analysis; and, Section 5 concludes.

2. BACKGROUND

2.1 Office Visit Utilization

According to one study, approximately a third of patients report avoiding a doctor visit that they consider to be necessary (Kannan & Veazie, 2014). There are a variety of barriers that prevent patients from pursuing office visits. Perhaps most common, insufficient insurance coverage, financial concerns, or difficulty taking time off of work are among the top reasons for avoiding care (Taber et al., 2015). In addition to these external factors, there are several internal factors that inhibit office visits, such as emotional concerns, personality idiosyncrasies, and a lack of useful information (Kannan & Veazie, 2014; Lacy et al., 2004; Taber et al., 2015). For example, many patients who suspect they should seek care have had negative experiences with the healthcare system, reporting feeling disrespected by their provider, or anticipating procedures that they suspect will be uncomfortable or embarrassing (Lacy et al., 2004). Other patients (and oftentimes entire patient populations) are also distrustful of the medical system and have lower likelihoods of voluntarily seeking out medical help because of this skepticism (Armstrong et al., 2007). For some conditions – particularly those associated with behavioral health issues – the stigma surrounding the condition or the treatment for the condition may also be a factor that prevents patients from seeking out care (Seervai & Lewis, 2018). Some patients' reluctance to seek out necessary medical help has been characterized as having a 'low perceived need' for the services they expect to have offered, instead opting to rely on alternative remedies or waiting for the symptoms to disappear on their own (Taber et al., 2015). Finally, some patients are simply forgetful or prone to procrastination, which may explain why they have sub optimal rates of engagement with the healthcare system (Taber et al., 2015).

The ability of DTCA to convey information and positively framed messages to large audiences can in theory increase office visit use through overcoming several of these barriers. First, the general framing of the messages may help to normalize the use of care and create

positive associations for the patients, which may help patients who avoid doctors because of negative stigma. In addition, DTCA can provide information on what symptoms may constitute a medically-treatable condition, and clarify what treatments exist for it. This could encourage patients who have a 'low perceived need' but an appropriate condition for treatment, or those who are completely unaware that their symptoms are abnormal to seek care. Finally, the presence of DTCA could remind forgetful patients to schedule or show up for appointments with their doctors in the same way that DTCA could potentially help with adherence to prescribed drug regimens. On the other hand, DTCA could also lead to unnecessary office visits if it encourages patients with low medical need to seek care.

2.2 DTCA Regulatory History

DTCA and its regulation has a long history in the US, much of which predates the invention of the television. In 1906, the newly founded Food and Drug Administration (FDA) passed the Pure Food and Drugs Act, which required that no information on the label for a drug could be false or misleading, and further required the disclosure of known harmful substances, such as heroin (Donohue, 2006). With the expansion of the FDA's regulatory power over the approval of new drugs, the Food, Drug, and Cosmetic Act (FDCA) of 1938 mandated that only drugs that had been sanctioned by the FDA could be marketed. In addition, this bill made it necessary to include information on directions-for-use, and required that the labels be written in a way that is accessible to the end-users of the product (Donohue, 2006).

Momentum to increase the scope of oversight by the FDA gained steam in the 1960s, partially driven by concerns over birth defects caused by the drug thalidomide. Direct regulatory authority over the contents of advertisements for prescription drugs was granted to the FDA in

1962 through the Kefauver-Harris Amendment to the FDCA, and by 1969, guidelines were in place whereby advertisements were required to present balanced evidence on drug effectiveness side-effects, as well as provide material relaying the relevant information on all risks associated with the drug (Donohue, 2006; Ventola, 2011). The regulations, as written, deterred pharmaceutical manufacturers from engaging in televised DTCA due to the prohibitive expense of purchasing the additional advertising time necessary to convey the information, and causing some manufacturers to lobby for regulatory change (Wilkes, Bell, & Kravitz, 2000).

In 1997, DTCA guidelines were revised after a public hearing, resulting in reduced burdens on advertisers which required them to convey only the most salient risks in their advertising, and the requirement to provide information to consumers regarding where to find more detailed drug information (Rosenthal et al., 2002; Wilkes, Bell, & Kravitz, 2000). After 1997, spending on televised DTCA began increasing at an exponential rate, increasing from $500 million in 1995 to a peak of $5.5 billion in 2006, before settling at just over $4 billion by 2010 (Dave, 2013). As noted above, spending per capita on prescription drugs has also increased at an accelerated pace over the same time period, rising from roughly $250 per person in 1996 to nearly $750 per person in 2006 (Alpert, Lakdawalla, & Sood, 2015).

2.3 Related Literature

Research on the effects of DTCA have largely found a positive, causal relationship with spending on prescription drugs (see Dave 2013 for a summary of this literature). These effects are sizeable, with studies showing that 19% of the increase in prescription drug spending between 1994 and 2005 is causally attributable to DTCA (Dave & Saffer, 2012). Since the 2013 review (Dave 2013), several additional studies have found a positive relationship between DTCA and drug use. Alpert, Lakdawalla, & Sood (2019) exploit the same exogenous variation as the

present study and show increased take-up of pharmacotherapy for several prominent chronic conditions resulting from increased DTCA. In addition to an increase in the use of advertised drugs, the authors also identify a sizeable spillover effect in which DTCA increases the use of non-advertised generic drugs. Two recent papers also finds significant spillover into generics and competitor drugs in the market for antidepressants (Shapiro, 2018), and a net market-expansion effect as opposed to market-stealing in the market for statins as a result of DTCA (Sinkinson & Starc, 2019).

One interpretation of these studies is that the mechanism through which DTCA operates is through increased demand by consumers with unmet medical needs as opposed to 'stealing' market share from competitors or encouraging costlier treatments. Overall, the majority of studies have found that DTCA expands the market by creating demand for treatment for the advertised conditions. The clinical literature is mixed on whether growing the market for drugs is always beneficial, and recommendations for use vary based on a variety of clinical factors, as in the case of age-related statin recommendations (US Preventative Services Task Force, 2016). In contrast, an economic counterfactual analysis looking specifically at the market for statins found that a ban on DTCA would reduce the number of users initiating statin use, which the authors find to be both welfare-reducing and not cost-effective, given the benefits of these drugs (Sinkinson & Starc, 2019).

We contribute to the literature by estimating the effects of DTCA for prescription drugs on office visits. We also examine the types of treatment received in these visits, as well as measure the trajectory of care that occurs after DTCA. While descriptive surveys have found that a large fraction of consumers exposed to DTCA discuss the advertising with their physician (Hollon 2005) and that primary care physicians fulfill a majority of these drug-specific requests

(Becker & Midoun, 2016), there has been only one study to our knowledge that has empirically estimated these effects. A study by Iizuka and Jin (2005) found that increases in DTCA spending is associated with an increase in visits to a physician's office – specifically in office visits that result in a prescription. However, the authors did not decompose the type of office visits resulting in a branded prescription or generic drug, or measure follow-up visits. Additionally, they acknowledge that the lack of a quasi-experimental design makes a causal interpretation of their results suggestive. Another contribution of our analysis is that, while most studies in the literature limit their analysis to a single class of drug (exceptions being Alpert et al., 2019 and Iizuka & Jin, 2005), our study captures the effects of DTCA on several therapeutic classes for common chronic conditions. This makes our results more generalizable and policy relevant, as any change in FDA regulations is likely to affect advertising for all classes of drugs.

3. METHODS

3.1 Data and Empirical Methods

3.1.1 Advertising Data

Our advertising data comes from the Nielsen Ad*Views^{TM} database. These data contain information about pharmaceutical television advertisements appearing in local media markets between 2004-2010. Our study focuses on television advertising, which accounts for more than two-thirds of total DTCA expenditures during our time period (Avery et al. 2012). Additionally, television advertising for prescription drugs is still common in more recent years (Statista 2021), as elderly populations are more likely to watch traditional television (Nielsen 2020). Television advertising decisions in the United States are made at the Designated Marketing Area (DMA)

level. There are 210 DMAs (each made up of one or more counties) and all homes within a DMA see the same commercials, conditional on watching the same programs at the same time.

We limit our advertising data on three key dimensions. First, we obtained data for the top 100 DMAs in the country–these 100 DMAs represent 86.5% of all television viewers and account for over 95% of prescription drug advertising spending (Alpert et al. 2019). Second, television advertisements are shown on a national and local basis. National advertisements are seen by viewers in all DMAs across the country, while local advertisements vary across DMAs. We use only data on local ads since there is scope for targeting different amounts of advertising to different markets and our identification strategy relies on geographic variation in advertising over time. Third, we limit our advertising data to advertisements for one of our five chronic conditions: hypertension, hyperlipidemia, diabetes, osteoporosis, depression. These conditions are among the most highly advertised during our study period (CDC 2008; CDC 2016; NIMH 2019).

Our measure of DTCA exposure is Nielsen's gross rating points (GRPs), the industry standard for measuring television viewership. Rating points are derived from data collected on actual viewership of television commercials for a sample of television-owning households in each DMA. Nielsen uses a combination of meters that are attached to televisions and paper diaries to record what each household television is watching each day. In our data, we observe "rating points" for each brand-name prescription drug, DMA, quarter, for those aged 2-64, which is defined as follows:

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

Where $Rating\ Points_{jmat}$ are computed as the total number of views of commercials for brand-name drug j in market (DMA) m, in age-group a, and in quarter t divided by the total number of

individuals in the sample in that group, multiplied by 100. In our analysis, we divide the rating points measure by 100 in order to interpret the measure as average views per person.

3.1.2 Ingenix Claims Data

We construct measures of outpatient and drug utilization using a database of insurance claims from more than 40 large national employers, including many Fortune 500 companies, for 2004-2010. 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; Alpert et. al. 2019). The pharmacy claims include detailed information on all outpatient prescription drug purchases and the outpatient claims provide detailed information on office visits (e.g. diagnoses, physician specialties, dates of service).

As with many claims datasets, we have limited demographic information and are only able to include gender, age, marital status, and the three-digit ZIP code of residence as covariates. For all of our analyses, we restrict our sample to individuals who are continuously enrolled for at least one calendar year and are aged 40-60.[13] We focus on this group as they are more likely to seek treatment for the chronic conditions we are studying.

In order to match the claims and enrollment data to the Nielsen advertising data, we must match each participant to a DMA based on their three-digit ZIP code of residence. Our data is limited in that DMAs are defined in terms of five-digit ZIP codes and our claims data is only available at the three-digit ZIP level. Some three-digit ZIP codes overlap multiple DMAs, so it is not possible to assign these individuals to a single DMA with certainty. To assign measures of

[13] We exclude ages 61-64 out of concern that individuals close in age to Medicare eligibility may change their drug utilization behavior in anticipation of future Part D coverage (Alpert, 2016; Alpert et al. 2019).

advertising to these individuals, we assign them the population-weighted[14] average of advertising exposure across all of the possible DMAs where they could reside.[15] Consequently, we use the three-digit ZIP code as the effective advertising market rather than the DMA, since all individuals residing in a three-digit ZIP code have the same advertising exposure.

3.1.3 Population Data

Our analysis leverages the fact that different DMAs contain different elderly population shares. To construct this instrument, we use data from the 2000 Census[16] to compute the fraction of each three-digit zip code that is aged 65 and over (i.e., eligible for Medicare). We keep this measure fixed at the 2000 levels so our identification comes only from differences in elderly populations share, not within three-digit zip code changes.

3.2 ECONOMETRIC MODEL

The goal of our analysis is to estimate the impact of DTCA on office visits for the near-elderly population. Our analytic strategy is separated into three parts. In the first part (Section 3.2.1) we examine the overall impact of DTCA on office visits. In the second part (Section 3.2.2), we focus on the type of office visits potentially created by DTCA and decompose this effect into office visits with and without a later drug claim. In the third and final part (Section 3.2.3), we aim to analyze the persistence of the DTCA effect by examining regular care received two, three, and four years after an initial office visit. In all parts, our identification relies on geographic variation in elderly population share within a three-digit ZIP, before and after the introduction of Medicare Part D.

3.2.1 Empirical Strategy

[14] Population weights for the 5-digit ZIP code level come from the 2000 Decennial Census.
[15] About 30 percent of individuals receive this probabilistic measure of advertising exposure.
[16] Individuals who cannot be matched to a single DMA are assigned the population-weighted average of the elderly share across all possible DMAs where they could reside.

Our identification of a causal effect of DTCA on office visits is based on quasi-experimental variation in exposure to advertisements induced by differential surges in advertising for drugs following the implementation of Medicare Part D. The implementation of Medicare Part D expanded the demand for drugs in the elderly population by providing prescription drug coverage for Medicare recipients. Since it is plausible that advertisers have access to demographic information regarding the share of the elderly population in a zip code, and that they are more likely to disproportionately advertise in zip codes with high shares of elderly citizens who gained access to this new prescription drug benefit, we expect to see disproportionately higher rates of DTCA in zip codes with large elderly populations after Medicare Part D was implemented (January 2006). While it is not possible to isolate the causal effect of DTCA on utilization for this elderly population because the effect is confounded by the receipt of Medicare Part D benefits, the near-elderly population would be exposed to similar levels of zip code-specific advertising without being affected by the additional insurance benefits. Therefore, we exploit this plausibly exogenous variation in DTCA exposure for the near-elderly population to isolate the causal effect of DTCA on our outcomes of interest.

In this section, we employ three different empirical strategies—a reduced form difference-in-differences model, an event-study, and an instrumental variable strategy.

Difference-in-differences design: We construct a reduced-form model difference-in-difference analysis to estimate the effect of being in a ZIP code with a high share of elderly adults after the implementation of Medicare Part D on our outcome variable. We accomplish this by creating a dichotomous variable, $post_q Xhigh_z^{65}$, indicating that an observation represents a quarter following implementation of Medicare Part D (2006-2010) and a ZIP code that has a

high share of elderly (65+) persons. A ZIP code with a high share of elderly is defined as having a share that is above the median value for all ZIP codes as of 2000. The model for this design is given below:

$$Y_{zqc} = \beta_1 post_q X high_z^{65} + \lambda_q + \pi_c + \gamma_z + \epsilon_{zqc} \quad (1)$$

Where Y_{zqc} represents the average number of office visits per 1,000 people (or other outcomes) with a diagnosis code for condition *c* in ZIP code *z* in quarter *q*. The vectors $\lambda_q, \pi_c, and\ \gamma_z$ denote quarter, condition, and ZIP code fixed effects, respectively, and ϵ_{zqc} is an error term. Standard errors are clustered at the ZIP code level to account for serial correlation.

Event study design: In order to test the effects of living in a ZIP code with a high elderly population share over time, we estimate an event-study design that allows us to estimate the effect in each quarter leading up to and following implementation of Medicare Part D. This design is similar to the difference-in-differences design described above, with the slight modification that the single independent variable in the difference-in-differences model becomes a vector of dichotomous variables, indicating that an observation represents a particular quarter in a ZIP code with a high share of elderly individuals. This vector is represented as $qtr_q X\ high_z^{65}$ in our model, which is a vector of 27 elements corresponding to the 28 quarters in our data, with the omission of quarter 4 in 2005 as our reference category. The model is as follows:

$$Y_{zqc} = \sum_Q qtr_q X\ high_z^{65} + \lambda_q + \pi_c + \gamma_z + \epsilon_{zqc} \quad (2)$$

Instrumental variables design: Our main independent variable of interest is advertisement viewership, though since we believe that advertising exposure is endogenous, we use an instrument to isolate the causal effect of viewership on the total number of office visits. The instrument used is the $post_q X high_z^{65}$ indicator that was the independent variable in the reduced-form model described above. We use this to instrument for per capita views (i.e.,

Nielsen ratings points, denoted as $ratings_{zqc}$) of advertisements related to chronic condition *c*, in ZIP code *z*, in quarter *q*. This predicted views per capita measure is then used as our independent variable to explain variation in our outcomes for the corresponding chronic condition. We operationalize this design using a two-stage least squares model, as shown below:

$$ratings_{zqc} = \delta_1 post_q X high_z^{65} + \lambda_q + \pi_c + \gamma_z + \mu_{zqc} \quad (3)$$

$$Y_{zqc} = \beta_1 \widehat{ratings}_{zqc} + \lambda_q + \pi_c + \gamma_z + \epsilon_{zqc} \quad (4)$$

Additionally, we test an alternative specification for all of our models where we let the share of elderly adults be a continuous variable as opposed to a dichotomous variable. In all models we cluster the standard errors at the ZIP code level.

Our empirical strategy relies on the assumption that the change in the use of office visits in the non-elderly population in high elderly share markets after the implementation of Part D is due to change in DTCA after Part D and not changes in other factors. For example, it is possible that our identification assumptions might be violated if Part D changed physician practice styles in high elderly share markets where a significant fraction of the population gained prescription drug coverage. To explore this possibility, Alpert et al. (2019) conduct two tests to validate the identification assumption.

The first test is a placebo test examining whether there were differential effects of Part D on non-elderly drug utilization for drug classes that *do not* advertise (e.g., diuretics). We would expect that other spillover effects from Part D (e.g., prescribing behavior changes) would affect utilization for all drug classes, whether or not they advertised. They find no differential change in use of non-advertised classes of drugs in high versus low elderly share markets after the implementation of Part D.

In another indirect test of the identification assumption, Alpert et al. (2019) rely on the fact that DTCA does not vary within a DMA, because local television station signals reach all households. Physician practice styles, however, are more localized and can vary within a DMA. For example, if Part D changed physician practice styles we should expect different effects in local areas within a DMA depending on the elderly share of the local area. They find that utilization did not respond to Part D differentially by elderly share within DMAs, which provides evidence against possible confounders of Part D that are correlated with elderly share at the sub-DMA level (e.g., changes in other promotional activities, physician behavior, pharmacy behavior, etc.). While this robustness check does not factor in alternative forms of advertisements, such as electronic advertisements that may be found on streaming services, it should be noted that this would be less of concern during our study period from 2004-2010 as spending on internet DTCA was less than 4% of spending on television DTCA as of 2009 (Mackey, Cuomo, & Liang, 2015). Another possibility would be that patients who gained Part D increased their demand for office visits. While this could crowd out visits by the near elderly leading to a decline in office visits in areas with high elderly share, it means that our estimates would provide a lower bound on the effects.

3.2.2 Impact of Advertising on Office visits

In the first analysis, our key outcome variable is the average number of office visits per 1,000 people[17] for a particular chronic condition[18] in a given three-digit ZIP code, in a given quarter. Our sample is composed of individuals aged 40-60 years old who have full-year

[17] An office visit is defined as a claim with a Common Procedural Terminology code of "99201", "99202", "99203", "99204", "99205" "99211", "99212", "99213", "99214", or "99215"

[18] Office visits for a particular chronic condition are identified as those having a diagnosis code (International Classification of Diseases, Ninth Revision) on a claim for an office visit that corresponds to a diagnosis defined by the Chronic Condition Warehouse for that chronic condition

insurance coverage for at least one calendar year between 2004-2010. These condition-specific visits are summed up for an individual in a quarter, and then the mean of all individuals is taken at the ZIP code, quarter, condition level, including all of the individuals with 'zeroes' for this measure. The result represents the average number of office visits for a condition that a person in a ZIP code has in each quarter. This number is then multiplied by 1,000, resulting in an interpretation of the outcome as the number of office visits for a condition per 1,000 people in a given ZIP code in a given quarter.

3.3.3 Decomposition Analysis

Our second analysis decomposes the DTCA effect into those that received advertised or non-advertised branded drugs, those that received generic drugs, and those that received no drugs at all. For this analysis, we restrict our sample to those who did not have an office visit and did not have a drug claim for a given chronic condition in 2005. We do this for three reasons. First, we are particularly interested in understanding the effect of DTCA on engaging individuals with the healthcare system who had not previously been engaged. Second, we want to observe behavior after an initial office visit, specifically what drugs individuals use after an office visit. For this analysis we limit our sample to those who were continuously enrolled from 2005-2010 but who did not receive care in 2005, which is our pre-period year. This allows us to more confidently isolate the effects of DTCA since the treatments will be on a more homogenous group of patients – those starting from the beginning of a treatment course – as opposed to a heterogeneous group in various stages of ongoing treatment. As before, we collapse the individual level outcomes to the ZIP code level taking the population means as our main outcomes.

The goal of this analysis is to understand what types of care are received after the initial office visit initiated by DTCA. First, we want to understand the extent to which exposure to DTCA has its intended effect of increasing the use of advertised drugs. Second, we want to understand spillovers of DTCA to non-advertised branded drugs and generic drugs (which are typically not advertised). Finally, we want to understand spillovers to non-drug therapy or drug-therapy for diseases not specified during the initial office visit due to increased engagement with the healthcare system spurred by DTCA. To this end, we created five measures of office visit utilization corresponding to different types of behaviors in an attempt to add nuance to the discussion of the mechanisms through which DTCA operates. The measures are:

1. Total summed office visits from 2006-2009 with a diagnosis code for one of our chronic conditions;
2. Total summed office visits from 2006-2009 that were followed by drug claim for a non-advertised, generic drug treating the same chronic condition that the office visit was for, within 365 days[19] of the office visit;
3. Total summed office visits from 2006-2009 that were followed by a drug claim for a non-advertised, branded drug treating the same chronic condition that the office visit was for, within 365 days of the office visit;
4. Total summed office visits from 2006-2009 that had a drug claim for an advertised drug treating the same chronic condition that the office visit was for, within 365 days of the office visit; and

[19] 365 days was chosen for our main specification as it allows a sufficient amount of time between an office visit which initiates drug use and receipt of a drug, while allowing for intervening non-pharmaceutical first-line therapies. It also allows for enough time for a provider to make an accurate diagnosis of a chronic condition through rule-outs and laboratory testing before starting a patient on drug therapy. Several other windows of time were tested to ensure that our results are robust to this particular assumption, including 30, 60, 90, 180, and 1460 days. These results are available in the Appendix.

5. Total office visits from 2006-2009 that had a drug claim for a drug treating a different chronic condition than what the office visit was for, or, had no drug claims within 365 days of the office visit.

For all five of these outcomes, we also estimate a binary outcome where we test for the presence of any office visit from 2006-2009 instead of total visits. Finally, while our decomposition analysis pools our five chronic conditions into a single measure, we further stratify these results by chronic condition to test for heterogenous effects (available in the Appendix).

Our identification strategy for this analysis will be similar to the one described above, where we leverage the exogenous variation in ZIP code-level exposure to advertising brought about by implementation of Medicare Part D. We again limit our sample to the near-elderly who do not receive the benefit of Medicare Part D, but still experience the increased exposure to DTCA as a result of living in a zip code with a high elderly population share.

We use an instrumental variable design, with the share of elderly in a ZIP code instrumenting the amount of DTCA in that ZIP code from 2006-2009 (entirely after the implementation of Medicare Part D). This instrumental variable design is similar to the ones used in the previous section, although with a slight modification to the main independent variables. Whereas the previous independent variable was an interaction of two indicators – one denoting that an observation represents the post-implementation period, and one identifying an observation as being in a ZIP code with a high elderly population share – the independent variable in this model is simply an indicator for being in a ZIP code with a high elderly population share. The reason for this is that our unit of analysis no longer has a temporal dimension since the outcome is the sum of all office visits from 2006-2009. Further, the entirety of our analysis happens post-implementation of Medicare Part D for this sample because no

individual in the sample had any office visits or drug claims for these chronic conditions in the year prior to 2006, by construction. Given that this method uses only the post-implementation period (unlike the analyses above), we interpret these results as more suggestive.

The model for our difference-in-differences design is as follows:

$$Y_{izc} = \beta_1 high_z^{65} + X_{iz} + \pi_c + \epsilon_{izc} \qquad (5)$$

Where Y_{izc} is our outcome variable for individual *i* in ZIP code *z* for condition *c*, π_c captures condition fixed-effects, and X_{iz} is a vector of age and gender covariates for individual *i* in ZIP code *z*.

Similar to before, we use presence in a ZIP code with a high elderly share as an instrument for advertisement viewership resulting from increased exposure to DTCA in these regions. The model is as follows:

$$ratings_{izc} = \delta_1 high_z^{65} + \pi_c + \mu_{izc} \qquad (6)$$

$$Y_{izc} = \beta_1 \widehat{ratings}_{izc} + \pi_c + \epsilon_{izc} \qquad (7)$$

As with our previous analyses, we test a specification where we replace our dichotomous instrument for being in a ZIP code with a high elderly share with a continuous instrument representing the share of elderly persons in the ZIP code as of the fourth quarter of 2005.

2.2.2. Persistence Analysis

In addition to understanding what type of office visits DTCA induces in new patients (e.g. receipt of an advertised pharmaceutical, engagement in non-pharmacological treatment, etc.), it is also of interest how persistent these DTCA-inspired health behaviors are. While it has been posited that spurring contact with providers is a potential positive externality of DTCA, it can be argued that if this contact does not lead to persistent health-seeking behavior then the DTCA may have simply encouraged overtreatment for a patient who had no need to see a

physician. To test for this, we use the same sample described in the decomposition analysis but create additional measures that capture follow-up visits to physician offices after the initial 'new' visit.

Our outcome variables represent persistent use over time, defined as having office-visits in consecutive calendar years in the period from 2006-2009. For each of our outcomes listed in the decomposition analysis above (e.g., any office visit, any office visit without a prescription drug within 365 days, etc.) we create a binary indicator for whether a patient had that particular outcome in 2, 3, and 4 consecutive calendar years. For example, a patient characterized as having four consecutive years of office visits with no prescription drugs would have to have an office visit for one of our chronic conditions in 2006, 2007, 2008, and 2009, and have no drug claim for a drug that treats a condition recorded on any of those office visits within 365 days of any of the visits. Since all of these patients were insured, but had no office visits or drug claims for our chronic conditions in 2005, finding persistence in drug treatment may indicate that a patient started a new course of therapy and continued on this course. The empirical strategies to identify the effect of DTCA on our persistence measures are the same as described for our decomposition analyses.

4 RESULTS

3.1. Impact of Advertising on Office visits

In Table 1, we present overall descriptive statistics at the three-digit ZIP code level. Prior to the implementation of Medicare Part D, the near elderly living in high elderly population share ZIP codes were slightly older (50.2 years vs 49.8 years) and slightly more likely to have had an office visit (8.2% vs 7.3% for hypertension; 4.6% vs 4.2% for hyperlipidemia; 1.9% vs 1.7% for diabetes; 0.3% vs 0.2% for osteoporosis; 0.7% vs 0.7% for depression). The treated prevalence

estimates are roughly comparable to external data sources (CDC 2008; CDC 2016; NIMH 2019). There does not appear to be a strong pre-period difference in DTCA views per person across ZIP codes, with high elderly population share ZIP codes having more views per person than low elderly population share ZIP codes for hypertension (0.48 vs 0.46), diabetes (0.93 vs 0.86), and osteoporosis (4.50 vs 4.34) and the reverse for hyperlipidemia (10.51 vs 10.54) and depression (5.96 vs 6.13).

In Figure 1, we present unadjusted trends in advertising pooled across conditions and separately for each of our five chronic conditions for those in high and low elderly population share ZIP codes. Prior to the introduction of Medicare Part D, trends in advertising are fairly similar across ZIP codes, however, we do begin to see a diversion in trends in the three quarters prior to implementation of Medicare Part D. This is not surprising as pharmaceutical companies knew Medicare Part D was coming and anticipatory effects of the policy have been shown in other contexts (Alpert 2016). After Medicare Part D implementation, we see stronger divergence between the two types of ZIP codes, with those in high elderly population share ZIP codes being exposed to significantly more advertising. Separating out by condition, this divergence is mostly driven by hypertension, hyperlipidemia, and osteoporosis.

Figures 2 and 3 present trends in any office visit utilization (Figure 2) and total office visits (Figure 3), separately by high and low elderly population share ZIP codes. Pre-implementation trends in office visit utilization appear fairly stable for most conditions, though those in high elderly population share ZIP codes have a consistently higher level of office visit utilization than those in low elderly population share ZIP codes and this divergence increases after the implementation of Part D. We explicitly test for pre-period trend differences in the context of our event study results below.

Table 2 presents regression results for our overall analysis of DTCA on office visit utilization. The columns on the left (1 and 2) present the reduced-form difference-in-differences results showing the effect of living in ZIP codes with a high elderly population shares. The panels on the right (4 and 5) present two-stage least squares estimates showing the direct effects of ZIP code-level advertisement viewership on our outcomes. In Panel A we use a continuous measure for elderly population share. We find that 43.2 more people per 1,000 would have at least one office visit in a given quarter after the implementation of Medicare Part D for ZIP codes with a one hundred percent elderly share relative to a zero percent share (Column 1A). Similarly, we find an effect of 65.3 additional total office visits per 1,000 people in a ZIP code, in a quarter (Column 2A). We find similar results in Panel B when we use a dichotomous measure of elderly population share, separating ZIPs into high and low elderly population share. Here, we find that high elderly population share ZIP codes have 2.8 more people with any office visit per 1,000 relative to low elderly population share ZIP codes (Column 1B) and 3.9 more total visits per 1,000 (Column 2B). These effects are fairly sizeable---2.8 more people with any office visit off a base of 32.5 people with office visits represents an 8.6% increase in people with office visits. On the right-hand side of Table 2, we present two stage least squares estimates. In Column 3, we display the results from our first stage and find that our interaction of elderly share and post-indicator ($post_q Xshare_z^{65};\ post_q Xhigh_z^{65}$) is a strong instrument for advertising views per person (F=32.7 for continuous instrument; F=21.2 for dichotomous instrument). In Columns 4 and 5 we show the second stage estimates for the 2SLS models and find large increases in office visits due to advertising. Column 4 shows that an additional ad viewed would lead to an increase of 6.8 office visits per 1000 people. The effect is similar for the continuous instrument and slightly larger for total office visits. In Appendix Table A1-1 through A1-5, we

present these results separately for each chronic condition and find our results are mostly driven by hypertension, hyperlipidemia, and osteoporosis, which are the conditions that saw the largest advertising increases.

Figures 4 and 5 show results from our event study analysis with *any office visit* as one outcome variable (Figure 4) and *total office office visits* as another (Figure 5). These event study results confirm our findings from Table 2. Prior to the implementation of Medicare Part D, the difference-in-differences coefficients are, for the most part, statistically indistinguishable from zero. This contrasts from the coefficients after Part D implementation, which are all above zero and statistically significant. Tabular model results (Appendix Table A2-1) and model results separately by condition (Appendix Tables A2-2 through A2-6) are available in the Appendix.

3.2. Spillover effects

In Table 3, we present results from our decomposition analysis. These estimates are the second stage estimates from our 2SLS, person-level models for individuals who did not have an office visit or pharmaceutical claim for one of the chronic conditions in the pre-period. We present results for each of our five separate outcome variables defined above. Descriptive statistics for this subsample are available in Appendix Table A3. In Table 3, the results from Column 1 are the most comparable to our findings in Table 2. We find that for our continuous instrument (dichotomous instrument), an additional DTCA view per person leads to a 3-percentage point (5.4 percentage point) increase in the likelihood of any office visit off a base of 11 percent. We decompose this effect into office visits that are followed by a drug claim for the chronic condition (Columns 2, 3, and 4) and office visits that are not followed by a drug claim

for the chronic condition (Column 5).[20] In Column 2, we see that part of this increase is coming from office visits that have a claim for a non-advertised generic afterwards (continuous instrument: 1.0 percentage point change; dichotomous instrument: 1.4 percentage point change) and, in Column 4, we see that part of the increase is coming from office visits that have a claim for an advertised branded drug afterwards (continuous instrument: 0.2 percentage point change; dichotomous instrument: 0.6 percentage point change). Column 5 shows that the largest increase comes from office visits that are either followed by a drug claim for a condition that is different than the condition recorded in the office visit or not followed by a drug claim at all (continuous instrument: 2.2 percentage point change; dichotomous instrument: 4.6 percentage point change).

We find similar results when examining the effect on total number of office visits (Table 4). Overall, we find that increases in office visits due to DTCA were associated with substantial spillovers. Of the total change in use of office visits due to DTCA (0.15 additional total office visits per an additional DTCA view per person), for the models using a continuous instrument, only 11% were associated with use of advertised drugs (0.02 additional visits) and the remaining 89% were associated with spillovers to non-advertised brands (<0.01 additional visits), generics (0.05 additional visits), and drugs for unrelated diseases or non-drug therapy (0.08 additional visits). Spillovers to drugs for unrelated diseases or non-drug therapy were the most significant and accounted for 54% of the total DTCA effect on office visits.

The results in Tables 3-4 examine office visits with and without a drug claim in the 365 days after the initial office visit. In Appendix Tables 4 and 5, we show how the results change

[20] It is important to note that the results in Columns 2-5 do not sum to the result in Column 1 as our outcome variable is examining if the individual had *any* care of that type. It is possible that some individuals had more than one type of event (a new office visit followed by a branded drug claim and a generic claim).

when we vary the length of the window allowed between the initial office visit and the drug claim from 30 days to 365 days.

3.3. Persistence Analysis

In Table 5, we use the same subsample as our decomposition analysis (i.e., no care received in the pre-period) to examine the effect of DTCA on the trajectory of care received. Specifically, we examine the effect of DTCA on consecutive, annual office visits, office visits with corresponding drug claims, and office visits without corresponding drug claims. In Column 1, we present the second stage results for the effect of advertising views per person on receiving care for two consecutive years after initiating a new treatment regimen. We see that an increased view per person leads to a 1.6 percentage point increase in the probability of having an office visit each year for two consecutive years. This is slightly more than half of the effect we found for a single office visit in Table 4, Column 1. This effect size drops as we move to Columns 2 and 3, which examines the effect on having an office visit for three and four consecutive years, respectively. Table 5, Panels 2-5 decompose this persistence effect into the probability of having consecutive years with an office visit with any drug that treats the chronic condition recorded for that visit, visits with a generic drug treatment, a non-advertised branded drug treatment, an advertised drug treatment, and those with unrelated or non-drug treatments. As with the decomposition analysis from Tables 3 and 4, the largest continuous effect is on office visits with unrelated or non-drug treatments. However, this increase in non-drug office visits diminishes over time such that by the fourth year after the initial visit, the increase in continuous non-drug utilization is indistinguishable from the increase in continuous office visits with a pharmacological component. There are several plausible explanations for this tapering over time. It could indicate that individuals are less likely to adhere to behavioral interventions in the long-

term, or that doctors are more likely to switch treatment regimens to those with a pharmacological component if patients are not responding to first-line treatments. However, it may also imply that the health of the individuals who undergo these behavioral changes improves such that they no longer need to frequently visit their physician. Lastly, it is also possible that the patient did not need additional office visits because they had low medical need and were simply induced to visit the doctor because of DTCA. This type of visit would not require follow ups.

4. DISCUSSION AND CONCLUSIONS

In this study, we examined the effect of DTCA on physician visits while decomposing the effect into visits that resulted in a drug claim and visits that did not, as well as examining the persistence of care created by DTCA. We find significant effects that add to the known direct effects of DTCA found in prior work (Alpert et al. 2019, Shapiro 2018, Eisenberg et al. 2017, Sinkerson and Stark 2015, Avery et al. 2012). Overall, our instrumental variable estimates suggest that 9.8 people per 1,000 have an office visit induced for every view-per-person of prescription drug advertising. While some share of this increase in office visits corresponds to increased prescribing of advertised branded drugs, the majority of these effects seem to be driven by office visits that result in the prescription of generic drugs, or in visits that result in the receipt of non-drug treatments or an unrelated drug. Finally, our results persist for up to four years after the initial increase in DTCA exposure, indicating that DTCA results in continuous engagement with the healthcare system, although these effects attenuate considerably over time. These overall results are consistent throughout our various study designs, including reduced-form difference-in-differences, event study models, and IV estimation using two-stage least squares.

They are also robust to alternate instrument specifications, as well as a variety of specifications for defining our outcome variables.

As policymakers continue to debate the appropriateness of DTCA, understanding the total welfare consequences of DTCA is necessary. Our analysis provides two important insights to this debate. First, we find that increased DTCA exposure is associated with increases in not just physician visits that eventually lead to a drug claim, but physician visits that never lead to a drug claim for that chronic condition. This latter effect may represent a positive or negative externality of DTCA---encouraging patients to engage with the non-pharmacological side of the healthcare system, or, alternatively, encourage waste and low value care. While it is not possible to definitively discern whether the increase physician visits are welfare enhancing or reducing, our results suggest that the increase in office visits with generic drugs, and office visits that do not result in a drug claim for the diagnosed condition are an order or magnitude larger than the increase in office visits resulting in a branded drug. Since one of the potential downsides to DTCA was hypothesized to be substitution of more expensive, brand-name drugs in place of generics or non-pharmacological treatments, it is plausible that this threat is not as large as opponents of DTCA have feared. The second important insight from our analysis is that a portion of the demand plausibly created by DTCA is persistent. While effect sizes decrease, we see continued engagement with physician up to at least four years after an initial office visit. The fact that consumers are continuing to engage with their physician suggest that DTCA may have a lasting effect, though, we are unable in this analysis to separate out a lasting DTCA effect from one of continued DTCA exposure.

Our analysis has several important limitations. First, our analysis is based on a natural experiment (the introduction of Medicare Part D) and does not use experimental variation. Large

field experiments on the effectiveness of advertising have suggested that measuring the accurate returns to advertising in an observational setting presents challenges (Lewis and Rao 2015), specifically, that it is difficult to precisely estimate small effects when the outcome variable has a high variance. While experimental studies come with their own challenges (i.e., challenges in external validity), we recognize that future research should attempt to confirm our findings in an experimental framework. Second, our claims data represent a convenience sample of large, self-insured U.S. firms. It is unclear if our results would be generalizable to those with different types of insurance. Third, in order to fully evaluate the welfare effects of DTCA, one must also consider externality effects outside of the healthcare system. For example, exposure to DTCA might encourage patients to engage in a host of healthy behaviors, or decide to engage in unhealthy behaviors now that they know pharmacological treatments are available at a later stage. While understanding these spillovers is important, they go beyond the scope of our claims data analysis.

In this study, we found that DTCA leads to increased office visits, both with and without a subsequent drug claim, and, that this increase is persistent for several years. As policymakers continue to debate the appropriateness of DTCA, they need to consider all effects of DTCA, not only direct effects on prescribing. Future research should continue to decompose these effects and better understand which increases in care attributable to DTCA are high and low value.

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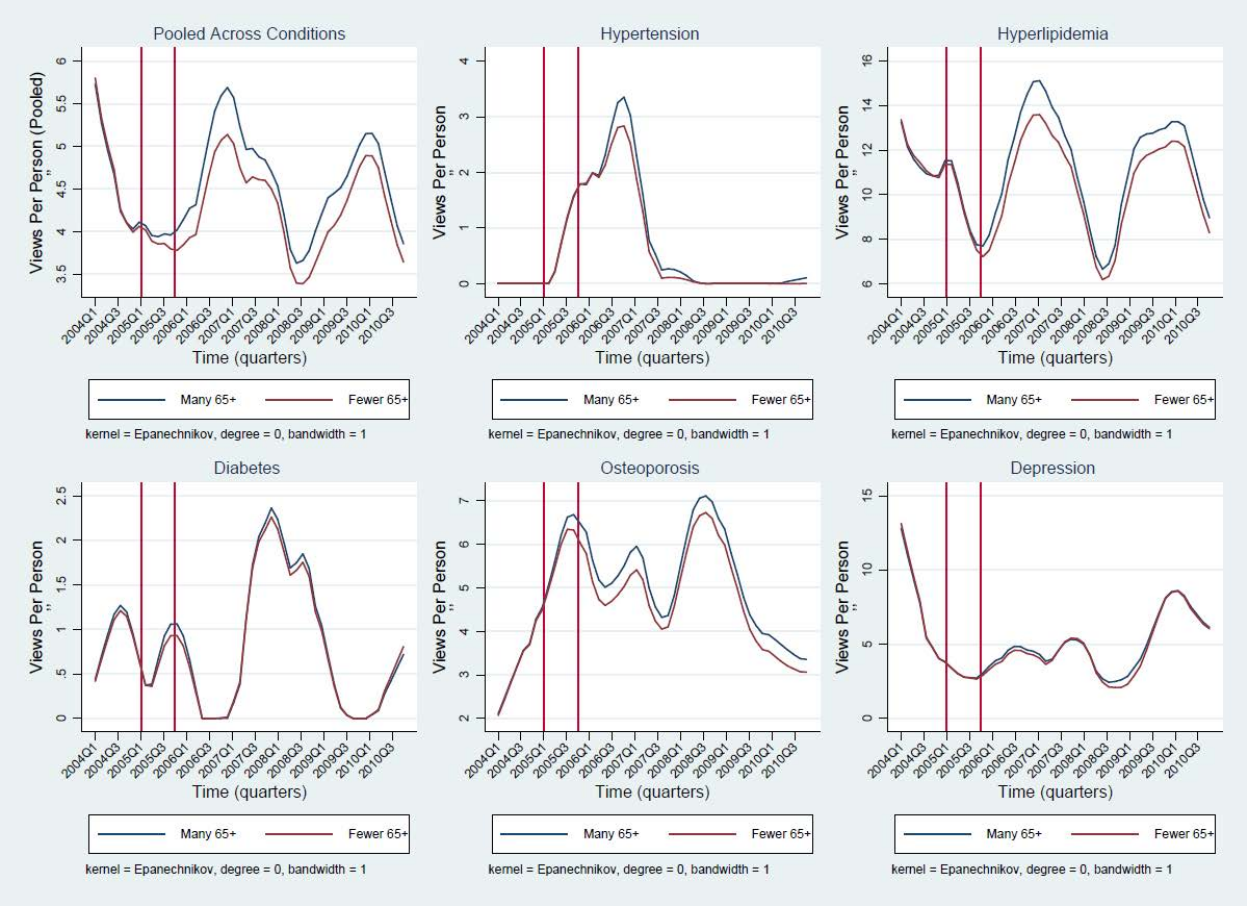
Table 1: Descriptive Statistics For High and Low Elderly Share ZIP Codes, Before and After Medicare Part D Implementation

		Pre				Post			
		Low 65+		High 65+		Low 65+		High 65+	
Variable	Chronic Condition	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age	Hypertension	49.8	1.4	50.2	1.3	49.9	1.4	50.6	1.4
	Hyperlipidemia	49.8	1.4	50.2	1.3	49.9	1.4	50.6	1.4
	Diabetes	49.8	1.4	50.1	1.3	49.9	1.4	50.6	1.4
	Osteoporosis	49.8	1.4	50.1	1.3	49.9	1.4	50.5	1.3
	Depression	49.8	1.4	50.1	1.3	49.9	1.4	50.5	1.3
Views Per Person	Hypertension	0.46	1.35	0.48	1.35	0.74	1.39	0.86	1.65
	Hyperlipidemia	10.54	4.59	10.51	4.45	10.57	3.99	11.58	3.94
	Diabetes	0.86	0.96	0.93	1.07	0.74	1.39	0.75	1.40
	Osteoporosis	4.34	2.22	4.50	2.26	4.75	1.90	5.11	1.82
	Depression	6.13	5.42	5.96	5.23	4.67	3.04	4.89	2.77
Any Office Visit	Hypertension	0.073	0.027	0.082	0.026	0.081	0.028	0.098	0.027
	Hyperlipidemia	0.042	0.012	0.046	0.015	0.045	0.012	0.052	0.015
	Diabetes	0.017	0.010	0.019	0.010	0.018	0.011	0.022	0.012
	Osteoporosis	0.002	0.002	0.003	0.002	0.002	0.002	0.003	0.002
	Depression	0.007	0.004	0.007	0.004	0.008	0.004	0.007	0.004
Total Office Visits	Hypertension	0.095	0.035	0.106	0.033	0.104	0.037	0.125	0.038
	Hyperlipidemia	0.048	0.015	0.053	0.018	0.051	0.014	0.059	0.018
	Diabetes	0.024	0.014	0.026	0.015	0.023	0.016	0.029	0.017
	Osteoporosis	0.003	0.002	0.003	0.002	0.003	0.002	0.004	0.002
	Depression	0.009	0.005	0.008	0.005	0.010	0.005	0.009	0.006
Observations		358		412		360		411	

Notes: Unit of observation is the three digit ZIP code. Variables are averaged across all quarters in the pre (before Medicare Part D, 2004-2005) and post (after Medicare Part D, 2006-2010) period. Low 65+ denotes that a person lives in a ZIP code with a low share of 65+ year olds, whereas High 65+ denotes living in a ZIP code with a higher share of 65+ year olds. High share is defined as having an elderly share that is above the median for all ZIP codes as of 2005 Q4.

Figure 1: Amount of Advertising (Average Views Per Person) For High and Low Elderly Share ZIP Codes Over Time, By Condition



Notes: Means taken at the ZIP code 3 level weighted by ZIP3 population. Pooled conditions are Hypertension, Hyperlipidemia, Diabetes, Osteoporosis, and Depression. Smoothing done with Stata 14.0 'lpoly' command. The vertical lines represent the anticipatory period in the year leading up to the enactment of Medicare Part D on January 1, 2006.

Figure 2: Fraction of Sample with Any Office Visit For High and Low Eldery Share ZIP Codes Over Time, By Condition

Notes: Means taken at the ZIP code 3 level weighted by ZIP3 population, and includes all enrolled patients in the ZIP regardless of utilization. Pooled conditions are Hypertension, Hyperlipidemia, Diabetes, Osteoporosis, and Depression. Smoothing done with Stata 14.0 'lpoly' command. The vertical lines represent the anticipatory period in the year leading up to the enactment of Medicare Part D on January 1, 2006.

Figure 3: Mean Total Office Visits For High and Low Elderly Share ZIP Codes Over Time, By Condition

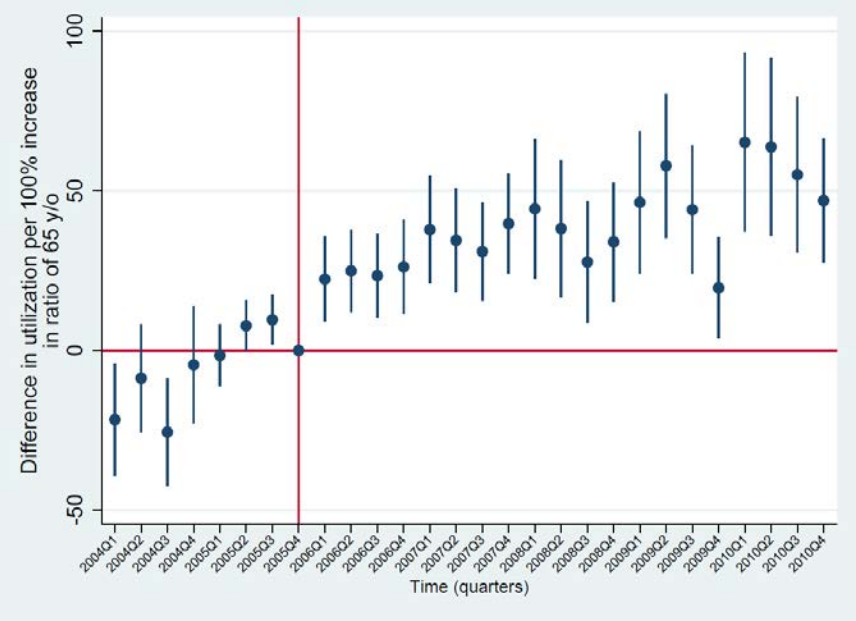
Notes: Means taken at the ZIP code 3 level weighted by ZIP3 population, and includes all enrolled patients in the ZIP regardless of utilization. Pooled conditions are Hypertension, Hyperlipidemia, Diabetes, Osteoporosis, and Depression. Smoothing done with Stata 14.0 'lpoly' command. The vertical lines represent the anticipatory period in the year leading up to the enactment of Medicare Part D on January 1, 2006.

Table 2: Effect of DTCA on Office Visit Utilization (per 1000 people)

	Intent-to-Treat		Two Stage Least Squares		
	(1) Any Office Visit (per qtr)	(2) Total Office Visits (per qtr)	(3) Views Per Person (Non-Elderly)	(4) Any Office Visit (per qtr)	(5) Total Office Visits (per qtr)
Panel A: Continuous					
Post X Ratio65	43.274***	65.271***	6.360***	6.804***	10.263***
	(9.446)	(13.549)	(1.116)	(1.745)	(2.624)
Mean	32.50	40.40	4.47	32.50	40.40
Observations	107345	107345	107345	107345	107345
Adj. R-Squared	0.862	0.848	0.704	0.567	0.445
F-stat			32.706	32.706	32.706
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel B: Dichotomous					
Post X High	2.791***	3.854***	0.285***	9.793**	13.520**
	(0.559)	(0.760)	(0.062)	(3.173)	(4.377)
Mean	32.50	40.40	4.47	32.50	40.40
Observations	107345	107345	107345	107345	107345
F-Stat			21.237	21.237	21.237
Adj. R-Squared	0.862	0.848	0.704	0.270	0.163
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes

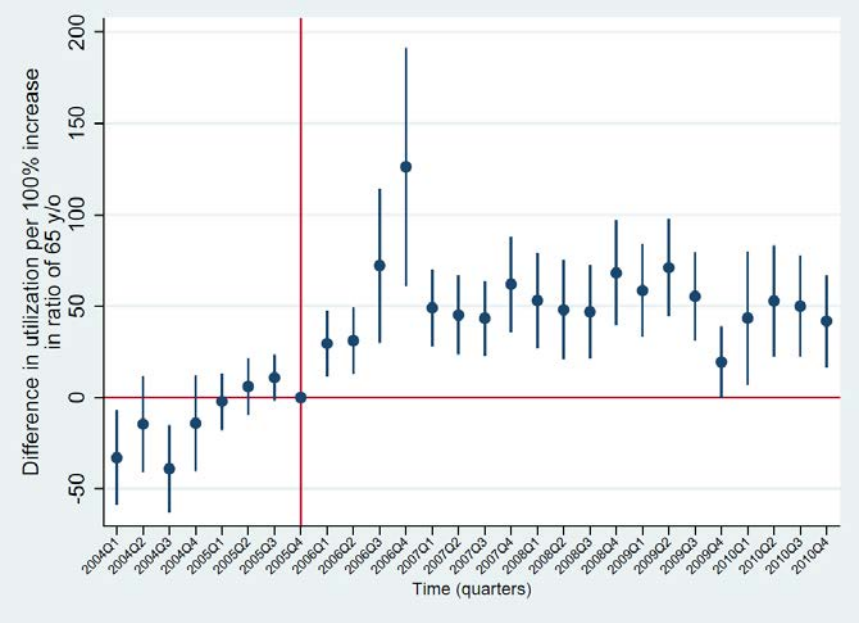
Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Intent-to-treat analysis results from OLS with analytic weights for number of individuals in each ZIP code, performed using Stata 14.0 'areg' command. Two Stage Least Squares analysis is similarly weighted by number of individuals in each ZIP code, and is performed using Stata 14.0 'xtivreg2' command. Data are from 2004-2010, where the post period is 2006-2010. The 'High' indicator represents a ratio of 65 year olds above the median of all ZIP codes as of Q4 2005. Coefficients in Panel A, intent-to-treat (Quadrant II) is interpreted as the effect of going from 0% 65 year olds to 100% 65 year olds. ZIP code fixed effects are in place. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hypertension, hyperlipidemia, diabetes, osteoporosis, or depression, per the Chronic Condition Warehouse definition. The same office visit can be counted multiple times if diagnosis codes indicate two or more chronic conditions on the same claim.

Figure 4: Event Study Coefficient Plot For the Interaction Effect of Post and Elderly Share on Any Office Visit



Notes: Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Analysis performed using OLS with analytic weights for number of individuals in each ZIP code, with Stata 14.0 'areg' command. Data are from 2004-2010, where the post period is 2006-2010. The dependent variable is number of people per 1000 that have any office visit in a ZIP code in a given quarter. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hypertension, hyperlipidemia, diabetes, osteoporosis, or depression, per the Chronic Condition Warehouse definition. The same office visit can be counted multiple times if diagnosis codes indicate two or more chronic conditions on the same claim. Point estimates represent the difference in number of people with an office visit per 1000 between those living in a ZIP code with 100% share of 65 year olds and those living in a ZIP code with 0% share.

Figure 5: Event Study Coefficient Plot For the Interaction Effect of Post and Elderly Share on Total Office Visits



Notes: Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Analysis performed using OLS with analytic weights for number of individuals in each ZIP code, with Stata 14.0 'areg' command. Data are from 2004-2010, where the post period is 2006-2010. The dependent variable is total number of office visits per 1000 people in a ZIP code in a given quarter. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hypertension, hyperlipidemia, diabetes, osteoporosis, or depression, per the Chronic Condition Warehouse definition. The same office visit can be counted multiple times if diagnosis codes indicate two or more chronic conditions on the same claim. Point estimates represent the difference in total office visits per 1000 people between those living in a ZIP code with 100% share of 65+ year olds and those living in a ZIP code with 0% share.

Table 3: Effect of DTCA on the Likelihood of Any Office Visit, Separately by Type of Office Visit

	(1) Any OV for CC	(2) Any OV with Generic	(3) Any OV with Non-Advertised Branded	(4) Any OV with Advertised Rx	(5) Any OV with no Rx or Rx for Dif Condition
Panel A: Continuous					
Advertising	0.027***	0.010***	-0.000	0.002*	0.022***
	(0.005)	(0.003)	(0.001)	(0.001)	(0.004)
Mean	0.11	0.03	0.01	0.02	0.08
Observations	3748	3748	3748	3748	3748
Adj. R-Squared	0.808	0.727	0.443	0.782	0.754
First Stage F-Stat	83.037	83.037	83.037	83.037	83.037
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel B: Dichotomous					
Advertising	0.054**	0.014**	0.001	0.006*	0.046**
	(0.017)	(0.005)	(0.001)	(0.003)	(0.015)
Mean	0.11	0.03	0.01	0.02	0.08
Observations	3748	3748	3748	3748	3748
Adj. R-Squared	0.612	0.660	0.439	0.730	0.485
First Stage F-Stat	9.914	9.914	9.914	9.914	9.914
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: *** $p < 0.001$, **$p<0.01$, *$p<0.05$. The unit of observation is the ZIP-condition level. The dependent variable is a ZIP code average of a binary measure of having an office visit for a one of our chronic-condition from 2006-2009 for individuals in that ZIP code. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hypertension, hyperlipidemia, diabetes, osteoporosis, or depression, per the Chronic Condition Warehouse definition. Attribution of a drug to an office visit is defined as having a drug claim within 365 days of the office visit, and multiple drug claims can be attributed to the same office visit (e.g. an office visit can count for both a generic drug and a branded drug if multiple drugs are dispensed). The independent variable is average views per person for advertisements for drugs for a chronic condition in the ZIP code where the patient resides. Model used is a two stage least squares performed using the Stata 14.0 'ivreg2' command. Data are from 2006-2009. Panel A uses a continuous measure of the ratio of 65+ year olds in a ZIP code as of Q4 2005 as an instrument for advertising. Panel B uses a dichotomous measure representing whether the ratio of 65+ year olds in a given ZIP code is above the median of all ZIP codes as of Q4 2005. Coefficients in Panel A are interpreted as the effect of going from having 0% 65+ year olds to 100% 65+ year olds. Models also control for age and sex. Standard errors are clustered at the ZIP code level.

Table 4: Effect of DTCA Total Office Visits, Separately by Type of Office Visit

	(1) Total OV for CC	(2) Total OV with Generic	(3) Total with Non-Advertised Branded	(4) Total with Advertised Rx	(5) Total with no Rx or Rx for Dif Condition
Panel A: Continuous					
Advertising	0.151***	0.048***	0.004	0.015***	0.084***
	(0.029)	(0.012)	(0.003)	(0.004)	(0.015)
Mean	0.38	0.09	0.03	0.06	0.20
Observations	3748	3748	3748	3748	3748
Adj. R-Squared	0.617	0.600	0.387	0.628	0.539
First Stage F-Stat	83.037	83.037	83.037	83.037	83.037
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel B: Dichotomous					
Elderly Share	0.301**	0.077**	0.014*	0.040**	0.170**
	(0.096)	(0.025)	(0.007)	(0.015)	(0.054)
Mean	0.38	0.09	0.03	0.06	0.20
Observations	3748	3748	3748	3748	3748
Adj. R-Squared	0.209	0.396	0.288	0.450	0.056
First Stage F-Stat	9.914	9.914	9.914	9.914	9.914
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: *** $p < 0.001$, **$p<0.01$, *$p<0.05$. The unit of observation is the ZIP-condition level. The dependent variable is a ZIP code average of the count of total office visits for individuals in that ZIP code for a given chronic-condition between 2006-2009. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hypertension, hyperlipidemia, diabetes, osteoporosis, or depression, per the Chronic Condition Warehouse definition. The same office visit can be counted multiple times if diagnosis codes indicate two or more chronic conditions on the same claim. Attribution of a drug to an office visit is defined as having a drug claim within 365 days of the office visit, and multiple drug claims can be attributed to the same office visit (e.g. an office visit can count for both a generic drug and a branded drug if multiple drugs are dispensed). The independent variable is average views per person for advertisements for drugs for a chronic condition in the ZIP code where the patient resides. Model used is a two stage least squares performed using the Stata 14.0 'ivreg2' command. Data are from 2006-2009. Panel A uses a continuous measure of the ratio of 65+ year olds in a ZIP code as of Q4 2005 as an instrument for advertising. Panel B uses a dichotomous measure representing whether the ratio of 65+ year olds in a given ZIP code is above the median of all ZIP codes as of Q4 2005. Coefficients in Panel A are interpreted as the effect of going from having 0% 65+ year olds to 100% 65+ year olds. Models also control for age and sex. Standard errors are clustered at the ZIP code level.

Table 5: Effect of DTCA on Trajectory of Care

	(1) 2 Consecutive Years	(2) 3 Consecutive Years	(3) 4 Consecutive Years
Office Visits			
Views per person	0.016***	0.009***	0.004***
	(0.003)	(0.002)	(0.001)
Mean	0.04	0.02	0.01
Adj. R-Squared	0.682	0.562	0.433
Office Visits + Any Drug			
Views per person	0.006***	0.003***	0.001***
	(0.002)	(0.001)	(0.000)
Mean	0.02	0.01	0.00
Adj. R-Squared	0.689	0.561	0.400
Office Visits + Generic Drug			
Views per person	0.005***	0.002***	0.001***
	(0.001)	(0.001)	(0.000)
Mean	0.01	0.00	0.00
Adj. R-Squared	0.612	0.450	0.251
Office Visits + Non-Advertised Branded Drug			
Views per person	<0.001	<0.001	<0.001
	(<0.001)	(<0.001)	(<0.001)
Mean	<0.01	<0.01	<0.01
Adj. R-Squared	0.342	0.172	0.113
Office Visits + Advertised Drug			
Views per person	0.001**	0.001*	0.000
	(0.001)	(0.000)	(0.000)
Mean	0.01	0.00	0.00
Adj. R-Squared	0.646	0.520	0.354
Office Visits + No Drug			
Views per person	0.009***	0.004***	0.002***
	(0.002)	(0.001)	(0.000)
Mean	0.02	0.01	0.00
Adj. R-Squared	0.546	0.390	0.281
Observations	3748	3748	3748

Notes: *** p < 0.001, **p<0.01, *p<0.05. The unit of observation is the patient-condition level. The dependent variable is a binary measure of having office visits in 2, 3, or 4 consecutive calendar years. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hypertension, hyperlipidemia, diabetes, osteoporosis, or depression, per the Chronic Condition Warehouse definition. Attribution of a drug to an office visit is defined as having a drug claim within 365 days of the office visit, and multiple drug claims can be attributed to the same office

visit. The independent variable is average views per person for advertisements for drugs for a chronic condition in the ZIP code where the patient resides. Model used is a two stage least squares performed using the Stata 14.0 'ivreg2' command. Data are from 2006-2009. The model uses a continuous measure of the ratio of 65+ year olds in a ZIP code as of Q4 2005 as an instrument for advertising. Coefficients are interpreted as the effect of going from having 0% 65+ year olds to 100% 65+ year olds. Models also control for age and sex. Standard errors are clustered at the ZIP code level.

APPENDIX

Table A1-1: Effect of DTCA on Office Visit Utilization for Hypertension (per 1000 people)

	Intent-to-Treat		Two Stage Least Squares		
	(1) Any Office Visit (per qtr)	(2) Total Office Visits (per qtr)	(3) Views Per Person (Non-Elderly)	(4) Any Office Visit (per qtr)	(5) Total Office Visits (per qtr)
Panel A: Continuous					
Post X Ratio65	127.674***	195.553***	2.158***	59.152**	90.600**
	(30.892)	(44.949)	(0.388)	(19.362)	(28.975)
Mean	85.90	110.28	0.70	85.90	110.28
Observations	21469	21469	21469	21469	21469
Adj. R-Squared	0.835	0.782	0.852		
F-stat			32.025	32.025	32.025
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel B: Dichotomous					
Post X High	8.192***	11.578***	0.126***	65.227***	92.194***
	(1.737)	(2.447)	(0.022)	(17.605)	(25.124)
Mean	85.90	110.28	0.70	85.90	110.28
Observations	21469	21469	21469	21469	21469
F-Stat			32.668	32.668	32.668
Adj. R-Squared	0.836	0.782	0.852		
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Intent-to-treat analysis results from OLS with analytic weights for number of individuals in each ZIP code, performed using Stata 14.0 'areg' command. Two Stage Least Squares analysis is similarly weighted by number of individuals in each ZIP code, and is performed using Stata 14.0 'xtivreg2' command. Data are from 2004-2010, where the post period is 2006-2010. The 'High' indicator represents a ratio of 65+ year olds above the median of all ZIP codes as of Q4 2005. Coefficients in Panel A, intent-to-treat (Quadrant II) is interpreted as the effect of going from 0% 65+ year olds to 100% 65+ year olds. ZIP code fixed effects are in place. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hypertension, per the Chronic Condition Warehouse definition.

Table A1-2: Effect of DTCA on Office Visit Utilization for Hyperlipidemia (per 1000 people)

	Intent-to-Treat		Two Stage Least Squares		
	(1) Any Office Visit (per qtr)	(2) Total Office Visits (per qtr)	(3) Views Per Person (Non-Elderly)	(4) Any Office Visit (per qtr)	(5) Total Office Visits (per qtr)
Panel A: Continuous					
Post X Ratio65	69.366***	88.362***	19.982***	3.471***	4.422***
	(12.815)	(16.415)	(4.146)	(0.769)	(0.990)
Mean	47.13	53.63	10.92	47.13	53.63
Observations	21469	21469	21469	21469	21469
Adj. R-Squared	0.732	0.701	0.837		
F-stat			24.101	24.101	24.101
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel B: Dichotomous					
Post X High	3.946***	4.639***	0.896***	4.403**	5.176**
	(0.789)	(0.969)	(0.202)	(1.385)	(1.643)
Mean	47.13	53.63	10.92	47.13	53.63
Observations	21469	21469	21469	21469	21469
Adj. R-Squared	0.732	0.700	0.835		
F-Stat			20.477	20.477	20.477
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Intent-to-treat analysis results from OLS with analytic weights for number of individuals in each ZIP code, performed using Stata 14.0 'areg' command. Two Stage Least Squares analysis is similarly weighted by number of individuals in each ZIP code, and is performed using Stata 14.0 'xtivreg2' command. Data are from 2004-2010, where the post period is 2006-2010. The 'High' indicator represents a ratio of 65+ year olds above the median of all ZIP codes as of Q4 2005. Coefficients in Panel A, intent-to-treat (Quadrant II) is interpreted as the effect of going from 0% 65+ year olds to 100% 65+ year olds. ZIP code fixed effects are in place. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hyperlipidemia, per the Chronic Condition Warehouse definition.

Table A1-3: Effect of DTCA on Office Visit Utilization for Diabetes (per 1000 people)

	Intent-to-Treat		Two Stage Least Squares		
	(1) Any Office Visit (per qtr)	(2) Total Office Visits (per qtr)	(3) Views Per Person (Non-Elderly)	(4) Any Office Visit (per qtr)	(5) Total Office Visits (per qtr)
Panel A: Continuous					
Post X Ratio65	14.999*	36.235**	-0.663*	-22.633	-54.678*
	(7.404)	(11.613)	(0.334)	(11.698)	(24.715)
Mean	19.26	25.83	0.79	19.26	25.83
Observations	21469	21469	21469	21469	21469
Adj. R-Squared	0.844	0.808	0.840		
F-stat			4.088	4.088	4.088
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel B: Dichotomous					
Post X High	1.660***	2.924***	-0.050**	-33.356*	-58.767*
	(0.497)	(0.696)	(0.019)	(15.386)	(25.236)
Mean	19.26	25.83	0.79	19.26	25.83
Observations	21469	21469	21469	21469	21469
Adj. R-Squared	0.845	0.808	0.840	-14.517	-18.952
F-Stat			7.371	7.371	7.371
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Intent-to-treat analysis results from OLS with analytic weights for number of individuals in each ZIP code, performed using Stata 14.0 'areg' command. Two Stage Least Squares analysis is similarly weighted by number of individuals in each ZIP code, and is performed using Stata 14.0 'xtivreg2' command. Data are from 2004-2010, where the post period is 2006-2010. The 'High' indicator represents a ratio of 65+ year olds above the median of all ZIP codes as of Q4 2005. Coefficients in Panel A, intent-to-treat (Quadrant II) is interpreted as the effect of going from 0% 65+ year olds to 100% 65+ year olds. ZIP code fixed effects are in place. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates diabetes, per the Chronic Condition Warehouse definition.

Table A1-4: Effect of DTCA on Office Visit Utilization for Osteoporosis (per 1000 people)

	Intent-to-Treat		Two Stage Least Squares		
	(1) Any Office Visit (per qtr)	(2) Total Office Visits (per qtr)	(3) Views Per Person (Non-Elderly)	(4) Any Office Visit (per qtr)	(5) Total Office Visits (per qtr)
Panel A: Continuous					
Post X Ratio65	6.214***	7.184***	5.349***	1.162***	1.343***
	(1.607)	(1.884)	(1.023)	(0.343)	(0.403)
Mean	2.73	3.04	4.78	2.73	3.04
Observations	21469	21469	21469	21469	21469
Adj. R-Squared	0.313	0.308	0.898		
F-stat			28.372	28.372	28.372
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel B: Dichotomous					
Post X High	0.356***	0.400***	0.225***	1.581**	1.779**
	(0.089)	(0.101)	(0.063)	(0.570)	(0.648)
Mean	2.73	3.04	4.78	2.73	3.04
Observations	21469	21469	21469	21469	21469
Adj. R-Squared	0.313	0.308	0.898		
F-Stat			13.153	13.153	13.153
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Intent-to-treat analysis results from OLS with analytic weights for number of individuals in each ZIP code, performed using Stata 14.0 'areg' command. Two Stage Least Squares analysis is similarly weighted by number of individuals in each ZIP code, and is performed using Stata 14.0 'xtivreg2' command. Data are from 2004-2010, where the post period is 2006-2010. The 'High' indicator represents a ratio of 65+ year olds above the median of all ZIP codes as of Q4 2005. Coefficients in Panel A, intent-to-treat (Quadrant II) is interpreted as the effect of going from 0% 65+ year olds to 100% 65+ year olds. ZIP code fixed effects are in place. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates osteoporosis, per the Chronic Condition Warehouse definition.

Table A1-5: Effect of DTCA on Office Visit Utilization for Depression (per 1000 people)

	Intent-to-Treat		Two Stage Least Squares		
	(1) Any Office Visit (per qtr)	(2) Total Office Visits (per qtr)	(3) Views Per Person (Non-Elderly)	(4) Any Office Visit (per qtr)	(5) Total Office Visits (per qtr)
Panel A: Continuous					
Post X Ratio65	-1.995	-1.122	4.966***	-0.402	-0.226
	(2.806)	(4.124)	(0.987)	(0.539)	(0.800)
Mean	7.46	9.16	5.18	7.46	9.16
Observations	21469	21469	21469	21469	21469
Adj. R-Squared	0.507	0.448	0.912		
F-stat			26.258	26.258	26.258
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel B: Dichotomous					
Post X High	-0.201	-0.277	0.228**	-0.881	-1.214
	(0.197)	(0.278)	(0.074)	(0.821)	(1.149)
Mean	7.46	9.16	5.18	7.46	9.16
Observations	21469	21469	21469	21469	21469
Adj. R-Squared	0.507	0.448	0.912		
F-Stat			9.975	9.975	9.975
Condition Fixed Effects	Yes	Yes	Yes	Yes	Yes
Qtr Fixed Effects	Yes	Yes	Yes	Yes	Yes

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Intent-to-treat analysis results from OLS with analytic weights for number of individuals in each ZIP code, performed using Stata 14.0 'areg' command. Two Stage Least Squares analysis is similarly weighted by number of individuals in each ZIP code, and is performed using Stata 14.0 'xtivreg2' command. Data are from 2004-2010, where the post period is 2006-2010. The 'High' indicator represents a ratio of 65+ year olds above the median of all ZIP codes as of Q4 2005. Coefficients in Panel A, intent-to-treat (Quadrant II) is interpreted as the effect of going from 0% 65+ year olds to 100% 65+ year olds. ZIP code fixed effects are in place. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates depression, per the Chronic Condition Warehouse definition.

TableA2-1 – Timing of the Impact on Total Office Visits for Chronic Conditions, for Non-Elderly (per 1000 people)

	(1) Total Office Visits (per qtr) b/se	(2) Total Office Visits (per qtr) b/se
Pre period		
Share 65+: Q1	-33.031*	
	(13.216)	
Share 65+: Q2	-14.597	
	(13.285)	
Share 65+: Q3	-39.021**	
	(12.085)	
Share 65+: Q4	-14.128	
	(13.247)	
Share 65+: Q5	-2.160	
	(7.865)	
Share 65+: Q6	6.034	
	(7.809)	
Share 65+: Q7	10.819	
	(6.375)	
Post period		
Share 65+: Q9	29.534**	
	(9.133)	
Share 65+: Q10	31.120***	
	(9.223)	
Share 65+: Q11	72.227***	
	(21.386)	
Share 65+: Q12	126.264***	
	(33.078)	
Share 65+: Q13	49.063***	
	(10.748)	
Share 65+: Q14	45.165***	
	(10.970)	
Share 65+: Q15	43.381***	
	(10.376)	
Share 65+: Q16	61.993***	
	(13.144)	
Share 65+: Q17	53.088***	
	(13.327)	
Share 65+: Q18	47.973***	
	(13.751)	
Share 65+: Q19	46.901***	
	(13.004)	
Share 65+: Q20	68.141***	
	(14.632)	
Share 65+: Q21	58.527***	
	(12.866)	
Share 65+: Q22	71.091***	
	(13.537)	
Share 65+: Q23	55.317***	
	(12.285)	
Share 65+: Q24	19.402	
	(9.968)	
Share 65+: Q25	43.477*	
	(18.466)	
Share 65+: Q26	52.848***	

	(15.377)	
Share 65+: Q27	49.947***	
	(13.958)	
Share 65+: Q28	41.791**	
	(12.856)	
Pre period		
HighShare: Q1		-2.236**
		(0.713)
HighShare: Q2		-1.164
		(0.642)
HighShare: Q3		-1.961**
		(0.624)
HighShare: Q4		-1.129
		(0.632)
HighShare: Q5		-0.288
		(0.426)
HighShare: Q6		0.061
		(0.377)
HighShare: Q7		0.243
		(0.338)
Post period		
HighShare: Q9		1.828**
		(0.703)
HighShare: Q10		1.973**
		(0.700)
HighShare: Q11		2.535**
		(0.973)
HighShare: Q12		4.912***
		(1.294)
HighShare: Q13		2.712***
		(0.707)
HighShare: Q14		2.715***
		(0.705)
HighShare: Q15		2.276***
		(0.685)
HighShare: Q16		3.616***
		(0.826)
HighShare: Q17		3.486***
		(0.760)
HighShare: Q18		2.961***
		(0.779)
HighShare: Q19		2.788***
		(0.757)
HighShare: Q20		3.424***
		(0.861)
HighShare: Q21		3.868***
		(0.740)
HighShare: Q22		4.423***
		(0.790)
HighShare: Q23		3.534***
		(0.778)
HighShare: Q24		1.851*
		(0.737)
HighShare: Q25		2.934*
		(1.138)
HighShare: Q26		3.665***

		(1.053)
HighShare: Q27		2.687**
		(1.019)
HighShare: Q28		2.591**
		(0.990)
Constant	8.465***	5.416***
	(1.675)	(0.792)
Observations	107345	107345
Condition Fixed Effects	Yes	Yes
Qtr Fixed Effects	Yes	Yes

Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Analysis performed using OLS with analytic weights for number of individuals in each ZIP code, with Stata 14.0 'areg' command. Data are from 2004-2010, where the post period is 2006-2010. The dependent variable is total number of office visits per 1000 people in a ZIP code in a given quarter. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hypertension, hyperlipidemia, diabetes, osteoporosis, or depression, per the Chronic Condition Warehouse definition. The same office visit can be counted multiple times if diagnosis codes indicate two or more chronic conditions on the same claim. Point estimates in the first column (Share 65+: QXX) represent the difference in total office visits per 1000 people between those living in a ZIP code with 100% share of 65+ year olds and those living in a ZIP code with 0% share. Point estimates in the second column (HighShare: QXX) represent the difference in total office visits per 1000 people between those living in a ZIP code with a high share of 65+ year olds and those living in a ZIP code a low share of 65+ year olds. The 'High' indicator represents a ratio of 65+ year olds above the median of all ZIP codes as of Q4 2005.

Table A2-2 – Timing of the Impact on Total Office Visits for Hypertension, for Non-Elderly (per 1000 people)

	(1) Total Office Visits (per qtr) b/se	(2) Total Office Visits (per qtr) b/se
Share 65+: Q1	-74.150	
	(41.417)	
Share 65+: Q2	-28.126	
	(37.126)	
Share 65+: Q3	-90.540**	
	(33.969)	
Share 65+: Q4	-19.145	
	(34.367)	
Share 65+: Q5	-9.740	
	(20.442)	
Share 65+: Q6	11.587	
	(22.818)	
Share 65+: Q7	38.499*	
	(19.362)	
Post Period		
Share 65+: Q9	86.711**	
	(27.673)	
Share 65+: Q10	103.310***	
	(26.689)	
Share 65+: Q11	225.168***	
	(60.635)	
Share 65+: Q12	386.235***	
	(100.316)	
Share 65+: Q13	145.980***	
	(32.625)	
Share 65+: Q14	137.704***	
	(31.173)	
Share 65+: Q15	149.422***	
	(32.776)	
Share 65+: Q16	202.955***	
	(39.315)	
Share 65+: Q17	173.594***	
	(40.581)	
Share 65+: Q18	171.876***	
	(40.793)	
Share 65+: Q19	158.003***	
	(39.219)	
Share 65+: Q20	237.340***	
	(52.434)	
Share 65+: Q21	197.192***	
	(46.093)	
Share 65+: Q22	213.550***	
	(42.030)	
Share 65+: Q23	171.773***	
	(40.561)	
Share 65+: Q24	59.394*	
	(29.883)	
Share 65+: Q25	126.746	
	(69.966)	

Share 65+: Q26	187.633***	
	(53.878)	
Share 65+: Q27	165.125**	
	(51.450)	
Share 65+: Q28	131.179**	
	(45.033)	
HighShare: Q1		-6.328**
		(2.084)
HighShare: Q2		-3.223
		(1.794)
HighShare: Q3		-5.636**
		(1.762)
HighShare: Q4		-2.778
		(1.778)
HighShare: Q5		-1.033
		(1.305)
HighShare: Q6		0.021
		(1.217)
HighShare: Q7		0.814
		(1.132)
Post Period		
HighShare: Q9		4.790*
		(2.223)
HighShare: Q10		6.034**
		(2.114)
HighShare: Q11		7.567**
		(2.920)
HighShare: Q12		15.302***
		(3.911)
HighShare: Q13		7.965***
		(2.252)
HighShare: Q14		8.028***
		(2.197)
HighShare: Q15		6.856**
		(2.335)
HighShare: Q16		10.579***
		(2.614)
HighShare: Q17		10.816***
		(2.444)
HighShare: Q18		9.944***
		(2.510)
HighShare: Q19		9.221***
		(2.446)
HighShare: Q20		11.975***
		(2.960)
HighShare: Q21		11.835***
		(2.553)
HighShare: Q22		12.936***
		(2.527)
HighShare: Q23		10.167***
		(2.560)
HighShare: Q24		5.672*
		(2.296)
HighShare: Q25		8.590*
		(4.069)
HighShare: Q26		11.621**

		(3.535)
HighShare: Q27		9.046**
		(3.471)
HighShare: Q28		7.593*
		(3.168)
Mean	110.28	110.28
Observations	21469	21469
Condition Fixed Effects	Yes	Yes
Qtr Fixed Effects	Yes	Yes

Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Analysis performed using OLS with analytic weights for number of individuals in each ZIP code, with Stata 14.0 'areg' command. Data are from 2004-2010, where the post period is 2006-2010. The dependent variable is total number of office visits per 1000 people in a ZIP code in a given quarter. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hypertension, per the Chronic Condition Warehouse definition. The same office visit can be counted multiple times if diagnosis codes indicate two or more chronic conditions on the same claim. Point estimates in the first column (Share 65+: QXX) represent the difference in total office visits per 1000 people between those living in a ZIP code with 100% share of 65+ year olds and those living in a ZIP code with 0% share. Point estimates in the second column (HighShare: QXX) represent the difference in total office visits per 1000 people between those living in a ZIP code with a high share of 65+ year olds and those living in a ZIP code a low share of 65+ year olds. The 'High' indicator represents a ratio of 65+ year olds above the median of all ZIP codes as of Q4 2005.

Table A2-3 – Timing of the Impact on Total Office Visits for Hyperlipidemia, for Non-Elderly (per 1000 people)

	(1) Total Office Visits (per qtr) b/se	(2) Total Office Visits (per qtr) b/se
Share 65+: Q1	-67.851**	
	(21.735)	
Share 65+: Q2	-34.891	
	(26.526)	
Share 65+: Q3	-72.296**	
	(26.411)	
Share 65+: Q4	-29.186	
	(27.274)	
Share 65+: Q5	1.144	
	(15.781)	
Share 65+: Q6	24.910	
	(13.639)	
Share 65+: Q7	14.087	
	(13.495)	
Post Period		
Share 65+: Q9	46.636*	
	(18.764)	
Share 65+: Q10	50.783**	
	(17.733)	
Share 65+: Q11	92.080**	
	(31.476)	
Share 65+: Q12	131.070**	
	(40.864)	
Share 65+: Q13	64.678**	
	(19.984)	
Share 65+: Q14	53.915**	
	(20.658)	
Share 65+: Q15	43.026*	
	(19.440)	
Share 65+: Q16	61.040**	
	(23.337)	
Share 65+: Q17	70.594**	
	(22.917)	
Share 65+: Q18	58.944*	
	(24.287)	
Share 65+: Q19	61.293*	
	(24.605)	
Share 65+: Q20	86.941**	
	(26.674)	
Share 65+: Q21	67.938***	
	(19.664)	
Share 65+: Q22	98.831***	
	(23.197)	
Share 65+: Q23	75.465***	
	(19.926)	
Share 65+: Q24	25.209	
	(25.168)	
Share 65+: Q25	71.086*	
	(27.833)	
Share 65+: Q26	48.151	

	(28.666)	
Share 65+: Q27	67.918**	
	(24.847)	
Share 65+: Q28	55.254*	
	(23.061)	
HighShare: Q1		-3.391*
		(1.320)
HighShare: Q2		-1.993
		(1.252)
HighShare: Q3		-3.073*
		(1.246)
HighShare: Q4		-1.729
		(1.233)
HighShare: Q5		0.266
		(0.862)
HighShare: Q6		1.487
		(0.786)
HighShare: Q7		1.095
		(0.764)
Post Period		
HighShare: Q9		2.717**
		(1.046)
HighShare: Q10		2.540*
		(1.084)
HighShare: Q11		3.336*
		(1.377)
HighShare: Q12		4.556**
		(1.711)
HighShare: Q13		3.250**
		(1.159)
HighShare: Q14		3.029**
		(1.164)
HighShare: Q15		2.275*
		(1.070)
HighShare: Q16		4.111**
		(1.271)
HighShare: Q17		4.203***
		(1.217)
HighShare: Q18		3.429**
		(1.234)
HighShare: Q19		3.115*
		(1.221)
HighShare: Q20		4.128**
		(1.375)
HighShare: Q21		4.340***
		(1.112)
HighShare: Q22		5.646***
		(1.228)
HighShare: Q23		4.478***
		(1.146)
HighShare: Q24		2.257
		(1.275)
HighShare: Q25		4.464**
		(1.591)
HighShare: Q26		5.216**
		(1.699)

HighShare: Q27		3.866*
		(1.595)
HighShare: Q28		3.928*
		(1.552)
Constant	54.756***	47.904***
	(2.667)	(0.664)
Mean	53.63	53.63
Observations	21469	21469
Condition Fixed Effects	Yes	Yes
Qtr Fixed Effects	Yes	Yes

Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Analysis performed using OLS with analytic weights for number of individuals in each ZIP code, with Stata 14.0 'areg' command. Data are from 2004-2010, where the post period is 2006-2010. The dependent variable is total number of office visits per 1000 people in a ZIP code in a given quarter. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hyperlipidemia, per the Chronic Condition Warehouse definition. The same office visit can be counted multiple times if diagnosis codes indicate two or more chronic conditions on the same claim. Point estimates in the first column (Share 65+: QXX) represent the difference in total office visits per 1000 people between those living in a ZIP code with 100% share of 65+ year olds and those living in a ZIP code with 0% share. Point estimates in the second column (HighShare: QXX) represent the difference in total office visits per 1000 people between those living in a ZIP code with a high share of 65+ year olds and those living in a ZIP code a low share of 65+ year olds. The 'High' indicator represents a ratio of 65+ year olds above the median of all ZIP codes as of Q4 2005.

Table A2-4 – Timing of the Impact on Total Office Visits for Diabetes, for Non-Elderly (per 1000 people)

	(1) Total Office Visits (per qtr) b/se	(2) Total Office Visits (per qtr) b/se
Share 65+: Q1	-3.686	
	(12.128)	
Share 65+: Q2	-3.493	
	(12.290)	
Share 65+: Q3	-11.296	
	(10.117)	
Share 65+: Q4	-6.497	
	(11.502)	
Share 65+: Q5	11.343	
	(10.111)	
Share 65+: Q6	4.666	
	(11.292)	
Share 65+: Q7	4.220	
	(11.647)	
Post Period		
Share 65+: Q9	13.731	
	(10.560)	
Share 65+: Q10	7.554	
	(10.654)	
Share 65+: Q11	34.831*	
	(14.073)	
Share 65+: Q12	88.478***	
	(23.497)	
Share 65+: Q13	31.324**	
	(10.653)	
Share 65+: Q14	35.895**	
	(12.661)	
Share 65+: Q15	33.302**	
	(10.506)	
Share 65+: Q16	49.524***	
	(12.659)	
Share 65+: Q17	28.389	
	(15.001)	
Share 65+: Q18	28.700	
	(15.019)	
Share 65+: Q19	22.926	
	(15.033)	
Share 65+: Q20	23.618	
	(14.238)	
Share 65+: Q21	44.037**	
	(14.978)	
Share 65+: Q22	49.813**	
	(15.346)	
Share 65+: Q23	37.272**	
	(14.020)	
Share 65+: Q24	20.952	
	(13.205)	
Share 65+: Q25	41.168**	
	(13.495)	
Share 65+: Q26	44.327**	

	(13.836)	
Share 65+: Q27	32.932*	
	(13.840)	
Share 65+: Q28	38.526**	
	(14.372)	
HighShare: Q1		-0.482
		(0.743)
HighShare: Q2		-0.488
		(0.777)
HighShare: Q3		-0.450
		(0.747)
HighShare: Q4		-0.604
		(0.791)
HighShare: Q5		-0.410
		(0.628)
HighShare: Q6		-0.804
		(0.553)
HighShare: Q7		-0.964
		(0.565)
Post Period		
HighShare: Q9		1.564
		(0.803)
HighShare: Q10		1.385
		(0.744)
HighShare: Q11		1.928*
		(0.824)
HighShare: Q12		4.179***
		(1.055)
HighShare: Q13		2.196**
		(0.782)
HighShare: Q14		2.499**
		(0.829)
HighShare: Q15		2.367***
		(0.694)
HighShare: Q16		3.427***
		(0.830)
HighShare: Q17		2.409**
		(0.920)
HighShare: Q18		2.479**
		(0.890)
HighShare: Q19		1.955*
		(0.865)
HighShare: Q20		1.492
		(0.915)
HighShare: Q21		3.554***
		(0.934)
HighShare: Q22		3.659***
		(1.002)
HighShare: Q23		3.068**
		(0.929)
HighShare: Q24		1.780*
		(0.903)
HighShare: Q25		2.582*
		(1.048)
HighShare: Q26		2.174*
		(1.024)

HighShare: Q27		1.380
		(1.064)
HighShare: Q28		1.667
		(1.029)
Constant	25.841***	25.605***
	(1.521)	(0.471)
Mean	25.83	25.83
Observations	21469	21469
Condition Fixed Effects	Yes	Yes
Qtr Fixed Effects	Yes	Yes

Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Analysis performed using OLS with analytic weights for number of individuals in each ZIP code, with Stata 14.0 'areg' command. Data are from 2004-2010, where the post period is 2006-2010. The dependent variable is total number of office visits per 1000 people in a ZIP code in a given quarter. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates diabetes, per the Chronic Condition Warehouse definition. The same office visit can be counted multiple times if diagnosis codes indicate two or more chronic conditions on the same claim. Point estimates in the first column (Share 65+: QXX) represent the difference in total office visits per 1000 people between those living in a ZIP code with 100% share of 65+ year olds and those living in a ZIP code with 0% share. Point estimates in the second column (HighShare: QXX) represent the difference in total office visits per 1000 people between those living in a ZIP code with a high share of 65+ year olds and those living in a ZIP code a low share of 65+ year olds. The 'High' indicator represents a ratio of 65+ year olds above the median of all ZIP codes as of Q4 2005.

Table A2-5 – Timing of the Impact on Total Office Visits for Osteoporosis, for Non-Elderly (per 1000 people)

	(1) Total Office Visits (per qtr) b/se	(2) Total Office Visits (per qtr) b/se
Share 65+: Q1	-8.591**	
	(3.192)	
Share 65+: Q2	-6.018	
	(3.558)	
Share 65+: Q3	-11.852***	
	(3.502)	
Share 65+: Q4	-7.560*	
	(3.375)	
Share 65+: Q5	-5.408	
	(3.644)	
Share 65+: Q6	-5.756	
	(3.642)	
Share 65+: Q7	-1.180	
	(3.191)	
Post Period		
Share 65+: Q9	3.726	
	(3.807)	
Share 65+: Q10	1.204	
	(3.503)	
Share 65+: Q11	0.760	
	(3.862)	
Share 65+: Q12	-1.085	
	(3.747)	
Share 65+: Q13	1.999	
	(3.750)	
Share 65+: Q14	-0.117	
	(4.114)	
Share 65+: Q15	0.216	
	(3.730)	
Share 65+: Q16	1.339	
	(4.047)	
Share 65+: Q17	2.088	
	(3.981)	
Share 65+: Q18	1.203	
	(4.541)	
Share 65+: Q19	-1.603	
	(4.029)	
Share 65+: Q20	0.365	
	(4.294)	
Share 65+: Q21	-2.539	
	(4.503)	
Share 65+: Q22	1.606	
	(4.648)	
Share 65+: Q23	3.045	
	(4.752)	
Share 65+: Q24	1.908	
	(4.541)	
Share 65+: Q25	0.481	
	(4.958)	

Share 65+: Q26	1.516	
	(5.334)	
Share 65+: Q27	6.413	
	(4.698)	
Share 65+: Q28	5.984	
	(5.343)	
HighShare: Q1		-0.564**
		(0.176)
HighShare: Q2		-0.413*
		(0.186)
HighShare: Q3		-0.397*
		(0.182)
HighShare: Q4		-0.287
		(0.194)
HighShare: Q5		-0.085
		(0.174)
HighShare: Q6		-0.327
		(0.173)
HighShare: Q7		0.076
		(0.167)
Post Period		
HighShare: Q9		0.185
		(0.190)
HighShare: Q10		0.224
		(0.184)
HighShare: Q11		0.069
		(0.205)
HighShare: Q12		-0.061
		(0.183)
HighShare: Q13		0.088
		(0.208)
HighShare: Q14		0.138
		(0.209)
HighShare: Q15		0.252
		(0.193)
HighShare: Q16		0.133
		(0.196)
HighShare: Q17		0.186
		(0.207)
HighShare: Q18		-0.015
		(0.223)
HighShare: Q19		-0.047
		(0.207)
HighShare: Q20		0.101
		(0.229)
HighShare: Q21		-0.096
		(0.221)
HighShare: Q22		0.253
		(0.239)
HighShare: Q23		0.209
		(0.221)
HighShare: Q24		0.203
		(0.212)
HighShare: Q25		0.139
		(0.241)
HighShare: Q26		0.326

		(0.237)
HighShare: Q27		0.342
		(0.228)
HighShare: Q28		0.463*
		(0.225)
Constant	3.357***	2.555***
	(0.406)	(0.108)
Mean	3.04	3.04
Observations	21469	21469
Condition Fixed Effects	Yes	Yes
Qtr Fixed Effects	Yes	Yes

Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Analysis performed using OLS with analytic weights for number of individuals in each ZIP code, with Stata 14.0 'areg' command. Data are from 2004-2010, where the post period is 2006-2010. The dependent variable is total number of office visits per 1000 people in a ZIP code in a given quarter. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates osteoporosis, per the Chronic Condition Warehouse definition. The same office visit can be counted multiple times if diagnosis codes indicate two or more chronic conditions on the same claim. Point estimates in the first column (Share 65+: QXX) represent the difference in total office visits per 1000 people between those living in a ZIP code with 100% share of 65+ year olds and those living in a ZIP code with 0% share. Point estimates in the second column (HighShare: QXX) represent the difference in total office visits per 1000 people between those living in a ZIP code with a high share of 65+ year olds and those living in a ZIP code a low share of 65+ year olds. The 'High' indicator represents a ratio of 65+ year olds above the median of all ZIP codes as of Q4 2005.

Table A2-6 – Timing of the Impact on Total Office Visits for Depression, for Non-Elderly (per 1000 people)

	(1) Total Office Visits (per qtr) b/se	(2) Total Office Visits (per qtr) b/se
Share 65+: Q1	-10.759*	
	(4.813)	
Share 65+: Q2	-0.363	
	(5.459)	
Share 65+: Q3	-9.010	
	(5.363)	
Share 65+: Q4	-8.150	
	(5.127)	
Share 65+: Q5	-8.032	
	(4.759)	
Share 65+: Q6	-5.176	
	(4.902)	
Share 65+: Q7	-1.592	
	(3.902)	
Post Period		
Share 65+: Q9	-3.063	
	(5.876)	
Share 65+: Q10	-7.263	
	(6.551)	
Share 65+: Q11	8.242	
	(10.515)	
Share 65+: Q12	26.402	
	(15.176)	
Share 65+: Q13	1.342	
	(6.047)	
Share 65+: Q14	-1.645	
	(5.689)	
Share 65+: Q15	-9.132	
	(5.183)	
Share 65+: Q16	-5.151	
	(5.826)	
Share 65+: Q17	-9.242	
	(6.473)	
Share 65+: Q18	-20.930**	
	(6.600)	
Share 65+: Q19	-6.241	
	(6.687)	
Share 65+: Q20	-7.889	
	(7.485)	
Share 65+: Q21	-13.983*	
	(6.331)	
Share 65+: Q22	-8.377	
	(6.506)	
Share 65+: Q23	-11.121	
	(6.847)	
Share 65+: Q24	-10.562	
	(6.772)	
Share 65+: Q25	-22.026*	
	(9.270)	

Share 65+: Q26	-17.355*	
	(7.433)	
Share 65+: Q27	-22.774**	
	(8.800)	
Share 65+: Q28	-22.079**	
	(7.816)	
HighShare: Q1		-0.412
		(0.390)
HighShare: Q2		0.300
		(0.374)
HighShare: Q3		-0.242
		(0.375)
HighShare: Q4		-0.246
		(0.381)
HighShare: Q5		-0.176
		(0.352)
HighShare: Q6		-0.071
		(0.349)
HighShare: Q7		0.193
		(0.280)
Post Period		
HighShare: Q9		-0.115
		(0.380)
HighShare: Q10		-0.321
		(0.428)
HighShare: Q11		-0.224
		(0.511)
HighShare: Q12		0.579
		(0.627)
HighShare: Q13		0.059
		(0.386)
HighShare: Q14		-0.125
		(0.364)
HighShare: Q15		-0.372
		(0.375)
HighShare: Q16		-0.185
		(0.371)
HighShare: Q17		-0.184
		(0.411)
HighShare: Q18		-1.035*
		(0.441)
HighShare: Q19		-0.311
		(0.422)
HighShare: Q20		-0.593
		(0.464)
HighShare: Q21		-0.294
		(0.426)
HighShare: Q22		-0.385
		(0.478)
HighShare: Q23		-0.259
		(0.530)
HighShare: Q24		-0.663
		(0.446)
HighShare: Q25		-1.102*
		(0.561)
HighShare: Q26		-1.012*

		(0.472)
HighShare: Q27		-1.207*
		(0.505)
HighShare: Q28		-0.699
		(0.483)
Constant	9.736***	8.589***
	(0.658)	(0.277)
Mean	9.16	9.16
Observations	21469	21469
Condition Fixed Effects	Yes	Yes
Qtr Fixed Effects	Yes	Yes

Unit of observation is the ZIP code-quarter-condition level. Standard errors are clustered at the ZIP code level. Analysis performed using OLS with analytic weights for number of individuals in each ZIP code, with Stata 14.0 'areg' command. Data are from 2004-2010, where the post period is 2006-2010. The dependent variable is total number of office visits per 1000 people in a ZIP code in a given quarter. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates depression, per the Chronic Condition Warehouse definition. The same office visit can be counted multiple times if diagnosis codes indicate two or more chronic conditions on the same claim. Point estimates in the first column (Share 65+: QXX) represent the difference in total office visits per 1000 people between those living in a ZIP code with 100% share of 65+ year olds and those living in a ZIP code with 0% share. Point estimates in the second column (HighShare: QXX) represent the difference in total office visits per 1000 people between those living in a ZIP code with a high share of 65+ year olds and those living in a ZIP code a low share of 65+ year olds. The 'High' indicator represents a ratio of 65+ year olds above the median of all ZIP codes as of Q4 2005.

Appendix Table A3: Decomposition/Persistence Descriptives

	New User, Low 65+		New User, High 65+		Former User, Low 65+		Former User, High 65+	
	mean	sd	mean	sd	mean	sd	mean	sd
Demographics								
Mean Age (in 2005)	46.628	4.54	47.143	4.65	48.928	4.75	49.265	4.66
40-44	0.38	0.49	0.341	0.47	0.22	0.41	0.194	0.4
45-50	0.343	0.48	0.334	0.47	0.298	0.46	0.289	0.45
50-56	0.277	0.45	0.324	0.47	0.482	0.5	0.517	0.5
Male	0.567	0.5	0.531	0.5	0.492	0.5	0.483	0.5
Advertising								
Views Per Person (Hypertension)	0.718	0.24	0.878	0.27	0.744	0.24	0.917	0.28
Views Per Person (Hyperlipidemia)	10.14	2.07	11.45	1.91	10.52	2.22	11.743	1.86
Views Per Person (Diabetes)	0.782	0.22	0.842	0.15	0.824	0.25	0.869	0.15
Views Per Person (Osteoporosis)	4.873	1.04	5.393	0.89	5.067	1.11	5.51	0.86
Views Per Person (Depression)	4.074	0.84	4.375	0.64	4.193	0.85	4.446	0.61
Any Utilization								
Any Office Visit for CC	0.314	0.46	0.373	0.48	0.792	0.41	0.827	0.38
Any Office Visit with Non-Advertised Generic	0.099	0.3	0.123	0.33	0.433	0.5	0.475	0.5
Any Office Visit with Non-Advertised Branded	0.038	0.19	0.04	0.2	0.24	0.43	0.246	0.43
Any Office Visit with Advertised Rx	0.06	0.24	0.072	0.26	0.406	0.49	0.428	0.5
Any Office Visit with Rx for Dif Condition	0.193	0.4	0.249	0.43	0.465	0.5	0.52	0.5
Any Office Visit for CC (no Rx)	0.07	0.26	0.076	0.27	0.088	0.28	0.075	0.26
Persistence Measures								
Any Visit (2 Consec Years)	0.129	0.34	0.171	0.38	0.568	0.5	0.631	0.48
Any Visit (3 Consec Years)	0.058	0.23	0.084	0.28	0.396	0.49	0.465	0.5
Any Visit (4 Consec Years)	0.025	0.16	0.039	0.19	0.297	0.46	0.355	0.48
Any Visit With Rx (2 Consec Years)	0.113	0.32	0.152	0.36	0.547	0.5	0.612	0.49
Any Visit With Rx (3 Consec Years)	0.051	0.22	0.075	0.26	0.378	0.49	0.449	0.5
Any Visit With Rx (4 Consec Years)	0.021	0.15	0.034	0.18	0.279	0.45	0.34	0.47
Any Visit No Rx (2 Consec Years)	0.011	0.11	0.013	0.12	0.02	0.14	0.019	0.14
Any Visit No Rx (3 Consec Years)	0.003	0.06	0.004	0.06	0.01	0.1	0.008	0.09
Any Visit No Rx (4 Consec Years)	0.001	0.03	0.001	0.04	0.005	0.07	0.004	0.07
Observations	63432		75046		48728		67689	

Notes: Unit of observation is the person. 'New Users' are defined as those having no office visit or drug claim for hypertension, hyperlipidemia, diabetes, osteoporosis, or depression in 2005. New users do not necessarily have any new utilization, but have the potential to start a new course of treatment. Former users received care for at least one of these conditions in 2005. Low 65+ denotes that a person lives in a ZIP code with a low share of 65+ year olds, whereas High 65+ denotes living in a ZIP code with a higher share of 65+ year olds. High share is defined as having an elderly share that is above the median for all ZIP codes as of 2005 Q4.

Appendix Table A4: Effect of DTCA Likelihood of Any Office Visit, Separately by Type of Office Visit, With Alternate Time Windows

	(1)	(2)	(3)	(4)	(5)
	Any OV for CC	Any OV with Generic	Any OV with Non-Advertised Branded	Any OV with Advertised Rx	Any OV with no Rx or Rx for Dif Condition
30 days					
Views per person	0.030***	0.007***	-0.000	0.001	0.030***
	(0.005)	(0.002)	(0.001)	(0.001)	(0.005)
Mean	0.110	0.020	0.010	0.010	0.090
Adj. R-Squared	0.094	0.025	0.003	0.022	0.085
90 days					
Views per person	0.030***	0.008***	-0.000	0.002*	0.028***
	(0.005)	(0.002)	(0.001)	(0.001)	(0.005)
Mean	0.110	0.020	0.010	0.010	0.080
Adj. R-Squared	0.094	0.027	0.004	0.024	0.077
180 days					
Views per person	0.030***	0.009***	-0.000	0.002**	0.026***
	(0.005)	(0.002)	(0.001)	(0.001)	(0.005)
Mean	0.110	0.030	0.010	0.020	0.080
Adj. R-Squared	0.094	0.028	0.004	0.025	0.072
365 Days					
Views per person	0.030***	0.010***	0.000	0.003**	0.023***
	(0.005)	(0.002)	(0.001)	(0.001)	(0.004)
Mean	0.110	0.030	0.010	0.020	0.080
Adj. R-Squared	0.094	0.029	0.004	0.026	0.068
Observations	1085698	1085698	1085698	1085698	1085698

Notes: *** p < 0.001, **p<0.01, *p<0.05. The unit of observation is the patient-condition level. The dependent variable is a binary measure of having an office visit for a one of our chronic-condition from 2006-2009. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hypertension, hyperlipidemia, diabetes, osteoporosis, or depression, per the Chronic Condition Warehouse definition. Attribution of a drug to an office visit is defined as having a drug claim within 30, 90, 180, or 365 days of the office visit, and multiple drug claims can be attributed to the same office visit (e.g. an office visit can count for both a generic drug and a branded drug if multiple drugs are dispensed). The independent variable is average views per person for advertisements for drugs for a chronic condition in the ZIP code where the patient resides. Model used is a two stage least squares performed using the Stata 14.0 'ivreg2' command. Data are from 2006-2009. The model uses a continuous measure of the ratio of 65+ year olds in a ZIP code as of Q4 2005 as an instrument for advertising. Coefficients are interpreted as the effect of going from having 0% 65+ year olds to 100% 65+ year olds. Models also control for age and sex. Standard errors are clustered at the ZIP code level.

Appendix Table A5: Effect of DTCA on Total Office Visits, Separately by Type of Office Visit, With Alternate Time Windows

	(1)	(2)	(3)	(4)	(5)
	Total OV for CC	Total OV with Generic	Total OV with Non-Advertised Branded	Total OV with Advertised Rx	Total OV with no Rx or Rx for Dif Condition
30 days					
Views per person	0.161***	0.026***	0.002	0.006**	0.127***
	(0.028)	(0.007)	(0.001)	(0.002)	(0.020)
Mean	0.36	0.05	0.02	0.03	0.26
Adj. R-Squared	0.036	0.015	0.002	0.01	0.03
90 days					
Views per person	0.162***	0.037***	0.003	0.011***	0.110***
	(0.028)	(0.009)	(0.002)	(0.003)	(0.018)
Mean	0.37	0.07	0.03	0.05	0.23
Adj. R-Squared	0.035	0.016	0.002	0.011	0.026
180 days					
Views per person	0.165***	0.043***	0.004*	0.015***	0.102***
	(0.029)	(0.010)	(0.002)	(0.004)	(0.016)
Mean	0.37	0.08	0.03	0.05	0.21
Adj. R-Squared	0.034	0.016	0.003	0.011	0.024
365 Days					
Views per person	0.168***	0.050***	0.006*	0.019***	0.093***
	(0.030)	(0.012)	(0.003)	(0.004)	(0.015)
Mean	0.38	0.09	0.03	0.06	0.20
Adj. R-Squared	0.033	0.017	0.003	0.011	0.023
Observations	1085698	1085698	1085698	1085698	1085698

Notes: *** p < 0.001, **p<0.01, *p<0.05. The unit of observation is the patient-condition level. The dependent variable is a count measure of total office visits for a given chronic-condition between 2006-2009. Office visits are only counted if one of the three diagnosis codes (ICD9) indicates hypertension, hyperlipidemia, diabetes, osteoporosis, or depression, per the Chronic Condition Warehouse definition. Attribution of a drug to an office visit is defined as having a drug claim within 30, 90, 180, or 365 days of the office visit, and multiple drug claims can be attributed to the same office visit (e.g. an office visit can count for both a generic drug and a branded drug if multiple drugs are dispensed). The independent variable is average views per person for advertisements for drugs for a chronic condition in the ZIP code where the patient resides. Model used is a two stage least squares performed using the Stata 14.0 'ivreg2' command. Data are from 2006-2009. The model uses a continuous measure of the ratio of 65+ year olds in a ZIP code as of Q4 2005 as an instrument for advertising. Coefficients are interpreted as the effect of going from having 0% 65+ year olds to 100% 65+ year olds. Models also control for age and sex. Standard errors are clustered at the ZIP code level.