Ask Your Doctor? Direct-to-Consumer Advertising of Pharmaceuticals

Michael Sinkinson and Amanda Starc*

The Wharton School, University of Pennsylvania

PRELIMINARY AND INCOMPLETE - DO NOT CIRCULATE OR CITE

November 2014

Abstract

We measure the impact of direct-to-consumer television advertising by statin manufacturers. Our identification strategy exploits shocks to local advertising markets generated by idiosyncrasies of the political advertising cycle. We document advertising competition among statin producers and show how strategic interaction biases OLS estimates. We show that political ads displace drug ads and use this exogenous variation to estimate the effect of both own and rival ads on revenue. Results indicate that advertising produces significant business-stealing effects among branded drugs as well as spillovers to unadvertised drugs, both of which would not be detected through OLS. Decomposition shows that the effect is due mostly to new customers as opposed to switching among current customers.

JEL classification:

Keywords:

*The Wharton School, University of Pennsylvania, 3620 Locust Walk, Philadelphia PA 19104 (e-mail: msink@wharton.upenn.edu; astarc@wharton.upenn.edu). The authors would like to acknowledge the valuable advice and suggestions provided by Jason Abaluck, Patricia Danzon, Liran Einav, Brett Gordon, Wes Hartmann, Gunter Hitsch, JF Houde, Ginger Jin, Marc Merdith, Andrew Sfekas, Brad Shapiro, Ashley Swanson, and Bob Town. We would further like to thank workshop participants at Wharton, the Columbia Commuter Strategy Conference, Marketing Dynamics, IIOC, QME, and the Econometric Society for their comments and feedback.

1 Introduction

Firms in the United States will spend nearly $180 billion dollars on advertising in 2014, with television capturing the largest share of spending.[1] Pharmaceutical companies are no exception, advertising their products directly to both physicians and consumers. Direct-to-consumer advertising (DTCA) accounted for over $3 billion in spending in 2012. This is a unique feature of the US drug market; New Zealand is the only other developed country that allows DTCA by drug manufacturers.[2] Given the size of advertising budgets and the potentially large financial and health consequences of DTCA, understanding its impact is of key economic importance and has first-order implications for policy.

While advertising is a ubiquitous part of life, economic theory offers few conclusions on the welfare effects of advertising (Bagwell 2007). Advertising can be informative or persuasive or complementary to the consumption of a product. Advertising can be market expanding, and thus potentially enhance welfare, or simply steal business from similar products, which is unlikely to improve welfare. Therefore, the impact and welfare consequences of advertising are empirical questions. Empirical studies have attempted to estimate the degree of market expansion and business stealing using a variety of assumptions and empirical strategies (Ackerberg 2001, Iizuka 2004), yet measurement and identification are a constant challenge.[3]

Estimating returns to advertising is challenging because firm advertising decisions are endogenous: they depend on both unobserved market characteristics and actions of rival firms. In this paper, we illustrate the empirical challenge with a stylized model of television advertising competition that captures the key features of the market we study. We then propose a novel instrument to identify the effectiveness of TV advertising for anti-cholesterol drugs known as statins.[4] Our instrument exploits the fact that the timing of primaries and caucuses and the competitiveness of different races create exogenous shocks to different local advertising markets over the course of the political cycle. For example, in January of 2008, large quantities of political advertisements aired in markets in New Hampshire, Iowa, and South Carolina, while in May of 2008, political

[1] eMarketer, August 2013. http://www.emarketer.com/Article/US-Total-Media-Ad-Spend-Inches-Up-Pushed-by-Digital/1010154

[2] In 2012, DTCA accounted for 11.3% of the $27 billion spent by pharmaceutical firms on promotion. The activity comprising the largest share (54.8%) of the promotional budgets of firms is detailing, which is marketing directly to physicians. See Donohue, Cevasco and Rosenthal 2007 for an overview.

[3] In the context of prescription drugs, researchers find a great deal of evidence for the market expanding or informational effects of DTCA on outcomes such as doctors visits and drug adherence (Berndt 2005, Jin and Iizuka 2005, Wosinska 2002, Wosinska 2005, Rosenthal et al. 2003, Berndt et al. 1995). The informational effect is especially relevant for large classes of pharmaceuticals where the societal benefits far outweigh the costs, including statins and SSRI/SNRIs.

[4] This paper focuses on television advertising only, but evidence is presented that the results are not contaminated by spending in other channels, such as print or radio. Television is the primary medium for advertising in the data, accounting for over twice the spending in any other channel.

advertising was concentrated in Indiana, Pennsylvania and North Carolina. In the months leading up to the general election, advertising was heaviest in "swing states" in the presidential contest, and where House and Senate races were most competitive.[5] We first show that political advertising displaces pharmaceutical advertising. Then, using this variation, we present both graphical evidence and advertising elasticity estimates. We conclude with implications of our estimates for policy.

DTCA has always been controversial. While the Federal Trade Commission has generally encouraged DTCA due to its informational qualities,[6] some in the industry are critical,[7] noting that it can effectively create a wasteful arms race among competitors selling similar products. There is ancedotal evidence that strategic interaction among firms is an important component of direct-to-consumer advertising, with advertising often used to "blunt the impact of ... competitors' ads."[8] Statins are an excellent market to examine the impact of DTCA for a number of reasons. First, there are a small number of advertised drugs - four during our sample period - allowing us to explore the importance of competitive interaction between firms. Second, the products are close substitutes, and idiosyncratic consumer preferences are less likely to be important. Third, the products are widely considered effective with few side-effects. Finally, the category is economically important, generating $34 billion in sales in 2007.[9] This paper provides empirical evidence of the relative magnitudes of the business stealing and market expansion effects in the statin market.

This research combines data from a number of primary sources. We utilize drug-market-month level revenues for two different groups of consumers. We estimate elasticities for both the commercially insured (largely under 65, employer-sponsored) population using data from Truven and for those consumers enrolled in Medicare Part D using data from the Medicare program. We obtain drug-market-month level advertising units and spending from Kantar Media. Finally, we have market-month levels of political advertising from the University of Wisconsin Advertising Project. We combine these sources to have monthly data for 189 DMAs (media markets) for 2007-2008. Our first stage estimates imply that the thousands of political ads aired through the election cycle had a significant, negative effect on the level of DTCA.

Graphical analyses show that primaries are associated with statistically significant reductions in drug sales. We show that primaries are simultaneously associated with reductions in drug ad-

[5] While the list of swing states varies from election to election and there is no clear definition, Politico determined that the 2008 presidential race was most competitive in Colorado, Florida, Indiana, Missouri, Nevada, New Hampshire, New Mexico, North Carolina, Ohio, Pennsylvania, and Virginia. Source: http://www.politico.com/convention/swingstate.html

[6] http://www.ftc.gov/sites/default/files/documents/reports/improving-health-care-dose-competition-report-federal-trade-commission-and-department-justice/040723healthcarerpt.pdf

[7] http://www.nytimes.com/2011/02/10/opinion/10spatz.html

[8] http://www.nytimes.com/2011/02/10/opinion/10spatz.html

[9] http://www.forbes.com/2008/10/29/cholesterol-pharmacuticals-statins-biz-cx_mh_1030cholesterol.html

vertising. We then present estimates of the elasticity of revenue with respect to advertising using Medstat data covering the commercially insured population. In our preferred specifications, our estimates range from 0.0764 to 0.125. We also provide estimates of revenue elasticities with respect to rival advertising. In our preferred specifications, we estimate an elasticity of -.0548, indicating substantial business stealing effects. We separately estimate the impact on non-advertised generics and estimate an elasticity with respect to branded advertising of 0.02. The implication is that while advertising for a given drug, such as Lipitor, steals market share from Crestor, it also increases the market size for unadvertised drugs, such as simvastatin, the off-patent version of Zocor. Therefore, advertising has both a market expansion and business stealing effect.

The results are consistent across settings. Results from the Medicare Part D data are very similar in magnitude, and we cannot reject that the elasticities estimated in the two datasets are the same. The Part D data also allow us to examine heterogeneity across different subsets of consumers. When we restrict the sample to first-time consumers, we estimate much larger elasticities. This is both intuitive and has dynamic implications for firms, which must take the present value of future sales into account. We also find smaller effects among the sickest consumers and those enrolled in more restrictive insurance plans. Both datasets tell a consistent story: DTCA has an economically important impact on drug sales. Competitive interaction between rivals is an important feature of the market, and rival advertising has a significant business stealing effect.

Our estimates also provide a set of sufficient statistics for quantifying the economic and potential health consequence of DTCA. We first show, using a simple back-of-the-envelope calculation, that our estimates imply sensible elasticities that are consistent with rational firm decisions. We then quantify the level of statin sales in the absence of DTCA and decompose this effect into business stealing and market expansion components. We find that business stealing is an especially important feature of this market: sales of advertised drugs would be nearly 25% higher in the absence of business stealing effects. We argue that the negative impact of business stealing outweighs the market expansion effect in this market. However, a ban on DTCA creates tradeoffs: it reduces welfare enhancing sales as well as advertising expenditure. We argue that the net effect on category sales is close to zero. These exercises place our empirical estimates in context.

This paper contributes to a substantial literature examining the impact of DTCA. Previous researchers has found a great deal of evidence for the market expanding or informational effects of DTCA on outcomes such as doctors visits and drug adherence (Berndt 2005, Jin and Iizuka 2005, Wosinska 2002, Wosinska 2005, Rosenthal et al. 2003, Berndt et al. 1995). The informational effect is especially relevant for large classes of pharmaceuticals where the societal benefits far outweigh the costs, including statins. The paper closest to our study is Shapiro (Shapiro 2014), which estimates economically significant spillover effects in the SSRI/SNRIs market using a cross-border strategy and structural model of demand. By contrast, our paper focuses on carefully estimating

the return to DTCA using a new source of exogenous variation and argues that competitive interactions have important implications for the level of advertising, firm profits, and consumer utilization. The paper also contributes to a literature that attempts to measure the causal impact of advertising. While large amounts of high quality data are often available, valid sources of exogenous variation and natural experiments are uncommon (Rossi 2014). Recent work (Lewis and Rao 2013, Blake, Nosko and Tadelis 2013) has utilized randomized experiments on online platforms. By contrast, our study utilizes a series of natural experiments that generate plausibly exogenous changes in consumer advertising. While we focus on the statin market, the identification strategy we propose is likely to be useful across many other product markets.

The paper is organized as follows. Section 2 describes the market and setting. Section 3 describes the data and empirical strategy, while Section 4 presents results. Section 5 describes robustness checks and explores the heterogeneity in the main results. Section 6 describes simulations, and Section 7 concludes.

2 Setting and Measurement Challenge

2.1 Cholesterol Treatment

Cholesterol is a waxy substance that is both created by the body and found in food. Low-density lipoprotein (LDL, or "bad" cholesterol) is associated with a higher risk of heart attack and stroke. While cholesterol can usually be well controlled with diet and exercise, drug therapy can also be effective. A large class of drugs - statins - work by preventing the synthesis of cholesterol in the liver. Statins are big business: each year during our sample period, Lipitor and Crestor alone had nearly $15 billion in sales. The first statin on the market was Mevacor, which was introduced in 1987 by Merck. Mevacor was followed by a large number of “me-too” drugs: similar, but chemically distinct, compounds with the same mechanism of action. Zocor was introduced by Merck in 1991, as was Pravachol.

During the 2007-2008 time period, four branded anti-cholesterol medications were being advertised. The major statins were Lipitor (Pfizer), approved in 1997, and Crestor (AstraZeneca), approved in 2003. Both are thought to be more effective than previous statins, but also well-timed. According to trade press and news, the instoduction of Lipitor heralded an increase in the “’arms race’ of drug marketing.”[10] The US began allowing direct-to-consumer advertising on television in 1997; Pfizer marketed Lipitor to consumers aggressively beginning in 2001.[11] Zocor’s patent

[10] http://www.ft.com/cms/s/0/d0f7af5c-d7e6-11de-b578-00144feabdc0.html

[11] See http://archive.fortune.com/magazines/fortune/fortune_archive/2003/01/20/335643/index.htm for additional details. While initially, Pfizer priced agressively and detailed heavily, they eventually turned to DTCA as a way to expand the market and gain market share.

expired in 2006, and heavy generic competition began shortly thereafter. This hurt the sales of not only Zocor, but also Crestor and, to a lesser extent, Lipitor, as cheaper generic substitutes flooded the market and Zocor gave aggressive rebates to insurers to keep consumers taking their product.[12]

In addition to Lipitor and Crestor, Vytorin and Zetia are both advertised during the earlier months of our sample period. However, in January 2008, the results of the ENHANCE trial were released. The study, completed in 2006[13], showed that Vytorin (Zetia and Zocor combined) was no better than Zocor alone. This led to the American Academy of Cardiologists recommending that doctors no longer prescribe Vytorin and strongly discouraging the use of Zetia.[14] The effect on Vytorin's market share was dramatic, falling 10% immediately and 40% over the course of 2008 in our sample data. By contrast, a recent, much larger study (18,000 subjects vs. just 750) found Vytorin to be more effective than simvastatin alone.[15] We do not take a strong stand on the role of these studies except to point out that the findings are often referenced in DTCA and this advertising, in addition to the information content of the studies themselves, may affect demand.

Both branded and generic statins are seen as cost-effective, especially for high-risk populations.[16] This makes statins ideal for study: statins have little to no downside, and given that they are cost-effective, we believe that expanding the market is at least weakly welfare enhancing.

Statins are widely covered by insurance plans insurance. Most consumers who obtain health insurance from their employer have prescription drug coverage as part of their benefits package.[17] Insurance coverage is likely to be generous, and consumers will face only a fraction of a branded statin's $3/day price tag. However, consumers in employer-sponsored insurance tend to have a limited number of choices (Dafny, Ho and Varela (2013)) and are unlikely to select into insurance plans based on their coverage or cost sharing for particular drugs. By contrast, most seniors obtain their drug coverage through the Medicare Part D program. Consumers in Medicare Part D face a very non-linear insurance contract: there is an initial deductible, followed by (an average of) 25% co-payment rates up to an initial coverage limit. Once a consumer hits the initial coverage limit, they must pay for all of their expenditure in the "donut hole" or coverage gap until they meet a catastrophic cap. In most markets, there are many plans available and these plans are likely to very substantially in terms of their formularies, that is, the specific drugs covered by the plan. A savvy consumer will choose a plan based on their expected drug demand over the course of the year. Meanwhile, insurers have incentives to steer consumers to lower cost drugs, especially generics. Therefore, plan selection is more likely to be a concern in the Medicare Part D sample.

[12] citation needed.

[13] http://jama.jamanetwork.com/article.aspx?articleid=181510

[14] http://content.onlinejacc.org/article.aspx?articleid=1188931&resultClick=3

[15] http://www.nytimes.com/2014/11/18/health/study-finds-alternative-to-statins-in-preventing-heart-attacks-and-strokes.html, update when actual study comes out

[16] citation needed.

[17] This insurance coverage may be provided by the consumer's health insurer of by a pharmacy benefits manager.

Finally, to obtain a statin, a patient must have a prescription. Physicians and consumers may disagree about the best course of treatment, and asymmetric information creates the potential for physician agency to be an important feature of prescription drug markets. Prescription drug manufacturers, aware of the influence of physicians, engage in substantial detailing at the doctor level in addition to DTCA (generally known as "push" techniques, as opposed to "pull" techniques that target the consumer). Both plan selection and physician agency are, in some sense, outside the scope of this paper. While they influence the market, their effects are likely to remain fixed over our short time period, allowing us to focus on measuring the impact of DTCA.

2.2 Advertising of Statins

Manufacturers advertise their products to physicians, through detailing, as well as directly to consumers. Manufacturer strategies for differentiating their products often rely on results from clinical trials showing efficacy. Zocor marked an early use of clinical trials in marketing drugs (largely to physicians): Merck showed in the Scandinavian Simvastatin Survival Study (4S) that Zocor prevented additional heart attacks among patients who had already suffered a heart attack. In April 2008, Merck released the results of the ECLIPSE trial, which favored Crestor relative to Lipitor for certain sub-populations of patients,[18] corresponding to the increase in Crestor marketing.

During the 2007-2008 period, there were a pair of issues that affected the marketing of statins. The first was the ENHANCE trial results, mentioned above, which led to the end of advertising of Vytorin in January of 2008.[19] The second came in April of 2008, when Lipitor was forced to halt its advertising campaign featuring Dr. Robert Jarvik (developer of the Jarvik artificial heart). Many, including Congress, had concluded that the advertisements were misleading.[20] As a result, Lipitor did no advertising to consumers from April 2008 until August 2008. For those months, the only statin advertising to consumers was Crestor. In 2008, Lipitor's sales fell by 2% and Crestor's sales rose by nearly 29%.[21]

Prescription drugs that are no longer protected by patents are not typically advertised by their manufacturers.[22] Lipitor's patent expired at the end of November 2011 and Crestor's is scheduled to expire in 2016.

[18] They use the results of this trial in marketing. http://www.crestor.com/c/about-crestor/crestor-clinical-studies.aspx

[19] Congress specifically sent a letter to the FDA to challenge marketing of Vytorin. http://blogs.wsj.com/health/2008/01/16/congress-investigates-vytorin-ads/

[20] Dr. Jarvik was not a licensed cardiologist and was replaced by a stunt double in some of the TV spots.

[21] http://www.pfizer.com/investors/sec_filings/sec_filings and http://www.astrazeneca.com/Investors/Annual-reports

[22] This is in contrast to over-the-counter medications, which are often advertised even through an exact molecular substitute is available. See Bronnenberg et al. (2014) for details.

2.3 Measurement Challange

Alternative models of the demand side effects of advertising have wide-ranging positive and normative implications. However, supply side incentives to advertise and supplier behavior have major implications for measurement and estimation. Consider a monopolist setting advertising and price. Dorfman and Steiner (1954) show that the firm should advertise until the marginal revenue from a dollar spent on advertising equals the price elasticity of demand. Yet the marginal revenue from advertising and willingness of consumers to substitute away from a firm's products may depend on the competitive environment and substitutes available, respectively. A monopolist will face different incentives than a firm selling a product in a perfectly competitive industry. Furthermore, in many settings, competitive interaction between firms will alter returns to advertising. Advertising could be a strategic complement, in the sense that my best response to a rival increasing their advertising is for me to also increase my advertising or, conversely, a strategic substitute, depending in part on whether advertising is market expanding or not.

In our setting, advertising is endogenous for at least two reasons. First, firms are more likely to advertise in markets where advertising is likely to be most effective, due to either a transitory or permanent demand shock such as genetic traits or physician agency. For example, firms may be more likely to advertise in markets where doctors are more likely to prescribe branded drugs over generics, or where insurance coverage for branded drugs is relatively higher. Second, firms also respond to rivals' strategic choices when setting the level of advertising. For example, suppose a firm's advertising increases its own revenues, while rival ads have either a positive (market expansion) or negative (business stealing) effect. Then a firm's level of advertising depends on its effectiveness as well as the actions of other firms. If advertising is largely business stealing, firms may find themselves in a prisoner's dilemma, where all would prefer to pre-commit to lower levels of advertising. By contrast, if advertising is largely market expanding, firms may under-advertise because of the positive externality to rivals. In general, the direction of the effect is specific to a product market. Given this, the econometrician requires an instrument for advertising to credibly estimate its effect.

As an illustration, consider a positive demand shock for Lipitor in a market, which increases the returns to advertising. We would then observe more Lipitor ads. A strategic response from AstraZeneca under business stealing would imply additional Crestor ads. However, mechanically, an OLS approach would then measure a market expansion effect of Crestor's ads because we see more Crestor ads in market with a high unobserved shock for Lipitor. The effectiveness of a firm's own advertising is more ambiguous. It could be that firms advertise more in markets where ads are more effective, leading to a upward bias. On the other hand, once accounting for strategic interaction, it may be that markets with large demand shocks see increased advertising from all firms. Given diminishing marginal returns, this would lead to a downward bias in OLS estimates.

Appendix A formalizes a simple model that captures these effects. The following table summarizes how both strategic interaction and unobserved market heterogeneity can bias estimation. The direction of the bias depends on both unobserved factors and strategic interaction. Measuring the causal impact of advertising therefore requires a source of exogenous variation in advertising levels.

Table 1: Potential Biases in OLS Estimation of the Effects of Advertising

	An unobserved positive demand shock...	
	Increase Marginal Benefit of Advertising	Decrease Marginal Benefit of Advertising
Rival advertising is...		
Business Stealing	Both advertise more; Own effect bias: ↑ Rival effect bias: ↑	Both advertise less; Own effect bias: ↓ Rival effect bias: ↑
Market Expanding	I advertise more, rival less; Own effect bias: ↑ Rival effect bias: ↓	I advertise less, rival more; Own effect bias: ↓ Rival effect bias: ↓

Appendix A.3 shows the results from estimating the effects of advertising on a simulated dataset where demand is Logit and firms choose optimal advertising levels. In the simulated model, parameters are chosen so that unobserved demand shocks reduce the return to advertising and the effect of advertising is business-stealing. The resulting bias is toward zero for both parameters, as expected.

3 Data and Empirical Strategy

3.1 Data

We combine two sources of advertising data. First, we have monthly DTCA data, both the number of ads and the level of spending, for 2007-2008 at the drug level for every DMA (Designated Market Area) in the United States from Kantar Media. We also have a record of every political ad (presidential, senate, house, and gubernatorial) aired during the 2007-2008 election cycle in every DMA from the Wisconsin Advertising Project, which we normalize to a 30-second length and aggregate into monthly figures.

The number of political ads in a market-month varies widely during the Jan 2007-Nov 2008 time period: half of the month-market observations during this period have zero ads, while some markets have over 20,000 political ads in a month (i.e. Denver, CO in October of 2008). Figure 1

shows graphically the progression of the political ad shocks for the first 6 months of 2008, where each DMA is represented by a circle sized proportionally to the number of political ads. The mean number of monthly ads in a market from Jan 2007 to Nov 2008 is 535, with a standard deviation of 1600. By contrast, there are fewer drug ads in general: when combining national ads with local ads, the average number of statin ads aired in a market during a month is 98 with a standard deviation of 59. (National and local refer to the level of the ad buy, not the content.) Figure 3 shows the levels of monthly national ads for the advertised statins during our sample period, while Figure 4 shows the highest number of monthly local ads for each of the drugs (the minimal number of local ads across markets is 0 for all drugs and months of our data). Local advertising can be a substantial portion of a firm's total advertising. While some markets receive no additional advertising, the maximum amount of local advertising is often higher than the national advertising, indicating that a substantial proportion of advertising comes from local ads.

We then combine this advertising data with prescription drug usage and revenue data from two sources. First, we used Truven Medstat data, which draws from a convenience sample of large, self-insured firms. These data represent individuals enrolled in traditional, employer-sponsored insurance, and are likely to be the primary target market of statin advertisers. Our sample consists of market-level aggregated revenues, quantities, and covered lives. We aggregate MSAs to DMAs to arrive at our analysis dataset. Summary statistics for the data sources are shown in Table 2. We have data for 189 DMAs and utilize 17 months of data, spanning July of 2007-November of 2008. On average, a relatively small proportion of this population takes statins, as the sample is younger than the population on the whole. The largest branded drug captures just less than 5% of the total market. We supplement this data with data from the Medicare Part D program. Our data are comprised of a 10% random sample of all Medicare Part D beneficiaries. The advantage of Medicare data is that it allows tracking of individual consumers. The disadvantage is that most consumers who ever take a statin do so before they reach Medicare eligibility, making the consumers in the Medicare data potentially less attractive to statin advertisers. We restrict our sample to the same 189 DMAs, seventeen months, and four drugs in the Truven data. We then aggregate the data to the product-month-DMA level and perform a parallel analysis. The combination of datasets allows us to explore heterogeneity in the effectiveness of DTCA and provides additional confidence in the magnitude of our empirical results.

3.2 Identification Strategy

We exploit shocks from political advertising in markets over time from the staggered nature of the party nomination processes, as well as the variation in competitiveness of different races in the general election. The United States holds quadrennial general elections for the Presidency, which

coincide with elections for all seats of the House of Representatives, numerous state governors, and approximately one third of seats in the Senate. The election is held on the Tuesday following the first Monday of the month of November in the election year. Campaigns for the presidency begin well over a year before the general election as candidates seek their party's nomination, which is conferred by delegates voting at each party's national convention a few months prior to the election. Individual states and state political parties determine the timing and format of the contest to determine the state's delegation to each party's national convention, with the majority of states using government-run primary elections, and the remainder using party-run caucuses. The staggered nature of the nominating contests results in national attention and importance thrown on early contests in Iowa and New Hampshire, as well as South Carolina, Florida and Nevada.[23] In 2008, the contest between Hillary Clinton and Barack Obama extended into June before enough delegates had been pledged to determine the outcome. John McCain secured the Republican nomination by March of 2008. Figure 1 highlights the staggered nature of the process by showing political ad concentrations for January to June, 2008.

Following the party nomination contests, the nature of political advertising changes. The "winner take all" method for state delegations to the Electoral College means that political advertising in swing states is likely to be far more valuable than in "safe states", and results in large variations in the numbers of ads different markets are exposed to (Gordon and Hartmann, 2013). For example, in October of 2008, New York, NY had 0 television ads for presidential candidates (547 for Governor/House/Senate candidates), while Cleveland, OH had 8,073 television ads for presidential candidates (and another 2,439 for Governor/House/Senate candidates).

While political advertising provides useful variation that allows us to identify the effect of advertising, we are interested in both the effect of the focal firm's advertising and their rival's advertising. We make use of an additional shock specific to the statin market. As discussed above, Pfizer was forced to halt its consumer advertising in mid-2008. In order to separately identify the effect of own and rival advertising, we interact the political advertising instrument with the timing of this Congressional action.

3.3 First Stage Results

Our initial estimates relate the level of drug advertising in a market to the level of political advertising. We believe that political advertising is plausibly exogenous to prescription drug outcomes given that the political primary and caucus schedule is set independently of any prescription drug

[23] New Hampshire law stipulates that no other state can have a primary earlier: "The presidential primary election shall be held on the second Tuesday in March or on a date selected by the secretary of state which is 7 days or more immediately preceding the date on which any other state shall hold a similar election, whichever is earlier, of each year when a president of the United States is to be elected or the year previous." NH RSA 653:9

market factors, and that the competitiveness of various races is unlikely to be correlated with the market for statins. However, we must also demonstrate that the level of political advertising predicts drug advertising. The mechanism through which this occurs is that political campaigns, and particularly outside influence groups, purchase premium advertising slots that pre-empt advertising previously purchased at lower rates (typically the Lowest Unit Rate, or LUR).[24] Table 3 presents a regression of the log of the number of statin advertisements for a drug in a market on the log of the number of political advertisements (in 1000s). The level of observation is a DMA-month for January 2007 until November 2008. We include a variety of fixed effects across different specifications. The OLS results show that a 10% increase in political advertising leads to a 1.2% decrease in statin advertising. The effect is slightly larger if you do not account for month fixed effects. Figure 5 shows a binned scatter plot highlighting the same effect. To account for the fact that drug ads cannot be negative, the last columns of Table 3 show estimates from a Tobit model, and we find a significantly larger effect: the elasticity of an individual drug's ads with respect to political ads in a market is -0.2598 in our preferred specification, implying that a 10% increase in political ads decreases each drug's ads by 2.6%. Appendix Table 17 shows the analogous results using levels instead of logs, with all results strongly negative and significant.

Our identification strategy uses political ads as an instrument, as these ads displaced prescription drug advertisements during the period leading up to the 2008 presidential election. We address four possible concerns about this strategy. First, since the political cycle is known in advance, firms could have substituted ads to months before or after a market received a large number of political ads. In Table, 16 we show that leads and lags of political advertising are not predictive of drug ads in the current month, indicating that there was not substitution to earlier or later months. Second, it is possible that firms substitute from TV advertising to other local media (radio, newspaper) when political ads displace television advertising. In Table 15, we show that total local spending is not affected by political ads once local TV ads are controlled for. The results appear to show that local TV ads and other local media are complements, not substitutes, and is consistent with the political cycle being a shock to all forms of media in a local market. Third, we would like to rule out that firms modify their detailing plans due to the displacement of their local TV ads by political ads. While we have no data to directly test for this, discussions with industry managers led us to conclude that this is infeasible, as detailing plans are set at the annual level and cannot be quickly scaled up or down at the market level. Fourth, we do not believe that drug firms are responding to political advertising shocks by buying more advertising in less desirable time slots, which would create measurement error in the number of ads in our data. The relationship between

[24] See the discussion in Gordon and Hartmann (2014) regarding how political campaigns purchase advertisements. As they discuss, campaigns and issue advocacy groups purchase premium "non-preemptible" advertising slots, which can displace advertising previously ordered at the lowest unit rate.

political advertising and drug advertising is largely driven by availability and pre-emption as opposed to prices. The Communications Act of 1934 limits media outlets from raising prices for polical campaigns, and Table 18 shows that the price per impression is not significantly changed due to political advertising. If firms were shifting their ad buys to lower-priced slots with lower ratings, we would expect a negative relationship.

4 Results

4.1 Graphical Evidence

We have shown that political advertising tends to displace statin advertising. Our first stage estimates are strongly significant and large in magnitude. Next, we need to show that this displacement has an effect on drug revenues. We first present a number of simple graphical analyses, initially focusing on unadvertised drugs, for which there is only one causal effect to estimate.

During the time leading up to a primary, consumers are exposed to fewer ads for Crestor, Lipitor, Vytorin, or Zetia. If these ads have spillover effects on unadvertised (largely generic) drugs, we would expect a drop in sales at the time of the primaries. The timing of primaries is staggered and exogenous to the prescription drug market, giving a simple test of the effect. Figure 6 shows the effect of primaries on market share growth for unadvertised drugs. While sales are stable in the months before the primary, there is a statistically significant reduction in sales growth concurrent to the primary. We argue that the natural mechanism for this reduction is a drop in statin advertising.

We are also interested in the effect on branded drugs. Here, the competitive interaction makes interpretation more difficult. While the political process displaces Lipitor ads, it displaces Crestor ads as well, and we will only be able to measure the net effect without additional variation or assumptions. However, many primaries take place during the months in which Lipitor was not advertising due to regulation. Given this additional fact, we would expect the direct effect of the primary to be larger for Crestor than for Lipitor. That is exactly what we see in Figure 7; the magnitude of the effect of primaries on Crestor sales is nearly twice as large as the effect on Lipitor sales. During this time period, Crestor and Lipitor are the primary advertisers. The overall effect is negative, indicating that the effect of a firm's advertising is not outweighed by its rival's advertising. Furthermore, these results imply that the absence of DTCA would lead to a drop in overall drug sales.

4.2 Regression Results

We utilize the identifying variation in a regression framework to estimate elasticities. We estimate the following equation:

$$log(revenue_{jtm}) = \beta_0 + \beta_1 log(1 + ad_{jtm}) + \beta_2 log(1 + \sum_{k \neq j} ad_{ktm}) + \beta_3 X + \varepsilon_{jtm}$$

where X represents a vector of product-year and market dummies. In some specifications, we allow for a time trend. Because the specification is log-log, we can interpret the coefficients as elasticities.

Table 4 shows the results of OLS specifications for advertised drugs. The first pair of columns use contemporaneous ads and revenues; the next pair regresses this month's revenue on the averages of this month's and the previous month's advertising levels; the final pair average the previous three months' advertising levels. We do this because previous research has shown that advertising can be cumulative and/or have a lagged effect (Dubé, Hitsch and Manchanda 2005), but that the effects of DTCA can depreciate quickly (Jin and Iizuka (2005)). In each regression, the level of analysis is the DMA-month-drug. We include each of the drugs advertised during our sample period from July 2007 through November 2008 that are classified in the same in Truven Redbook class 059: Lipitor, Crestor, Vytorin, and Zetia. The dependent variable is logged drug revenue per insured individual in the market.

We control for time trends in product demand in two ways: drug-year fixed effects and a drug-specific time trend. Figure 2 shows that there are important time trends during our sample period: Lipitor's market share is steadily decreasing over the entire sample period. There does not seem to be a distinct, national break at the time that Pfizer pulled the Jarvik ads. At the same time, Crestor's market share is increasing, though not as dramatically. Because we will eventually utilize the regulatory shock to Lipitor advertising, we cannot allow for finer (monthly- or quarterly-) product-specific fixed effects. However, we can can allow for a linear, product-specific time trend that approximates the data reasonably well. Regardless of controls, the OLS regressions consistently show a small, but statistically significant and positive effect of DTCA on sales. The specifications that allow for a product specific time trend are typically smaller in magnitude.

The results in Table 5 allow us to document the causal impact of advertising. Here we instrument own and rival advertising levels using (i) the level of political ads, as well as 2nd and 3rd order polynomials of political ads, (ii) a dummy for the congressional action that halted Lipitor advertising, and (iii) an interaction of this dummy with the polynomials of political advertising. By comparing these results to the previous table, we see that OLS underestimates the effectiveness of advertising. The own advertising effect in column 3 (.02) is less than 20% of the effect mea-

sured in the IV specification (.13). Similarly, we find substantial evidence of business stealing in the IV specifications that is absent from the OLS results. Both biases are consistent with a model in which advertising is business stealing and creates an arms race. Unsurprisingly, we find that the effects are attenuated as we look at a broader window. The effect of contemporaneous advertising in the drug-year fixed effects regression is the largest (0.1559), while the two-month (0.1252) and three-month (0.1048) moving averages are smaller. Despite this attenuation, the results are stable across specifications. While the estimates that allow for product-specific time trends are smaller in magnitude, we cannot reject that they are statistically the same. We focus on the two-month trailing average specification with drug specific time trends moving forward. Our preferred own-revenue elasticity estimates for advertised drugs is 0.0764, from column 5. This implies that a 10% increase in advertising would yield a 0.76% increase in revenue. Our preferred cross-revenue elasticity estimates range is -0.055.

We believe there are a number of reasons our OLS estimates are biased towards zero. First, as discussed in the model, this direction of the bias is theoretically ambiguous and depends heavily on strategic interaction between firms. Second, measurement error may be attenuating the OLS estimates. Finally, we measure a local average treatment effect that captures the short run elasticity of sales with respect to advertising expenditures. The long run elasticity may be smaller in magnitude.

Table 6 explores this effect further. Columns 3 and 4 replicate the last set of specifications in Table 5 in which two month moving averages of drug advertising are the independent variables of interest. However, columns 1 and 2 present OLS and IV specifications in which logged revenue of unadvertised antihyperlipidemia drugs (as classified by Redbook) is the dependent variable. In the OLS specifications, we find no effect of rival advertising. Once we instrument for advertising, we find evidence that advertising has a small, but significant spillover effect, consistent with other research (Lewis and Nguyen, 2014). A 10% increase in advertising for the class leads to a 0.23% increase in sales of unadvertised drugs. Our results support a model in which advertising has largely persuasive or business stealing effects, but allows for small spillovers to unadvertised drugs, consistent with informational effects.

5 Robustness Checks and Heterogeneity

5.1 Robustness Checks

We perform a number of additional analyses and robustness checks. We present three key sets of specifications here, and defer additional discussion to the appendix First, in Table 7, we explore the direction of the bias in OLS results. We argue that strategic interaction is an important determi-

nant of returns to advertising. In the absence of a rival response, we would expect a different bias: if positive demand shocks lead to additional advertising, then estimates will be biased upward. Columns 1 and 3 illustrate this point. We note that these specifications explicitly violate our exclusion restriction: shocks to political advertising affect drug sales not only through changes in my own advertising, but changes in my rival's advertising as well. Therefore, we do not interpret these estimates as causal. When we do not control for rival advertising, the estimated own-advertising elasticity is much smaller (0.0163), less than 15% of the effect measured in columns 2 and 4. Both my advertising and my rivals' advertising are endogenous and the outcome of dynamic game; our identification strategy allows us to capture both effects.

Table 8 shows that our results are robust to the different assumptions about the timing of advertising effectiveness. Column 1 presents our preferred specification, while column 3 presents a specification where advertising is measured with a one-month lag, rather than a two-month trailing average. The estimates are quite similar, though larger in magnitude and closer to the contemporaneous estimates in column 2 of Table 5. The specification in column 2 attempts to control for the fact that advertising stock might also have an effect on drug revenues by including a one-year lag of advertising as a control. Again, we obtain statistically indistinguishable estimates as compared to our preferred specification.

Finally, our identification strategy exploits both the timing of the political process and regulatory actions: in particular, the pulling of Lipitor ads featuring Dr. Robert Jarvick. We have more confidence with the first source of identification; it is possible that the pulling of Lipitor ads also led to numerous news stories and this publicity, while it actually contained no content about the quality of the drug itself, may have had an impact on sales. However, in all specifications, we interact the regulatory action with the level of political advertising and utilize the "intensity of treatment" across areas as a second instrument. Basically, we are comparing those states where a primary would have had a large impact on Lipitor ads if not for the regulatory action with those states where a primary affects all drugs more equally. We run additional specifications that include the main effect of the Jarvik regulatory action in both stages of the regression and present the results in Table 9. The estimates are noisier, which isn't surprising, but confirm our basic story. The point estimate on the own advertising elasticity in the preferred specification in column 4 is larger in magnitude than our main results, but not statistically different. This provides us with additional confidence.

Additional results, available in the appendix, explore the robustness of the instrument, show that the elasticities are stable to the inclusion of additional controls and the specification of the first stage, and present "reduced form" estimates of the direct effect of political advertising on drug sales.

5.2 Part D Sample

The results utilizing the Truven data are compelling, but they represent only a fraction of the potential statin market. While there is no reason to believe the consumers in the Truven are not representative of employees of large, self-insured firms, the Truven sample is not representative of the population as a whole. In order to further explore the effect of DTCA, we utilize Medicare Part D claims data. Medicare Part D will cover a population that is significantly older and sicker than the Truven data. Furthermore, the contractual features of plans may do more to alter utilization or steer consumers towards particular drugs. This analysis gives us an opportunity to compare elasticities across settings and explore additional heterogeneity in the data.

In all our specifications, we aggregate the Part D claims data, which exist at the individual prescription fill level, to the DMA-product-month level. We keep only those markets for which we have Truven data, leaving us with the same number of observations in each specification and identical first stage regressions. Any differences in the estimates are due to differences in sales across the two samples.

Table 10 shows the results of OLS specifications for advertised drugs. The results are remarkably similar in magnitude to the estimates in Table 4, though slightly larger in magnitude. The differences between the estimates are rarely statistically significant. The same pattern plays out in the IV regressions. The own advertising elasticities in our preferred specifications utilizing the Truven sample ranged from 0.076-0.125, while the own advertising elasticities utilizing the Part D sample range from 0.054-0.147. In both samples, we see significant evidence of business stealing effects, though the (negative) effect of rival advertising is smaller in magnitude than the (positive) effect of own advertising. By replicating our main results using data covering a very different consumer population, we reinforce the empirical magnitudes of our results as well as the qualitative pattern.

5.3 Heterogeneity

The Part D data also allows us to explore heterogeneity in the effect of DTCA across different demographic groups, utilization patterns, and insurance regimes. A natural question is whether the effects we see are driven by new consumers, with no history of statin use, or by switchers, who may be more likely to try an alternative statin after seeing an ad for it. In order to quantify the separate effects on consumers without a history of statin use, we focus on revenue from new prescriptions. We restrict the claims data to first time prescriptions, defined by the first fill of Crestor, Lipitor, Vytorin, or Zetia. We then collapse the data to the market-month-product level and replicate the same analysis. We have slightly fewer observations as we do not observe "new" prescriptions in every market-month-product cell. Otherwise, the specifications are the same as

previous specifications but utilize a different dependent variable.

The results are presented in Table 12. We report specifications with product specific time trends. There are two key observations. First, the own advertising elasticity is five times as large in magnitude for new consumers (0.288 versus 0.054 for the entire sample). The OLS estimates are also larger in magnitude. Second, while the rival elasticities are larger in magnitude, business stealing effects are relatively less important among new consumers. We conclude that the effect is largely being driven by new consumers, rather than switchers. This has important implications for firm strategy, which we hope to explore in future research.

We also explore additional dimensions of heterogeneity in the appendix. Medicare Part D has four phases, corresponding to total spending. What phase a consumer ends the year in reflects both the marginal cost of drugs to the consumers and their relative utilization. We show that advertising does not have a significant effect on consumption for the sickest consumers - those who end the year in the "catastrophic coverage" phase of Medicare Part D. The results do not depend on effective marginal prices: the results for the initial coverage phase, in which the consumer has a relatively small co-pay, and the donut hole, where they have effectively no coverage, is statistically the same. This is not particularly surprising, as consumers typically do not respond to the end-of-year marginal price (Aron-Dine et al. (2014)). Finally, consumers can choose between two alternative types of insurance plans under the Part D program. They can enroll in a stand-alone Part D plan, or a comprehensive Medicare Advantage (MA) plan. The MA plans tend to have more supply-side restrictions, and advertising has a smaller impact among these enrollees.

Our results present a consistent story. First, OLS estimates of the effectiveness of DTCA are biased due to firms strategically advertising in response to both consumer demand and competitor actions. Second, we find significant returns to advertising in the statin market and our estimates indicate that a 10% increase in advertising leads to a 0.7% increase in revenues, holding rival actions constant. However, in order to perform simulation exercises, we require a formal model of firm decision making and advertising effectiveness.

6 Implications and Discussion

A back-of-envelope calculation shows that our estimates are quite sensible. Lipitor spent $175M on DTCA in 2009, or $15M a month. US revenue was approximately $490M/month, and their financial statements indicate that costs were 25% of revenue. Our elasticity estimates are 0.0764 and 0.0543 for the Truven and Part D samples, respectively. This implies that a 1% increase in advertising ($150,000) increases revenues net of costs by by $200,000-$281,000. While this does not exactly equate marginal costs and marginal revenues, it does hold fixed rival advertising, and so is a partial elasticity.

6.1 Simulations

Our results can be used to quantify the relative importance of business stealing and spillovers in this market. First, we calculate sales in the absence of a business stealing effect of competitor advertising. To do this, we set the coefficient on rival ads equal to zero in the main specification (column 4 of 5) and calculate the percentage change in sales. We do not alter the level of the ads themselves. This is important for two reasons. First, firms still benefit from the content of their own advertising. Second, we are not measuring an equilibrium outcome; firms may choose higher or lower levels of advertising absent a business stealing effect.

Table 13 presents the results. Business stealing has a sizable impact on sales. Absent the negative impact of rival ads, sales would be 21% higher for Lipitor, 24% higher for Crestor, and over 27% higher for Vytorin and Zetia. This is a substantial increase, but not unreasonable given our estimates and the data. At $90 for a month's supply, this amounts to approximately 250 more monthly prescriptions in the average market.

To the extent that business stealing is less likely to be seen as welfare-enhancing, this has important implications for policy. We now turn to analyzing the impact of changes in the regulatory environment. Our model allows us to perform a number of simulation exercises. We focus on two key scenarios: a ban on DTCA and an elimination of political advertising. First, we estimate the impact of a ban on DTCA. This eliminates both the effect of my own ads and my rival's ads. The results are a negative impact for Lipitor, the market leader, but a surprising positive effect for Crestor. This illustrates how strong the business stealing effects are in the data. We can also measure the impact of spillovers to generic drugs in a separate regression shown in Panel B. We set the coefficient on category ads equal to zero in the IV specification in Table 6 and compute the change in the level of sales of non-advertised generics. Here we find much smaller effects. Eliminating the spillover effects of advertising reduces sales by less than 2% (though on a larger base). This amounts to about 95 fewer monthly prescriptions in the average market. In the absence of DTCA, firms would spend less on promotion with a modest effect on total sales. This suggests that DTCA creates a prisoners' dilemma, where an individual firm has a strong incentive to advertise, but in equilibrium, all are spending more on advertising and seeing minimal effects. Table 13 highlights that there are winners and losers from a policy banning ads. Crestor benefits, while Lipitor is more likely to be harmed.

Finally, an interesting implication of our identification strategy is the potential campaigns have to impact economic activity. To capture this effect, we predict statin ad spending conditional on no political advertising and statin sales conditional on the higher levels of statin advertising. Because the business stealing effect almost completely offsets the main effect, the absence of political ads has little effect on the market over, as seen in the final rows of each panel of Table 13. Our results prove to be sensible in simple, back of the envelope calculations. Furthermore, we argue

that the business stealing features of advertising are especially important and empirically larger in magnitude than any market expansion effects.

Based on these calculations, we conclude that the business stealing impact of advertising in our market is empirically much larger in magnitude than any market expansion effect. The spillovers we estimate are less than 40% of the magnitude of the business stealing we estimate. This finding is in contrast to studies that have found evidence of positive spillovers in other drug categories. We argue this is primarily for two reasons. First, we have multiple sources of exogenous variation to estimate the elasticities of interest; our OLS results would imply small market expansion effects. Second, the statin market has a small number of players that are very close substitutes. The empirical effects may just be different than other drug classes with a larger number players or where the "match" of a patient to a drug is more important. Finally, we note that we estimate spillovers to all unadvertised drugs, but argue that in addition to market expansion effects, business stealing is a critical feature of statin advertising.

These are only partial equilibrium calculations. Firms may alter their pricing or detailing strategies in response to changes in the competitive environment. Advertising is likely to be much lower in the absence of business stealing effects. Future work should further explore firm decisions to advertise in an equilibrium model. Here, we argue that substantial advertising expenditure is defensive and may not provide a great deal of value from a social perspective.

7 Conclusion

The impact of DTCA for prescription drugs is an empirical question of critical policy importance. Our paper illustrates firm incentives to advertise and how strategic interactions, in addition to market unobserverbles, can bias elasticity estimates. Our estimation strategy utilizes exogenous variation in the level of advertising generated by the political cycle. We estimate an own advertising elasticity of 0.0764 among the privately insured and confirm our main results in a sample covering Medicare beneficiaries. In the Medicare sample, we show that our effect is primarily driven by new prescriptions. We find support for both business stealing and market expansion effects of advertising across multiple settings. Our results indicate that business stealing effects are especially strong. Therefore, our simulations highlight the potential for an advertising ban to reduce wasteful advertising spending and highlights the role of advertising competition.

References

Ackerberg, Daniel A. 2001. "Empirically Distinguishing Informative and Prestige Effects of Advertising." *The RAND Journal of Economics* 32(2):316–333.

Aron-Dine, Aviva, Liran Einav, Mark Cullen and Amy Finkelstein. 2014. "Moral Hazard in Health Insurance: Do Dynamic Incentives Matter?" *Working Paper* .

Bagwell, K. 2007. "The Economic Analysis of Advertising." *Handbook of Industrial Organization* 3:1701–1844. Mark Armstrong and Rob Porter (eds.).

Berndt, Ernst R. 2005. "To inform or persuade? Direct-to-consumer advertising of prescription drugs." *New England Journal of Medicine* 352(4):325–8.

Berndt, Ernst R, Linda T. Bui, David H. Reiley and Glen L. Urban. 1995. "Information, Marketing and Pricing in the U.S. Anti-Ulcer Drug Market." *American Economic Review* 85(2):100–105.

Blake, T., C. Nosko and S. Tadelis. 2013. "Consumer Heterogeneity and Paid Search Effectiveness: A Large Scale Field Experiment.".

Bronnenberg, Bart J., Jean-Pierre Dubé, Matthew Gentzkow and Jesse M. Shapiro. 2014. "Do pharmacists buy Bayer? Informed shoppers and the brand premium." University of Chicago mimeo.

Dafny, Leemore, Kate Ho and Mauricio Varela. 2013. "Let Them Have Choice: Gains from Shifting Away from Employer-Sponsored Health Insurance and toward an Individual Exchange." *American Economic Journal: Economic Policy* 5(1):32–58.

Donohue, Julie M., Marisa Cevasco and Meredith B. Rosenthal. 2007. "A Decade of Direct-to-Consumer Advertising of Prescription Drugs." *The New England Journal of Medicine* 357:673–681.

Dorfman, Robert and Peter O. Steiner. 1954. "Optimal Advertising and Optimal Quality." *American Economic Review* (44):826–36.

Dubé, Jean-Pierre, Günter J Hitsch and Puneet Manchanda. 2005. "An Empirical Model of Advertising Dynamics." *Quantitative Marketing and Economics* 3(2):107–144.

Gordon, Brett R. and Wesley R. Hartmann. 2013. "Advertising Effects in Presidential Elections." *Marketing Science* 32:19–35.

Gordon, Brett R. and Wesley R. Hartmann. 2014. "Advertising Competition in Presidential Elections." Stanford University mimeo.

Iizuka, Toshiaki. 2004. "What Explains the Use of Direct-to-Consumer Advertising of Prescription Drugs." *Journal of Industrial Economics* 52(3):349–379.

Jin, Ginger Zhe and Toshiaki Iizuka. 2005. "The Effects of Prescription Drug Advertising on Doctor Visits." *Journal of Economics & Management Strategy* 14(3):701–727.

Lewis, R.A. and J.M. Rao. 2013. "On the near impossibility of measuring the returns to advertising.".

Lewis, Randall A. and Dan Tri Nguyen. 2014. "A Samsung Ad for the iPad? Display Advertising's Competitive Spillovers to Search." Working paper.

Rosenthal, M.B., E.R. Berndt, J.M. Donohue, A.M. Epstein and R.G. Frank. 2003. "Demand effects of recent changes in prescription drug promotion." *Frontiers in Health Policy Research* 6(1):1–26.

Rossi, Peter E. 2014. "Even the Rich Can Make Themselves Poor: a critical examination of the use of IV methods in marketing." *Marketing Science* 33(5):655–672.

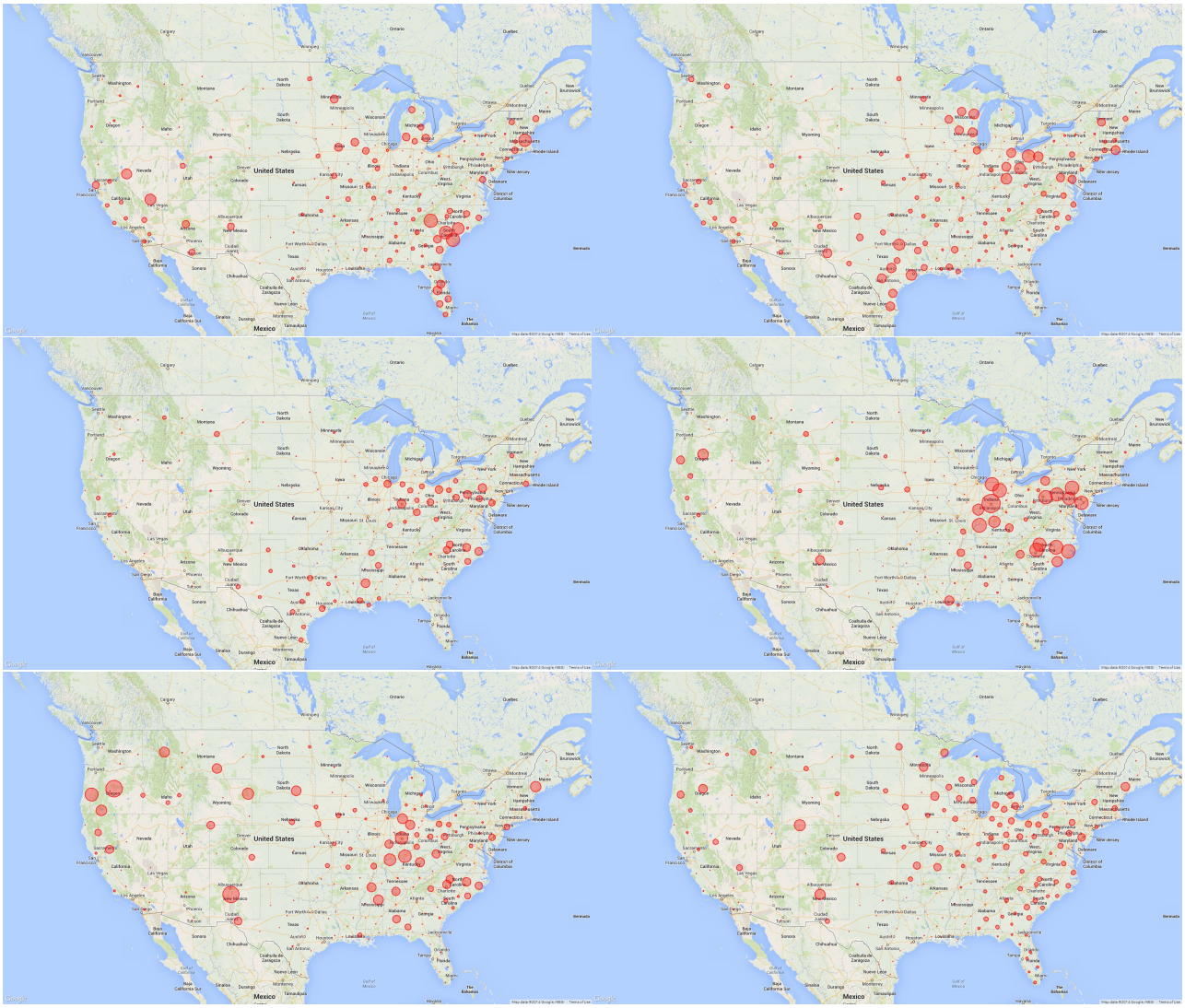
Shapiro, Brad. 2014. "Positive Spillovers and Free Riding in Advertising of Prescription Pharmaceuticals: The Case of Antidepressants." University of Chicago Working Paper.

Wosinska, Marta. 2002. "Just What the Patient Ordered? Direct-to-Consumer Advertising and the Demand for Pharmaceutical Products." Harvard Business School mimeo.

Wosinska, Marta. 2005. "Direct-to-Consumer Advertising and Drug Therapy Compliance." *Journal of Marketing Research* 42(3):323–332.

Figures

Figure 1: Political Ad Levels, January-June 2008



Notes: The above maps show a dot for each DMA in the USA. The diameter of each dot is proportional to the number of political ads aired in that market, in that month, for all races (Presidential, Senatorial, House, Gubernatiorial). The first row are January and February; second row are March and April, and third row are June and July.

Figure 2: Time Trends

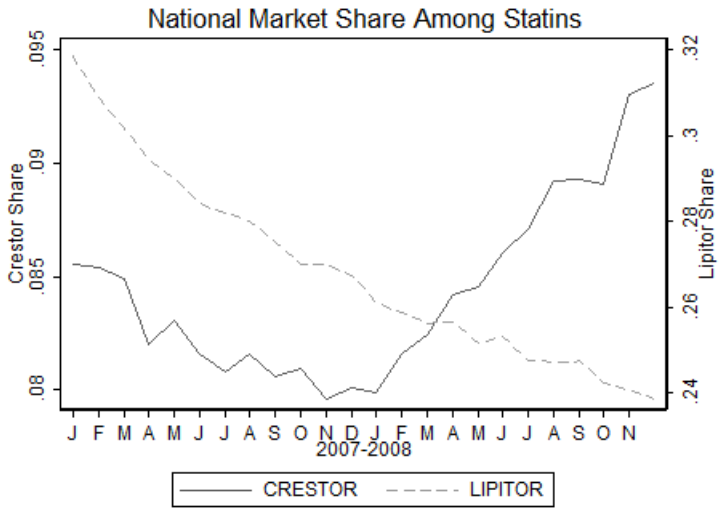


Figure 3: National Pharmaceutical Ad Levels for Statins

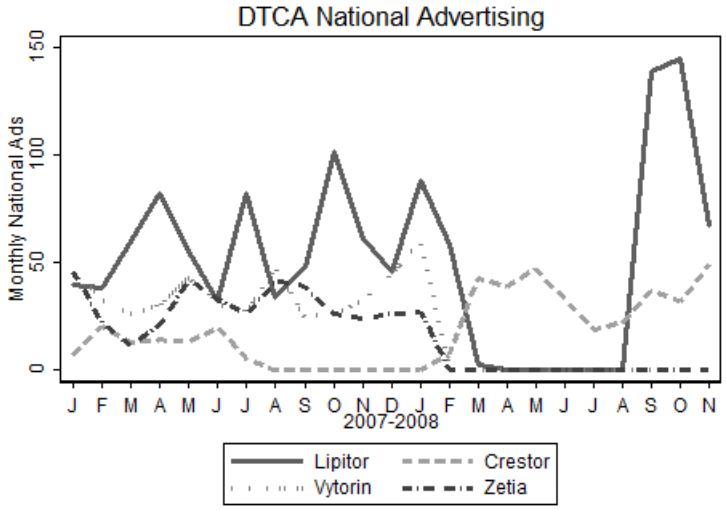


Figure 4: National Pharmaceutical Ad Levels for Statins

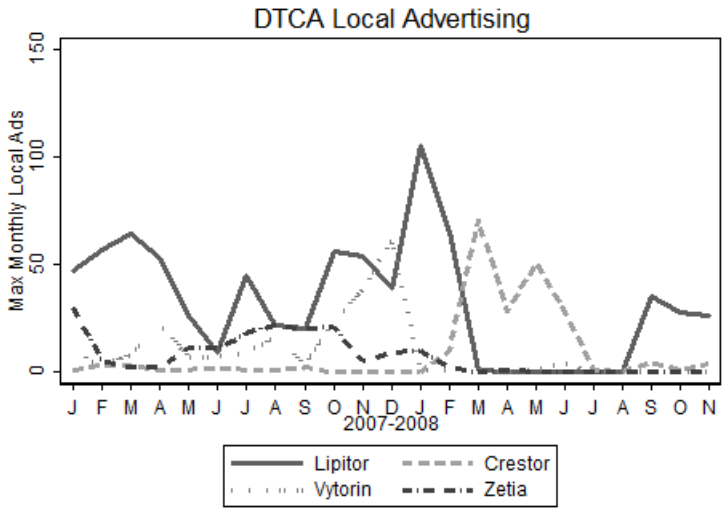
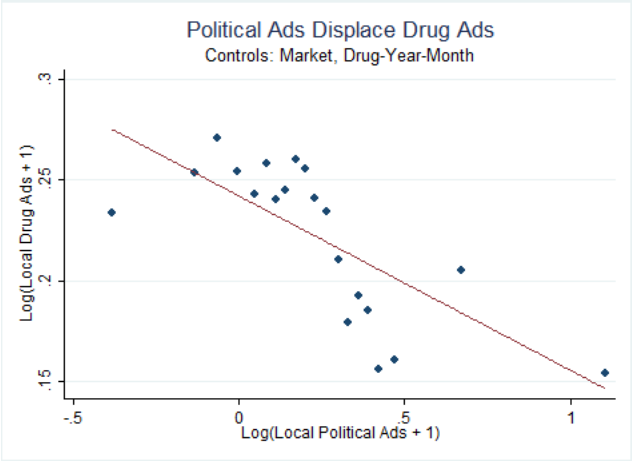
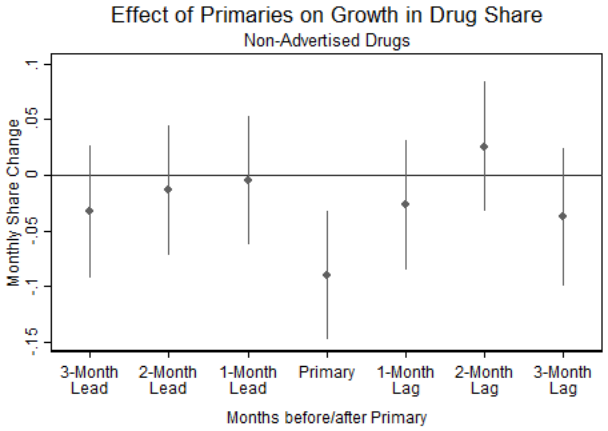


Figure 5: Political Ads Displace Local Drug Ads, Binned Scatterplot



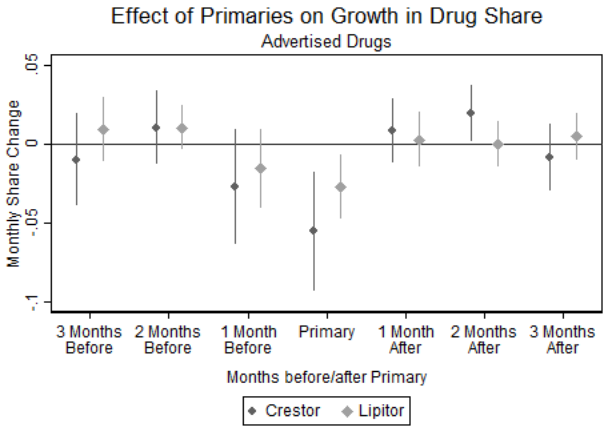
Notes: The above plots bins of observations from January 2007 to November 2008 at the market-month level after residualizing by market and year-month fixed effects, and adding back the sample mean. Twenty bins are used. The red line is based on a regression of all underlying data, not only the binned values.

Figure 6: Effect of Primaries on Sales of Non-Advertised Statins



Note: The above plots estimated coefficients for timing dummies relative to a market's primary month.

Figure 7: Effect of Primaries on Sales of Crestor and Lipitor



Note: The above plots estimated coefficients for timing dummies relative to a market's primary month.

Tables

Table 2: Summary Statistics (Analysis Dataset)

Drug		Drug Usage	
Number of Markets	189	Average Branded Share	0.829%
Number of Months	17	Range, Branded Share	(0.000%, 4.71%)
Advertised Statins	4	Average Generic Share	3.05%
		Range, Generic Share	(0.000%, 7.62%)
Political Ads		Drug Ads	
Average	774	Average Local Ads by Drug	1.56
Standard Deviation	1,897	Range, Local Ads	(0, 105)
Minimum	0	Average National Ads by Drug	19.71
Maximum	22,636	Range, National Ads	(0, 145)

Notes: The analysis dataset limits the sample to months that are most active in political advertising, July 2007-November 2008. Average Branded Share is by drug, not aggregate for all brands.

Table 3: Political Ads Displace Drug Ads

	Dependent Variable: Log(Local Statin Ads + 1), Drug-Market-Year-Month Level					
Model:	OLS	OLS	OLS	Tobit	Tobit	Tobit
Log(Political Ads in 1000s + 1)	-0.1895^{***}	-0.1208^{***}	-0.1208^{***}	-0.8479^{***}	-0.3097^{***}	-0.2598^{***}
	(0.0098)	(0.0116)	(0.0116)	(0.0494)	(0.0613)	(0.0103)
Controls:						
Market FEs	X	X	X	X	X	X
Year-Month FEs		X	X		X	X
Drug FEs	X	X	X	X	X	X
Drug-Year-Month FEs			X			X
N	24,150	24,150	24,150	24,150	24,150	24,150
R^2	0.314	0.364	0.478	0.305	0.402	0.552

Notes: Unit of observation is the drug-market-month level. There are 5 advertised drugs, 210 markets and 23 months of data. OLS and Tobit standard errors clustered at the market-year-month level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***. Reported R^2 is adjusted for OLS, pseudo for Tobit.

Table 4: OLS Revenue Regressions for Advertised Drugs

Dependent Variable: Log(Revenue per Insured) Drug-Market-Year-Month Level						
	This Month		Two Month Trailing Average		Three Month Trailing Average	
Own Ads	0.0194***	0.0064***	0.0239***	0.0066***	0.0316***	0.0086***
	(0.0022)	(0.0020)	(0.0021)	(0.0021)	(0.0020)	(0.0023)
Rival Ads	0.0042*	0.0056**	0.0016	0.0036	0.0008	0.0028
	(0.0025)	(0.0023)	(0.0027)	(0.0026)	(0.0029)	(0.0029)
Controls:						
Market FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Drug FEs	X	X	X	X	X	X
Drug FE*Time Trend		X		X		X
Drug-Year FEs	X		X		X	
N	11,551	11,551	11,550	11,550	10,875	10,875
R^2	0.842	0.847	0.843	0.847	0.845	0.849

Notes: OLS and IV standard errors clustered at the market-year-month level. Includes revenues for July 2007 until November 2008. Advertised drugs are Crestor, Lipitor, Vytorin and Zetia during this period. "Own Ads" and "Rival Ads" are constructed as Log(1+X). "Two Month Trailing Average" indicates that the independent variables are constructed as the average of the revenue month and one month before. The "Three Month Trailing Average" is constructed accordingly using three months. First stage excluded instruments are political advertising, its square and cube, and interactions with a dummy that takes on a one during April 2008-August 2008. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 5: IV Revenue Regressions for Advertised Drugs

Dependent Variable: Log(Revenue per Insured) Drug-Market-Year-Month Level						
	This Month		Two Month Trailing Average		Three Month Trailing Average	
Own Ads	0.1559^{***}	0.0131	0.1252^{***}	0.0764^{***}	0.1048^{***}	0.0536^{***}
	(0.0251)	(0.0412)	(0.0136)	(0.0258)	(0.0099)	(0.0235)
Rival Ads	-0.1064^{***}	0.0009	-0.0966^{***}	-0.0548^{***}	-0.0908^{***}	-0.0407^{*}
	(0.0179)	(0.0299)	(0.0112)	(0.0212)	(0.0095)	(0.0230)
Controls:						
Market FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Drug FEs	X	X	X	X	X	X
Drug FE*Time Trend		X		X		X
Drug-Year FEs	X		X		X	
N	11,551	11,551	11,550	11,550	10,875	10,875
R^2	0.755	0.819	0.788	0.824	0.810	0.840

Notes: OLS and IV standard errors clustered at the market-year-month level. Includes revenues for July 2007 until November 2008. Advertised drugs are Crestor, Lipitor, Vytorin and Zetia during this period. "Own Ads" and "Rival Ads" are constructed as Log(1+X). "Two Month Trailing Average" indicates that the independent variables are constructed as the average of the revenue month and one month before. The "Three Month Trailing Average" is constructed accordingly using three months. First stage excluded instruments are political advertising, its square and cube, and interactions with a dummy that takes on a one during April 2008-August 2008. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 6: Revenue Effect Decomposition

Dependent Variable:	Revenues, Non-Advertised Drugs		Revenues, Advertised Drugs	
Model:	OLS	IV	OLS	IV
Own Ads	-	-	0.0239^{***}	0.0764^{***}
			(0.0021)	(0.0258)
Rival Ads	0.0018	0.0233^{***}	0.0016	-0.0548^{***}
	(0.0037)	(0.0089)	(0.0027)	(0.0212)
Controls:				
Market FEs	X	X	X	X
Drug FEs and Time Trends	X	X	X	X
N	3,146	3,146	11,500	11,500
R^2	0.875	0.874	0.843	0.824

Notes: OLS and IV standard errors clustered at the market-year-month level. Revenue data are for July 2007 until November 2008. "Own Ads" and "Rival Ads" are constructed as Log(1+X), where X is the two-month trailing average of the number of ads. First stage excluded instruments are political advertising, its square and cube, and interactions with a dummy that takes on a one during April 2008-August 2008. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 7: Effect of Business Stealing

Dependent Variable: Log Drug Revenue Per Capita				
Exposure:	2-Month		3-Month	
Log Own Ads	0.0163^{***}	0.1252^{***}	0.0198^{***}	0.1048^{***}
	(0.0030)	(0.0136)	(0.0028)	(0.0099)
Log Rival Ads		-0.0966^{***}		-0.0908^{***}
		(0.0112)		(0.0095)
Controls				
Market FE	X	X	X	X
Product-Year FE	X	X	X	X
N	11,550	11,550	10,875	10,875
R^2	0.843	0.788	0.845	0.810

Notes: OLS and IV standard errors clustered at the market-year-month level. Revenue data are for July 2007 until November 2008. "Own Ads" and "Rival Ads" are constructed as Log(1+X), where X is a trailing average of the number of ads. T-statistics in parentheses. First stage excluded instruments are political advertising, its square and cube, and interactions with a dummy that takes on a one during April 2008-August 2008. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 8: Advertising Timing

Dependent Variable:	Log(Revenue per Insured)		
Own Ads (2-Month Trailing Average)	0.1252^{***}	0.1209^{***}	
	(0.0136)	(0.0131)	
Rival Ads (2-Month Trailing Average)	-0.0966^{***}	-0.0931^{***}	
	(0.0112)	(0.0107)	
Own Ads (1-Month Lagged)			0.1981^{***}
			(0.0190)
Rival Ads (1-Month Lagged)			-0.1442^{***}
			(0.0150)
Own Ads (1 Year Lagged)		-0.0006^{***}	
		(0.0002)	
Controls:			
Market FEs	X	X	X
Year FEs	X	X	X
Drug FEs	X	X	X
Drug-Year FEs	X	X	X
N	11,500	11,500	10,877
R^2	0.788	0.793	0.655

Notes: OLS and IV standard errors clustered at the market-year-month level. Revenue data are for July 2007 until November 2008. "Own Ads" and "Rival Ads" are constructed as Log(1+X), where X is the two-month trailing average of the number of ads unless otherwise indicated (specifically, in column 3). First stage excluded instruments are political advertising, its square and cube, and interactions with a dummy that takes on a one during April 2008-August 2008. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 9: Alternative Specifications of First Stage, Congressional Action Not Excluded

	Dependent Variable: Log(Revenue per Insured) Drug-Market-Year-Month Level		
	This Month	Two Month Trailing Average	Three Month Trailing Average
Model:	IV	IV	IV
Own Ads	0.2921^{***}	0.1332^{**}	0.2878
	(0.0901)	(0.0677)	(0.2177)
Rival Ads	-0.1458^{***}	-0.0834^{***}	-0.1147^{*}
	(0.0462)	(0.0299)	(0.0632)
Controls:			
Market FEs	X	X	X
Year FEs	X	X	X
Drug FEs	X	X	X
Drug FEs*Time Trends	X	X	X
N	11,551	11,550	10,875
R^2	0.707	0.834	0.787

Notes: OLS and IV standard errors clustered at the market-year-month level. Includes revenues for July 2007 until November 2008. Advertised drugs are Crestor, Lipitor, Vytorin and Zetia during this period. "Own Ads" and "Rival Ads" are constructed as Log(1+X). "Two Month Trailing Average" indicates that the independent variables are constructed as the average of the revenue month and one month before. The "Three Month Trailing Average" is constructed accordingly using three months. First stage excluded instruments are political advertising, its square and cube and their interaction with the FDA dummy. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 10: OLS Revenue Regressions for Advertised Drugs, Part D Data

	Dependent Variable: Log(Revenue per Insured) Drug-Market-Year-Month Level					
	This Month		Two Month Trailing Average		Three Month Trailing Average	
Own Ads	0.0229***	0.00991***	0.0259***	0.00817***	0.0324***	0.00792***
	(0.00215)	(0.00186)	(0.00197)	(0.00192)	(0.00192)	(0.00208)
Rival Ads	0.00457**	0.00692***	0.000423	0.00206	−0.000383	0.000453
	(0.00200)	(0.00187)	(0.00217)	(0.00209)	(0.00238)	(0.00235)
Controls:						
Market FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Drug FEs	X	X	X	X	X	X
Drug FE*Time Trend		X		X		X
Drug-Year FEs	X		X		X	
N	11,551	11,551	11,550	11,550	10,875	10,875
R^2	0.871	0.877	0.871	0.877	0.873	0.878

Notes: Data created by collapsing Medicare Part D event data to the market-month-product level. OLS and IV standard errors clustered at the market-year-month level. Includes revenues for July 2007 until November 2008. Advertised drugs are Crestor, Lipitor, Vytorin and Zetia during this period. "Own Ads" and "Rival Ads" are constructed as Log(1+X). "Two Month Trailing Average" indicates that the independent variables are constructed as the average of the revenue month and one month before. The "Three Month Trailing Average" is constructed accordingly using three months. First stage excluded instruments are political advertising, its square and cube, and interactions with a dummy that takes on a one during April 2008-August 2008. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 11: IV Revenue Regressions for Advertised Drugs, Part D Data

Dependent Variable: Log(Revenue per Insured) Drug-Market-Year-Month Level						
	This Month		Two Month Trailing Average		Three Month Trailing Average	
Own Ads	0.124^{***}	-0.0522	0.147^{***}	0.0543^{***}	0.128^{***}	0.0428^{**}
	(0.0194)	(0.0330)	(0.0121)	(0.0180)	(0.00924)	(0.0184)
Rival Ads	-0.0867^{***}	0.0459^{*}	-0.119^{***}	-0.0401^{***}	-0.118^{***}	-0.0350^{**}
	(0.0140)	(0.0243)	(0.0101)	(0.0151)	(0.00892)	(0.0177)
Controls:						
Market FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Drug FEs	X	X	X	X	X	X
Drug FE*Time Trend		X		X		X
Drug-Year FEs	X		X		X	
N	11,551	11,551	11,550	11,550	10,875	10,875
R^2	0.819	0.859	0.792	0.866	0.814	0.872

Notes: Data created by collapsing Medicare Part D event data to the market-month-product level. OLS and IV standard errors clustered at the market-year-month level. Includes revenues for July 2007 until November 2008. Advertised drugs are Crestor, Lipitor, Vytorin and Zetia during this period. "Own Ads" and "Rival Ads" are constructed as Log(1+X). "Two Month Trailing Average" indicates that the independent variables are constructed as the average of the revenue month and one month before. The "Three Month Trailing Average" is constructed accordingly using three months. First stage excluded instruments are political advertising, its square and cube, and interactions with a dummy that takes on a one during April 2008-August 2008. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 12: Revenue Regression for First Prescriptions Only, Part D Data

Dependent Variable: Log(Revenue per Insured) Drug-Market-Year-Month Level						
	This Month		Two Month Trailing Average		Three Month Trailing Average	
Model:	OLS	IV	OLS	IV	OLS	IV
Own Ads	0.0496***	0.206	0.0469***	0.288***	0.0472***	0.255***
	(0.00408)	(0.130)	(0.00418)	(0.0769)	(0.00467)	(0.0800)
Rival Ads	0.0528***	−0.0504	0.0511***	−0.149**	0.0497***	−0.134*
	(0.00531)	(0.101)	(0.00577)	(0.0667)	(0.00631)	(0.0788)
Controls:						
Market FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Drug FEs	X	X	X	X	X	X
Drug FE*Time Trend	X	X	X	X	X	X
N	11,321	11,321	11,320	11,320	10,651	10,651
R^2	0.575	0.573	0.582	0.574	0.589	0.574

Notes: Data created by restricting event data to first prescriptions only and collapsing to the market-month-product level. OLS and IV standard errors clustered at the market-year-month level. Includes revenues for July 2007 until November 2008. Advertised drugs are Crestor, Lipitor, Vytorin and Zetia during this period. "Own Ads" and "Rival Ads" are constructed as Log(1+X). "Two Month Trailing Average" indicates that the independent variables are constructed as the average of the revenue month and one month before. The "Three Month Trailing Average" is constructed accordingly using three months. First stage excluded instruments are political advertising, its square and cube. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 13: Simulations

Panel A: Simulations for Advertised Drugs

% Change in Sales by Drug:	Crestor	Lipitor
Eliminating Business Stealing Effect	0.2113	0.2355
Ban DTCA	0.0381	−0.0142
No Political Ads	0.013	0.0093

Panel B: Simulations for Non-Advertised Drugs

% Change in Sales by Drug:	Unadvertised
Ban DTCA	−0.0176
No Political Ads	0.000005

Notes: Specifications with a "Two Month Trailing Average" and drug-specific time trends are used in all simulations. The first row sets the coefficient on rival advertising in column 4 of Table 5 equal to zero. The second row performs the same exercise using the coefficient on rival advertising in column 2 of Table 6 equal to zero. The third row computes advertising using a linear prediction if all statin ads were set to zero and the fourth row does the same setting all political ads equal to zero.

Appendix

Supplemental Appendix For Online Publication

Table 19 presents additional robustness checks. First, Panel A presents alternative specifications testing estimate stability across a range of fixed effects. We find that flexibly allowing controls for product quality over our sample period are important. In the final column, we show that our results are not driven by diffferences between swing and non-swing states. The estimates are not statistically different if we only use variation from the primaries to estimate advertising effectiveness. Panel B presents a "reduced form" version of our central results. Similar to Figure 6, the results show that political advertising in a market is correlated with lower statin sales. In the final column, we use expenditure, rather than units, to measure the effect of advertising and obtain qualitatively similar results.

Table 23 estimates reduced form policy functions. The results show that local advertising follow national advertising and is increasing in firm market share. Perhaps more critical to our analysis, the IV results indicate that firms react to an increase in rival advertising by increase their own local ad buy. The OLS analysis does not detect this effect. We think that stategic reaction between firms is likely to be critical. From these results, we conclude that advertising has both a business stealing effect among branded drugs and a smaller spillover effect to generics. Given this dynamic, in the next section we examine the strategic implications of advertising by modeling advertising competition explicitly. Finally, in our main specifications, we use two separate outcomes of the political process – political advertising levels and regulation of drug advertising – to instrument for drug advertising. Table 20 presents robustness checks that use only the level of political advertising and higher order terms, noting that political advertising will affect firms differently due to institutional factors. The results are quantitatively and qualitatively similar to the main results in Table 5.

A Model of Advertising

Suppose demand for drug $j \in 0,1,...J$ is given by

$$D_j(a_j, a_{-j}, \xi)$$

where a_j is own advertising and a_{-j} is rival advertising. The vector ξ are shocks to demand for goods in a market, $\xi = \xi_1, \xi_2, ...\xi_J$.

Assumption 1. *Function D_j is smooth and continuous in all its arguments; first- and second-derivatives are defined everywhere. Function D_j is concave in all j arguments.*

Note that Logit demand satisfies this assumption, as do many other standard demand formulations. The per-unit cost of advertising in a market is c. Profit per unit is ρ. In order for there to be an incentive to advertise, it must be that $\frac{\partial D_j}{\partial a_j} > 0$ and $\left.\frac{\partial D_j}{\partial a_j}_{a_j=0}\right| > \frac{c}{\rho}$.

In equilibrium, we expect firms to choose a_j such that $\frac{\partial D_j}{\partial a_j} = \frac{c}{\rho}$. The econometrician observes the realized D_j and the chosen a_j for all firms, but not the vector ξ. Firms observe their own ξ_j when choosing their advertising but not their rivals' ξ. Suppose the econometrician desires to esimate the marginal effect of advertising.

A.1 Unobserved Heterogeneity

The shocks ξ are unobserved to the econometrician, but observed to the firm when choosing a_j. This creates the classic omitted variables challenge as the economist would observe $D_j(a_j(\xi), a_{-j}(\xi), \xi)$ and $a = a_j$, but not ξ, and correlation between a_j and the omitted ξ_j leads to bias. It is common to think of the shock as positive in the sense that $\frac{\partial D_j}{\partial \xi_j} > 0$ and rival shocks as negative $\frac{\partial D_j}{\partial \xi_j} < 0$, as we will do here. In the Labor literature, it is also typically the case that this heterogeneity is positively correlated with the input of interest, e.g. $\frac{\partial a_j}{\xi_j} > 0$, such as in the returns to schooling literature, although this need not be the case in this setting.

Consider for now the case of a single firm, and suppose that the effect of advertising is dimishing in the level of drug demand so that $\frac{\partial D_j{}^2}{\partial a_j \partial \xi_j} < 0$; we would then expect a positive demand shock to be associated with fewer ads; this would unambigiously overstate the impact of advertising in an OLS analysis. Suppose instead that the effect of advertising were complementary to the level of drug demand so that $\frac{\partial D_j{}^2}{\partial a_j \partial \xi_j} > 0$. Measuring D_j and a_j across markets, we then expect an attenuated estimate of advertising effectiveness.

A.2 Market Expansion vs Business Stealing

So far we have considered effects only of ξ. However, the advertising decision is made across multiple markets every time period, and for many time periods. This implies that observed levels of a are equilibrium objects

Define adverising as market expanding iff $\frac{\partial D_j}{\partial a_k} > 0$ and define advertising as business stealing iff $\frac{\partial D_j}{\partial a_k} < 0$.

Given concavity in own arguments (Assumption 1), advertising that is market expanding implies that rival advertising decreases the marginal benefit to my own advertising. This implies that $\frac{\partial D_j^2}{\partial a_k \partial a_j} < 0$, and so we should expect lower levels of advertising from all firms in equilibrium compared to a situation where $\frac{\partial D_j}{\partial a_k} = 0$. The analogy is to the positive externality literature where a

firm's advertising generates a positive externality for other firms which the first firm cannot capture, and so advertising will be under-produced. Conversely, if advertising is business stealing, given concavity, this would increase my returns to advertising, implying $\frac{\partial D_j^2}{\partial a_k \partial a_j} > 0$. Thus we would expect higher levels of advertising from all firms.

Taken together, we see that a positive demand shock ξ can be positively or negatively correlated with own and rival advertising, depending on whether the shock increases or decreases the returns to advertising, and whether advertising is market-expanding or business stealing.

A.3 Model Simulation

Consider a Logit formulation of the above model. It is straightforward to simulate markets and optimal firm decisions to illustrate the measurement bias.

Below are results from regressions on data generated in Matlab where D_j comes from a Logit framework with $\delta_j = \alpha + \beta_1 \log(1+a_j) + \beta_2 \log(1+a_{-j}) + \xi_j$. The flexbility of the Logit frameworks allows for ξ_j to either increase or decrease the returns to advertising depending on parameter β_1, while $\beta_2$captures business-stealing versus market expansion.

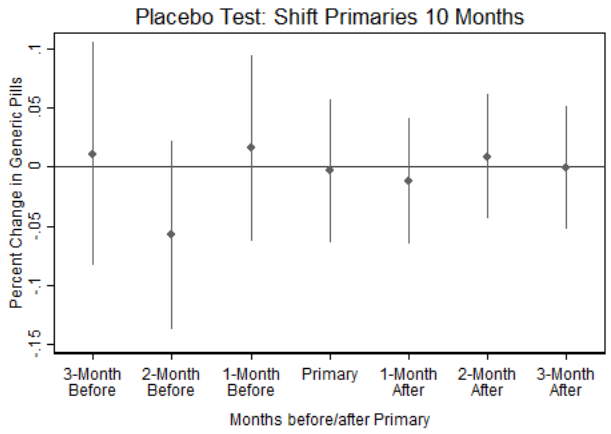
The number of simulated markets is 1,000, and parameters were set to the following values: $\beta_1 = 0.1$, $\beta_2 = -0.3$, $\alpha = 0$, $\xi \sim N(0, 0.5)$,$c = 1$, $\rho = 1000$. Given simulated datasets, estimates of own and rival ad effects were computed in Stata either using or omitting the information contained in ξ. The results are below. These confirm that the bias when a positive demand shock is correlated with lower advertising, and advertising is primarily business-stealing, is exactly the same as is found in our data.

Table 14: Model Simulation Results

Specification:	Naive	Exact	True Values
	(1)	(2)	(3)
Own Ads	0.0228^{*}	0.1000^{***}	0.1
	(0.0132)	(0.0000)	
Rival Ads	-0.1341^{***}	-0.3000^{***}	-0.3
	(0.0134)	(0.0000)	
ξ_j		1.0000^{***}	1.0
		(0.0000)	
N	1,000	1,000	
R^2	0.208	1.000	

B Additional Reduced Form Evidence

Figure 8: Effect of Placebo Primaries on Sales of Non-Advertised Sales



Notes: The above plots the change in sales of unadvertised drugs in reponse to the political process.

Table 15: Robustness: No Substitution to Other Media

	Dependent Variable: Local Non-TV Advertising Spending, Product-Market-Year-Month Level		
Model:	OLS	OLS	OLS
Political Ads (1000s)	-0.4474^{**}	-0.2477	-0.2802
	(0.1830)	(0.1843)	(0.1849)
Local TV Drug Ads		1.0554^{***}	1.1303^{***}
		(0.1357)	(0.1379)
National TV Drug Ads			-0.0867^{***}
			(0.0125)
Controls:			
Market FEs	X	X	X
Year-Month FEs	X	X	X
Drug FEs	X	X	X
N	20,087	20,087	20,087
R^2	0.080	0.100	0.101

Notes: OLS standard errors clustered at the market-year-month level. Results differ from Table 3 as this is at the individual drug level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 16: Robustness: No Substitution to Earlier/Later Months

	Dependent Variable: Local Drug Ads, Product-Market-Year-Month Level			
Model:	OLS	OLS	OLS	OLS
Political Ads (1000s)	-0.0819^{***}		-0.0632^{**}	
	(0.0263)		(0.0304)	
One Month Lag	0.0265	0.0012		
	(0.0284)	(0.0299)		
One Month Lead			−0.0239	-0.0405
			(0.0301)	(0.0294)
Controls:				
Market FEs	X	X	X	X
Year-Month FEs	X	X	X	X
Drug FEs	X	X	X	X
Drug National Ads	X	X	X	X
N	8,925	8,925	8,120	8,120
R^2	0.225	0.225	0.219	0.218

Notes: OLS standard errors clustered at the market-year-month level. Results differ from Table 3 as this is at the individual drug level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 17: Political Ads Displace Drug Ads

	Dependent Variable: Statin Ads, Drug-Market-Year-Month Level					
Model:	OLS	OLS	OLS	Tobit	Tobit	Tobit
Political Ads (1000s)	-0.2903^{***}	-0.2257^{***}	-0.2257^{***}	-1.5484^{***}	-0.8438^{***}	-0.9257^{***}
	(0.0212)	(0.0216)	(0.0217)	(0.1271)	(0.1084)	(0.0239)
Controls:						
Market FEs	X	X	X	X	X	X
Year-Month FEs		X	X		X	X
Drug FEs	X	X	X	X	X	X
Drug-Year-Month FEs			X			X
N	24,150	24,150	24,150	24,150	24,150	24,150
R^2	0.226	0.258	0.374	0.198	0.254	0.337

Notes: Unit of observation is the drug-market-month level. OLS and Tobit standard errors clustered at the market-year-month level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 18: Political Ads and Ad Pricing

	Dependent Variable: Cost per Unit of Drug Advertising			
Political Ads (1000s)	0.0029	0.0037	0.0023	0.0012
	(0.0059)	(0.0051)	(0.0064)	(0.0063)
Controls:				
Market FEs		X	X	X
Month FEs			X	X
Drug FEs				X
N	2584	2584	2584	2584
R^2	0.000	0.578	0.610	0.634

Notes: Unit of observation is the drug-market-month level. Standard errors clustered at the market-year-month level. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 19: Alternative Specifications

	Dependent Variable: Log(Revenue per Insured)			
Panel A: Estimate Stability				
Log Own Ads	0.1895***	0.1843***	0.1252***	0.1546***
	(0.0284)	(0.0088)	(0.0136)	(0.0499)
Log Rival Ads	-0.1477***	-0.1389***	-0.0966***	-0.1231**
	(0.0284)	(0.0083)	(0.0112)	(0.0529)
Controls:				
Market FE		X	X	X
Product-Year FE			X	X
Time Period	all months	all months	all months	primaries
N	11,550	11,550	11,550	8838
R^2	0.036	0.274	0.788	0.753
Panel B: Alternative Explanatory Variables				
1(Any Political Ads)	-0.0403***		-0.0365***	
	(0.0057)		(0.0069)	
1(Above Median Pol. Ads)		-0.0309***	-0.0079	
		(0.0062)	(0.0075)	
Log Own Expenditure				0.2418***
				(0.0282)
Log Rival Expenditure				-0.0991***
				(0.0125)
Controls:				
Market FE	X	X	X	X
Drug-Year FE	X	X	X	X
N	11,550	11,550	11,550	10,877
R2	0.841	0.841	0.841	0.703

Notes: Standard errors clustered at the market-month level. In Panel A, we use a "Two Month Trailing Average" of political and drug ads, indicating that the independent variables are constructed as the average of the revenue month and one month before. First stage excluded instruments are political advertising, its square and cube, and interactions with a dummy that takes on a one during April 2008-August 2008. In Panel B, 1(Any Political Ads) is a indicator that takes on a 1 if there was any political advertising in a market in the previous two months, and 1(aboove Median Political Ads) is constructed similarly. Logged own and rival expenditures are constructed as a two month trailing average, with instruments as in Panel A.

Table 20: Alternative Specifications of First Stage

Dependent Variable: Log(Revenue per Insured) Drug-Market-Year-Month Level						
	This Month		Two Month Trailing Average		Three Month Trailing Average	
Model:	OLS	IV	OLS	IV	OLS	IV
Own Ads	0.0194***	-0.0462	0.0239***	0.2210***	0.0316***	0.1327***
	(0.0022)	(0.3557)	(0.0021)	(0.0807)	(0.0020)	(0.0235)
Rival Ads	0.0042*	-0.0087	0.0016	-0.1487***	0.0008	-0.1032***
	(0.0025)	(0.1962)	(0.0027)	(0.0367)	(0.0029)	(0.0115)
Controls:						
Market FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Drug FEs	X	X	X	X	X	X
Drug-Year FEs	X	X	X	X	X	X
N	11,551	11,551	11,550	11,550	10,875	10,875
R^2	0.842	0.829	0.843	0.664	0.845	0.788

Notes: OLS and IV standard errors clustered at the market-year-month level. Includes revenues for July 2007 until November 2008. Advertised drugs are Crestor, Lipitor, Vytorin and Zetia during this period. "Own Ads" and "Rival Ads" are constructed as Log(1+X). "Two Month Trailing Average" indicates that the independent variables are constructed as the average of the revenue month and one month before. The "Three Month Trailing Average" is constructed accordingly using three months. First stage excluded instruments are political advertising, its square and cube. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 21: Heterogeneity, Part D Data

Dependent Variable: Log(Revenue per Insured)				
	Two-Month Trailing Average		Three-Month Trailing Average	
Panel A: Beneficiaries Ending Year in ICP				
Log Own Ads	0.0347***	0.221***	0.0437***	0.186***
	(0.00219)	(0.0177)	(0.00215)	(0.0132)
Log Rival Ads	0.00883***	-0.166***	0.00908***	-0.157***
	(0.00275)	(0.0148)	(0.00300)	(0.0129)
N	11,550	11,550	10,875	10,875
R^2	0.842	0.682	0.845	0.735
Panel A: Beneficiaries Ending Year in Donut Hole				
Log Own Ads	0.0212***	0.203***	0.0273***	0.184***
	(0.00238)	(0.0181)	(0.00235)	(0.0143)
Log Rival Ads	-0.00875***	-0.186***	-0.00922***	-0.194***
	(0.00287)	(0.0151)	(0.00312)	(0.0139)
N	11,547	11,547	10,872	10,872
R^2	0.824	0.666	0.825	0.691
Panel A: Beneficiaries Ending Year in the Catastrophic Phase				
Log Own Ads	0.0135***	-0.0128	0.0149***	0.000359
	(0.00260)	(0.0164)	(0.00260)	(0.0129)
Log Rival Ads	-0.00290	0.0100	-0.00766**	-0.00157
	(0.00323)	(0.0140)	(0.00351)	(0.0130)
N	11,491	11,491	10,819	10,819
R^2	0.795	0.793	0.796	0.795

Notes: Data created by restricting event data to beneficiaries ending the year in each phase and collapsing to the market-month-product level. OLS and IV standard errors clustered at the market-year-month level. Includes revenues for July 2007 until November 2008. Advertised drugs are Crestor, Lipitor, Vytorin and Zetia during this period. "Own Ads" and "Rival Ads" are constructed as Log(1+X). "Two Month Trailing Average" indicates that the independent variables are constructed as the average of the revenue month and one month before. The "Three Month Trailing Average" is constructed accordingly using three months. First stage excluded instruments are political advertising, its square and cube. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 22: Heterogeneity II, Part D Data

Dependent Variable: Log(Revenue per Insured)				
	Two-Month Trailing Average		Three-Month Trailing Average	
Panel A: Beneficiaries in MA Plans				
Log Own Ads	0.0203***	0.106***	0.0271***	0.0963***
	(0.00345)	(0.0219)	(0.00344)	(0.0172)
Log Rival Ads	-0.00876**	-0.0994***	-0.0118**	-0.104***
	(0.00445)	(0.0191)	(0.00482)	(0.0177)
N	10,996	10,996	10,364	10,364
R^2	0.813	0.795	0.814	0.800
Panel A: Beneficiaries in Stand-alone Part D Plans				
Log Own Ads	0.0267***	0.167***	0.0330***	0.143***
	(0.00192)	(0.0128)	(0.00186)	(0.00975)
Log Rival Ads	0.00295	-0.134***	0.00251	-0.130***
	(0.00215)	(0.0107)	(0.00236)	(0.00935)
N	11,550	11,550	10,875	10,875
R^2	0.893	0.800	0.894	0.826

Notes: Data created by restricting event data to beneficiaries ending the year in each plan type and collapsing to the market-month-product level. OLS and IV standard errors clustered at the market-year-month level. Includes revenues for July 2007 until November 2008. Advertised drugs are Crestor, Lipitor, Vytorin and Zetia during this period. "Own Ads" and "Rival Ads" are constructed as Log(1+X). "Two Month Trailing Average" indicates that the independent variables are constructed as the average of the revenue month and one month before. The "Three Month Trailing Average" is constructed accordingly using three months. First stage excluded instruments are political advertising, its square and cube. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.

Table 23: Policy Functions

Dependent Variable:	Advertising Level	
Model:	OLS	IV
Own National	0.127***	0.134***
	(26.62)	(26.66)
Rival Local	-0.0495***	0.121***
	(-4.77)	(12.68)
Rival National	0.530***	0.575***
	(5.94)	(5.90)
Market Share	0.0018	0.0730***
	(0.0037)	(0.0095)
Controls:		
Market FEs	X	X
Year FEs	X	X
Drug FEs	X	X
Drug-Year FEs	X	X
N	16,216	16,216
R^2	0.875	0.863

Notes: OLS and IV standard errors clustered at the market-year-month level. Revenue data are for July 2007 until November 2008. "Own Ads" and "Rival Ads" are constructed as Log(1+X), where X is the two-month trailing average of the number of ads. T-statistics in parentheses. Statistical significance at the 10%, 5% and 1% levels are denoted by *, **, and ***.