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

Michael Sinkinson
The Wharton School, University of Pennsylvania
Amanda Starc
The Wharton School, University of Pennsylvania and NBER

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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 find that a 10% increase in the quantity of a firm's advertising leads to a 0.76% increase in revenue, while the same increase in rival advertising leads to a 0.55% decrease in firm revenue. Results also indicate that a 10% increase in category advertising produces a 0.2% revenue increase for non-advertised drugs. Both the business-stealing and spillover effects would not be detected through OLS. Decomposition using micro data comfirms that the effect is due mostly to new customers as opposed to switching among current customers. Simulations show that an outright ban on DTCA would have modest effects on the sales of advertised drugs as well as on non-advertised drugs.

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 Meredith, 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. Starc gratefully acknowledges funding from the Leonard Davis Institute.

1 Introduction

advertise. Both issues highlight the need for exogenous variation in advertising levels to measure effectiveness.

Our identification strategy exploits novel variation in advertising due to political campaigning during the 2008 national election. Idiosyncrasies of the US political process meant that in January

While we believe our paper is the first to exploit this form of political advertising as an instrument, we build on a substantial literature examining the impact of DTCA.[5] Previous researchers have found significant evidence for the market-expanding or spillover effects of DTCA on outcomes such as doctors visits, drug sales, and drug adherence (Berndt 2005, Jin and Iizuka 2005, Wosinska 2002, Wosinska 2005, Rosenthal et al. 2003, Berndt et al. 1995). The paper closest to our study is Shapiro (2014), which estimates economically significant spillover effects in the anti-depressant market using a cross-border strategy and structural model of demand. Our paper is consistent with these previous studies, while finding an additional, economically important role for business stealing in the statin market. This paper also contributes to a literature that attempts to measure the causal impact of advertising. Recent work (Lewis and Rao 2013, Blake, Nosko and Tadelis 2013) has utilized randomized experiments on online platforms. Similar to these studies and work by Ackerberg 2001, our natural experiment finds heterogeneity in the effect of advertising in a setting with plausibly exogenous variation in advertising levels. While our focus is on the statin market, the identification strategy we propose is likely to be useful in many other product markets.

The paper is organized as follows. Section 2 describes the market and setting. Section 3 presents of model of strategic interaction and simulation results. Section 4 describes the data and empirical strategy, while Section 5 presents results. We perform robustness checks and explore heterogeneity in the main results in Section 6. Section 7 details simulations, and Section 8 concludes.

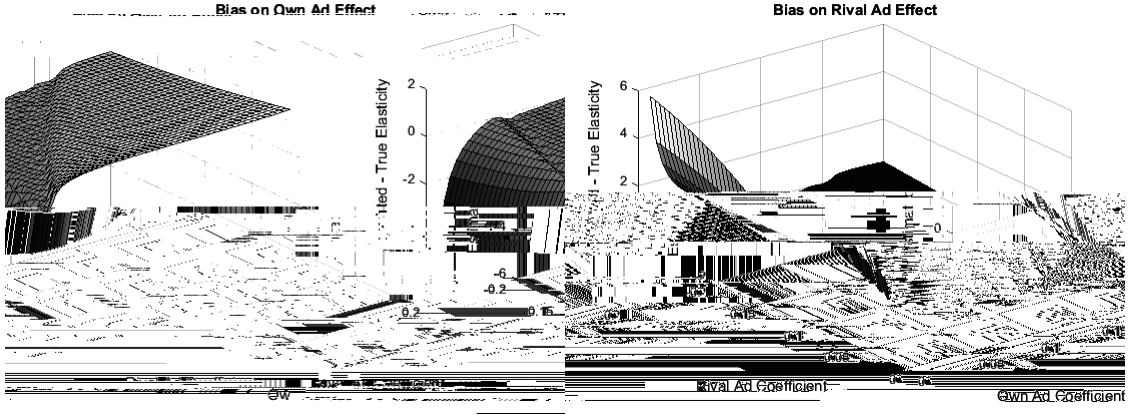
2 Setting

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 combined 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.

Between 2007 and 2008, four branded anti-cholesterol medications were being advertised. The two largest advertisers were Lipitor (Pfizer), approved in 1997, and Crestor (AstraZeneca),

approved in 2003. According to trade press and news, the introduction of Lipitor heralded an

Figure 1: Simulations of OLS Estimate Bias



4 Data and Empirical Strategy

4.1 Identification Strategy

We exploit shocks from political advertising in markets over time. These shocks are a result of the staggered nature of the party nomination processes and 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. Presidential campaigns 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. 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 primaries increases the national attention on and importance of early contests in Iowa and New Hampshire, as well as South Carolina, Florida and Nevada.[20] In 2008, the Democratic party contest between Hillary Clinton and Barack Obama extended into June, while John McCain secured the Republican nomination by March of 2008. Figure 2 highlights the staggered nature of the process by showing political ad concentrations for January to June, 2008.

During the general election, the "winner take all" nature of the Electoral College means that

[20] 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 seven days or more immediately preceding the date on which any other state shall rAati(is)-3 s17. SDuringother Ctl12(run)-3 ghligr-311i0c-dl4C24

political advertising in swing states is likely to be far more valuable than in "safe states", leading to 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). Political campaigns and outside influence groups often purchase premium advertising slots that can pre-empt previously purchased advertising.[21]

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. To separately identify the two effects, we use 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 regulatory action. We assume that the relative impact of this shock across markets is uncorrelated with drug demand.

4.2 Data

We combine two sources of advertising data. First, data from Kantar Media contain both the number of ads and the level of spending for 2007-2008 at the month-drug level for every DMA in the United States. 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

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 combine this advertising data with prescription drug usage and revenue data from two sources. First, we used Truven MarketScan data, which draws from a convenience sample of large,

unlikely to be correlated with the market for statins. We next demonstrate that the level of political advertising predicts drug advertising. Figure 5 shows a binned scatter plot highlighting the relationship between political advertising and statin advertising, where observations are de-meaned by market and drug-year-month, and then binned to create a scatter plot of the data. There is a strong negative correlation between the two series.

Table 3

5.2 Graphical Evidence

quarterly-) product-specific fixed effects. However, we can can allow for a linear, product-specific time trend that approximates the data reasonably well. In 18, we show that higher order, drug-specific time trends have a negliable effect on the estimates. 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. 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. 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.

We document the causal impact of advertising in Table 5. We instrument own and rival advertising levels using (i) the level of political ads, as well as second- and third-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. Our instruments are remarkably strong predictors of own and rival advertising. The F-statistic for a test of joint signification of the excluded instruments in the first stage of our main specifications is 493.66 for own advertising and 67.30 for rival advertising.

Based on the results in the previous table, the OLS analysis underestimates the effects of own and rival advertising. The own advertising effect in column 4 (.0064) is less than 10% of the effect measured in the IV specification (.0764). Similarly, we find substantial evidence of business stealing in the IV specifications that is absent from the OLS results. As discussed in Section 3, the direction of OLS bias is ambiguous, but in this case it appears that the strategic interaction between firms leads to the effect of own advertising being biased downward, while the effect of rival advertising is biased upward.[24]

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 (0.0808), while the two-month (0.0764) and three-month (0.0536) moving averages are smaller. Despite this

[24]One other possible explanation for the bias we find is that measurement error could be attenuating the OLS estimates. Alternatively, we measure a local average treatment effect that captures the short run elasticity of sales with

larger in magnitude and closer to the contemporaneous estimates in column 2 of Table 5. The specification in column 1 controls 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. We obtain statistically indistinguishable estimates as compared to our preferred specification.

Finally, our identification strategy exploits both the timing of the political process and the pulling of Lipitor ads featuring Dr. Robert Jarvik. We have more confidence in 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 contained no content about the quality of the drug itself, may have had an impact on sales. However, in the third column of 18, we still interact the regulatory action with the level of political advertising and utilize the "intensity of treatment" across areas as a second instrument, while omitting the main effect from both stages. 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 also run an additional specification that includes the main effect of the Jarvik regulatory action and interactions in both stages of the regression and present the results in column 4 Table 18. The estimates are noisier, but confirm our basic story. The own advertising elasticity in both of these specifications is larger in magnitude than our main results, but not statistically different.

6.2 Part D Sample

These results are compelling, but the Truven MarketScan data represent only a fraction of the potential statin market. While there is no reason to believe the consumers in the Truven MarketScan are not representative of employees of large, self-insured firms, the 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 covers a population that is significantly older and sicker than the Truven MarketScan data. Furthermore, the contractual features of plans 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 are individual-prescription fill level observations, 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 relative sales across the two samples.

Table 16 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. The differences between the estimates are rarely statistically significant. In the IV regressions in Table 7, the own

7 Implications and Discussion

A back-of-envelope calculation shows that our estimates are quite sensible.[26] 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 $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. Furthermore, the OLS estimates would imply an increase of revenue net of costs by $75,000 assuming our *largest* estimates. The OLS estimates imply marginal revenue far below marginal cost, or that firms are not maximizing profits.

7.1 Simulations

Our results can be used to quantify the magnitudes of business-stealing and spillovers in this market. In all simulations below, we bootstrap by re-sampling the data set 100 times (with replacement), re-estimate our main specifications, and then compute a simulated object such as the change in revenue or quantity. We report the mean of the bootstrapped results, as well as the 95% confidence interval.

First, we calculate sales of advertised drugs 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 revenue. 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 9 presents the results. Panel A shows thatpresen 0lusins-250(of)-cws innumbher of ats.

would fall by 9.7%. This indicates a potentially large role for welfare-enhancing spillovers in drug advertising.

We can also quantify the impact that the political process's shock had on drug firm revenues. We first predict what advertising levels would have been in the absence of any political ads, and then use our main results to predict revenues in the absence of political ads. Panel A shows that if the political process had not displaced drug advertising, revenues for Crestor and Lipitor would have been roughly two percent higher over the study period.

Finally, we analyze the impact of changes in the regulatory environment: a ban on DTCA. This eliminates both the effect of a firm's own ads and their rival's ads. The FDA is unlikely to be concerned about firm revenues, and so the outcome of interest is the quantity (share) of We can a7.559 -Bate

(2004); Narayanan, Desiraju and Chintagunta (2004) and, most recently Shapiro (2014)). Our results are consistent with these studies; for example, Shapiro (2014) finds that a cooperative advertising campaign that internalized spillovers would generate five times as many ads and increase category size by 13.7%. Our simulations are different in flavor and eliminate ads completely, but find a 5% reduction in the sales on unadvertised drugs, which comprise the bulk of the market. Here, we argue that substantial advertising expenditure is also defensive and may not provide a great deal of value from a social perspective, but that eliminating DTCA would significantly reduce the number of patients taking an effective, safe drug. Our identification strategy is likely to be useful in a number of product markets, including other drug classes. However, additional variation will be necessary to separately identify the impact of rival advertising.

A final caution is that these are only partial equilibrium calculations. Firms may alter their

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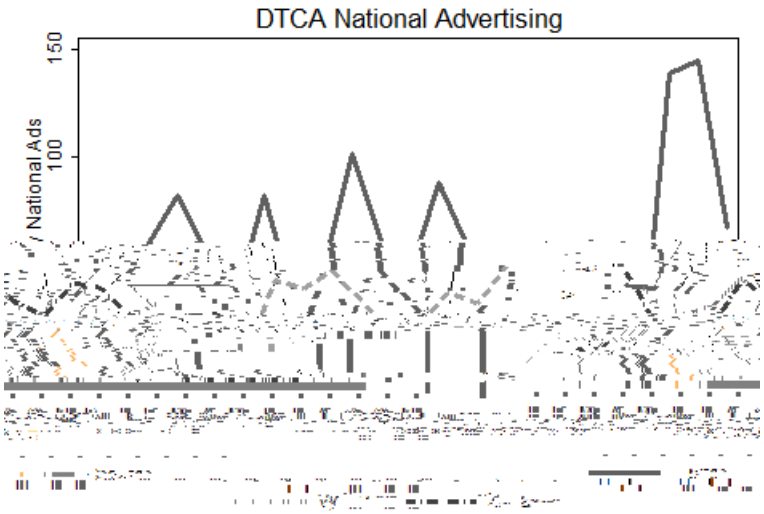
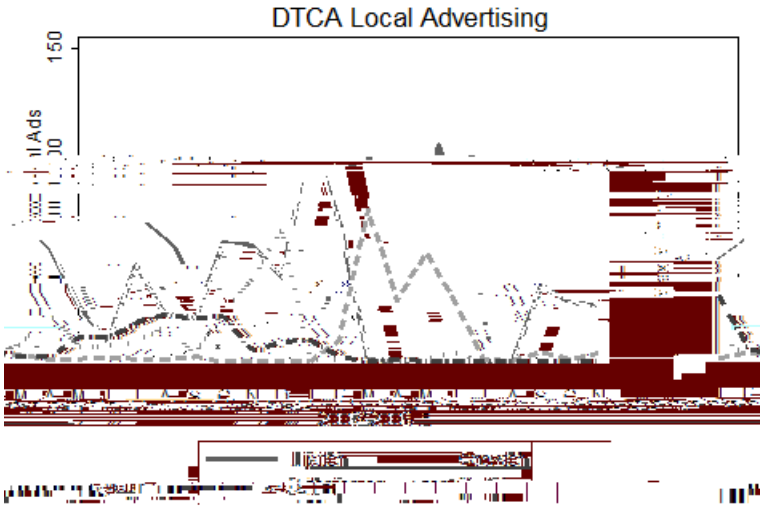
Figure 3: National Pharmaceutical Ad Levels for Statins



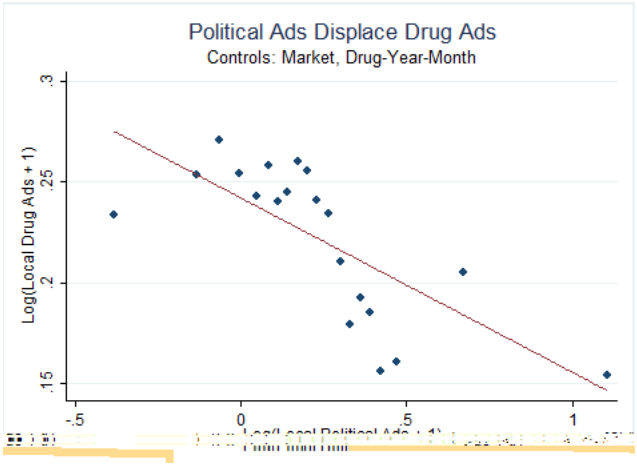
Notes: The above graphic plots spending on national advertising buys from the Kantar data. Data spans January 2007-November 2008.

Figure 4: National Pharmaceutical Ad Levels for Statins



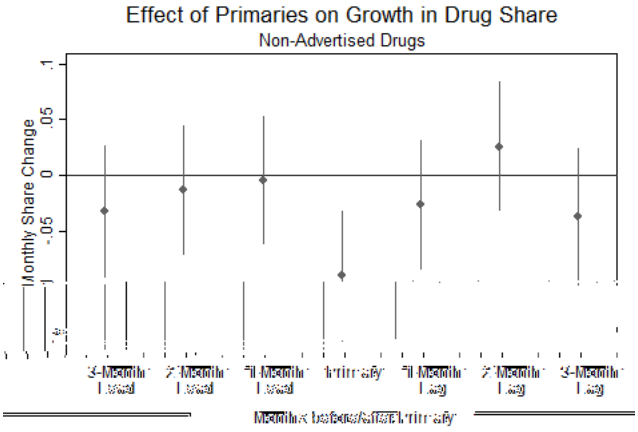
Notes: The above graphic plots spending on local advertising buys from the Kantar data. Data spans January 2007-November 2008. The axes are the same as the previous figure.

Figure 5: Political Ads Displace Local Drug Ads, Binned Scatter plot



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 fitted line is based on a regression of all underlying data, not only the binned values.

Figure 6: Effect of Primaries on Growth in Market Share of Non-Advertised Statins

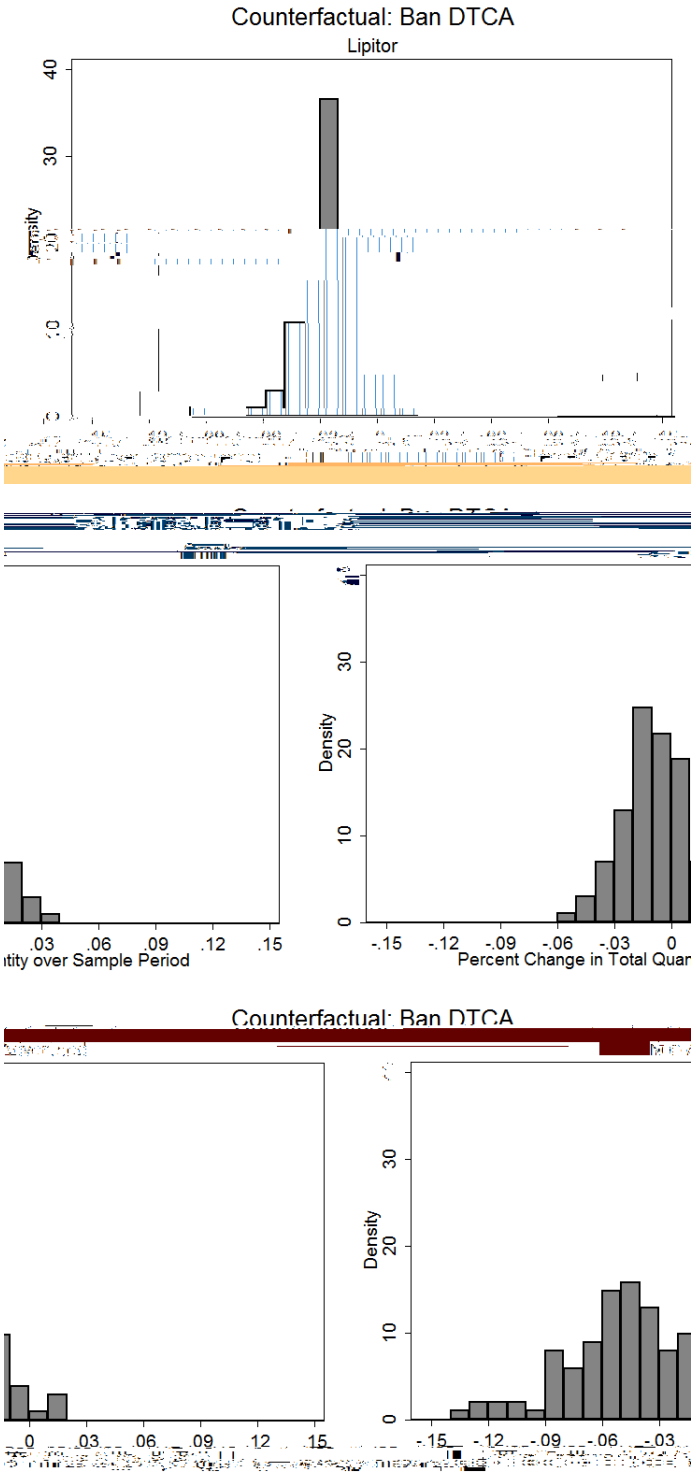


Note: The above plots estimated coefficients for timing dummies relative to a market's primary month. The dependent variable is the (one-month) change in market share, defined as the percentage of the population taking a non-advertised statin.

Figure 7: Effect of Primaries on Growth in Market Share of Crestor and Lipitor

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

Figure 8: Simulation Results: Eliminating DTCA



Note: The above plots are histograms of the change in quantity for each drug (or drug group) from bootstrapped simulations that eliminate DTCA from the market over the sample period. See section XX for an extended discussion of the methodology.

Tables

Table 1: Summary Statistics

Drug		Drug Usage (Truven Analysis Data set)	
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 Truven analysis data set 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 2:

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

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	0:0808	0:1252	0:0764	0:1048	0:0536
	(0:0251)	(0:0344)	(0:0136)	(0:0258)	(0:0099)	(0:0235)
Rival Ads	0:1064	0:0492	0:0966	0:0548	0:0908	0:0407
	(0:0179)	(0:0247)	(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: Regressions are based on the Truven data. 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:	Log(Revenue per Insured),		Log(Revenue per Insured),	
	Non-Advertised Drugs		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: Regressions are based on the Truven data. 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: 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	0:0317	0:147	0:0543	0:128	0:0428
	(0:0194)	(0:0242)	(0:0121)	(0:0180)	(0:00924)	(0:0184)
Rival Ads	0:0867	0:0162	0:119	0:0401	0:118	0:0350
	(0:0140)	(0:0177)	(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

Table 8: IV 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	0:361	0:0469	0:288	0:0472	0:255
	(0:00408)	(0:0973)	(0:00418)	(0:0769)	(0:00467)	(0:0800)
Rival Ads	0:0528	0:173	0:0511	0:149	0:0497	0:134
	(0:00531)	(0:0743)	(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

Table 9: Revenue Simulations

Panel A: Simulations for Advertised Drugs

	% Change in Revenue:	Crestor	Lipitor
(1)	Eliminating Business-Stealing	0:2107	0:2327
	Confidence Interval	(0:0047; 0:5639)	(0:0054; 0:6082)
(2)	Eliminate Political Ads	0:0207	0:0163
	Confidence Interval	(0:0039; 0:0689)	(0:0038; 0:0484)

Panel B: Simulations for Non-Advertised Drugs

	% Change in Revenue:	Unadvertised Drugs
(3)	Eliminate Spillovers	0:0974
	Confidence Interval	(0:1539; 0:0262)
(4)	Eliminate Political Ads	0:0030
	Confidence Interval	(0:0049; 0:0008)

Notes: Estimates from “Two Month Trailing Average” and drug-specific tim2 Tf 4.nwred dpecific

Appendix

Supplemental Appendix For Online Publication

A Model Assumptions and Simulation Details

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 arguments.*

Note that Logit demand satisfies this assumption, as do many other standard demand formulations. Concavity gives the result that rival advertising lowers the return to own advertising under spillovers, and raises it under business-stealing.

Assumption 2. *The following conditions hold:* $\frac{\partial D_j}{\partial a_j} > 0$ *and* $\frac{\partial D_j}{\partial a_j}_{a_j=0} > \frac{c}{r}$.

Assumption 2 guaratees there is an incentive to advertise. If a firm's advertising creates spillovers for rivals, that implies that $\frac{\partial D_j}{\partial a_{-j}} > 0$ in our notation, while business-stealing implies $\frac{\partial D_j}{\partial a_{-j}} < 0$. When we say that the effectiveness of advertising is diminishing in the level of drug demand, we mean that $\frac{\partial D_j^2}{\partial a_j \partial x_j} < 0$, while if it is complementary to the level of drug demand we have $\frac{\partial D_j^2}{\partial a_j \partial x_j} > 0$. A firm's first-order condition for advertising is satisfied when $\frac{\partial D_j}{\partial a_j} = \frac{c}{r}$.

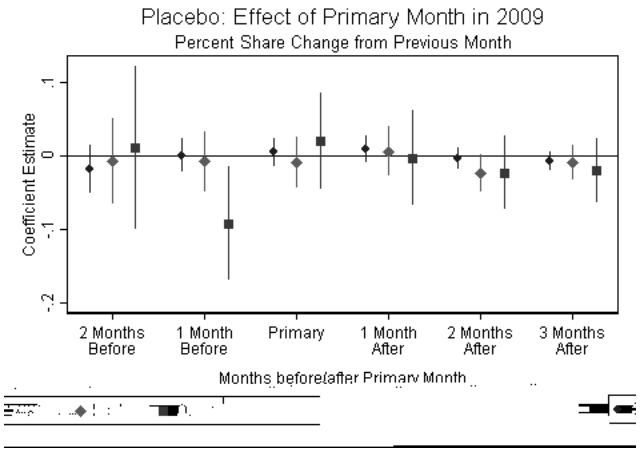
Parameters were set to the following values: $a_1 = a_2 = 0$, $c = 1$, $r = 1000$. Matlab's FSOLVE function was used to set a system of first-order conditions to zero. We use 200 markets and we draw values of x for each firm in each market where $x \quad N(0; 0.25)$.

Analytic values of own and rival advertising elasticities are calculated as the mean over all observations of

$$h_{own} = b_1(1 \quad s_j) \quad b_2 s_{-j}$$
$$h_{rival} = b_2(1 \quad s_j) \quad b_1 s_{-j}$$

We drop any simulations where Matlab's FSOLVE function failed to converge to a solution for firm first-order conditions for advertising levels. The full space of simulations covered b_1 2 [0:01; 0:3] and b_2 2 [0:4; 0:01]; both in increments of 0.005. The share of simulations where the bias in estimating own advertising elasticity was less than 5%, was only 1.54% of simulations, and 1.20% for rival advertising elasticity. The table below shows for one particular set of parameter values the OLS bias in estimating elasticities of own and rival ads.

Figure 10: Effect of Placebo Primaries on Shares of Non-Advertised Sales



Note: The above plots estimated coefficients for timing dummies relative to a market's primary month, with the "timing" of the primary shifted 12 months forward. The dependent variable is the (one-month) change in market share, defined as the percentage of the population taking a non-advertised statin.

Table 12: 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: Regressions combine the Wisconsin and Kantar data sets. 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 13: 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: Regressions combine the Wisconsin and Kantar data sets. 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: Effect of Business Stealing (IV Results)

Dependent Variable: Log(Revenue per Insured)				
Exposure:	2-Month		3-Month	
	(1)	(2)	(3)	(4)
Log Own Ads	0:0121	0:0764	0:0119	0:0536
	(0:0022)	(0:0258)	(0:0026)	(0:0235)
Log Rival Ads		0:0548		0:0407
		(0:0212)		(0:0230)
Controls				
Market FE	X	X	X	X
Drug FEs and Time Trends	X	X	X	X
N	11;550	11;550	10;875	10;875
R^2	0:847	0:824	0:849	0:840

Notes: 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 14: 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: Regressions combine the Wisconsin and Kantar data sets. 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 15:

Table 16: 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

Table 19: Heterogeneity, Part D Data

Dependent Variable: Log(Revenue per Insured)				
	Two-Month Trailing Average		Three-Month Trailing Average	
	OLS	IV	OLS	IV
Panel A: Beneficiaries Ending Year in Initial Coverage Phase				
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

Table 18: Robustness Checks (IV Results)

	Dependent Variable: Log(Revenue per Insured)					Dependent Variable: Log(Days Supply per Insured)	
Own Ads (2-Month Trailing)	0:766		0:1306	0:1189	0.0734***	0:1495	0:0657
	(0:0258)		(0:0492)	(0:0549)	(0.0270)	(0:0141)	(0:0255)
Rival Ads (2-Month Trailing)	0:0550		0:0958	0:0915	-0.0425**	0:1202	0:0488
	(0:0212)		(0:0383)	(0:0451)	(0.0215)	(0:0116)	(0:0209)
Jan.-Jun. '07 Ads	0:0699						
	(0:0322)						
1-Month Lagged Own Ads		0:1444					
		(0:0466)					
1-Month Lagged Rival Ads		0:1041					
		(0:0365)					
Market FEs	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X
Drug FEs	X	X	X	X	X	X	X
Drug FE*Time Trend	X	X	X	X	X		X
Drug FE*Time Trend^2					X		
Drug-Year FEs						X	
1(FDA), in first stage	X	X		X	X	X	X
1(FDA), in second stage				X			
N	11;551	11;551	11;550	11;550	11,550	11;550	11;550
R^2	0:871	0:877	0:776	0:787	0.832	0:745	0:822

Notes: Data created by collapsing Medicare Part D event data to the market-month-product level. 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

Table 20: Heterogeneity II, Part D Data

	Dependent Variable: Log(Revenue per Insured)			
	Two-Month Trailing Average		Three-Month Trailing Average	
	OLS	IV	OLS	IV
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;			