The Effects of Direct-to-Consumer Advertising in the Prescription Drug Market *

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Abstract

The year of 1997 witnessed an important change in direct-to-consumer (DTC) advertising of ethical drugs. For the first time, the Food and Drug Administration (FDA) permitted brand-specific DTC ads on TV without a "brief summary" of comprehensive risk information. This led to a three-fold growth of DTC advertising expenditure in four years, followed by an intensive debate about the effects of DTC advertising on patient and doctor behaviors. This paper empirically examines the effects of DTC ads on ethical drugs by combining 1996-1999 DTC advertising data with the annual National Ambulatory Medical Care Survey (NAMCS).

We find that DTC advertising leads to a large increase in the number of outpatient drug visits, a moderate increase in the time spent with doctors, but no effect on doctors' specific choice among prescription drugs within a therapeutic class. Consistent with the proponents' claim, this finding suggests that DTC ads encourage patient visits but do not challenge doctors' authority in the specific choice of prescription drugs. We cannot rule out the possibilities, however, that DTC ads may induce doctors to use prescription drugs over alternative treatments and doctors may spend extra time clarifying DTC ads if they do not prescribe the most advertised drug(s). Our results suggest that the effect of DTC advertising is primarily market-expanding rather than business-stealing, and therefore DTC advertising is a public good for all drugs in the same therapeutic class.

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1 Introduction

Consumer empowerment is prevalent in the U.S. Thanks to new technologies and new regulatory rules, consumers receive more and more product information before making a choice of purchase.[1] While an increase in product information is often believed to be welfare enhancing, this wisdom is not obvious for every type of products. The effects of such information are particularly debatable in health care markets because treatment decisions are made by doctors rather than consumers.

A recent change in direct-to-consumer (DTC) advertising of ethical drugs gives us a rare opportunity to address this issue. Prior to 1997, any DTC advertising that contained both drug brand and medical claims must disclose a "brief summary" of drug effectiveness, side effects and contraindications. Consequently, TV advertising was prohibitively expensive and DTC advertising was limited to newspapers and magazines. In 1997, the Food and Drug Administration (FDA), for the first time, permitted brand-specific DTC ads on TV without "brief summary."[2] This led to a three-fold growth of DTC advertising expenditure from $800 million in 1996 to $2.5 billion in 2000. Now prescription drugs is the fourth largest advertising category in the U.S., surpassed only by automobiles, restaurants and movies.

The effects of DTC advertising are controversial. Opponents argue that DTC advertising misleads patients to demand drugs that are heavily advertised. This may undermine the doctor's authority in drug prescription, leading to inappropriate drug use and unnecessary purchase of expensive drugs. Proponents, however, suggest a couple of benefits. For example, DTC ads may inform consumers of new treatment options and therefore generate new office visits. If true, this could be welfare improving as many diseases are under diagnosed. DTC advertising may also facilitate the communication between patients and doctors, hence helping the doctor make a better treatment choice. These controversies urged the FDA to reevaluate its policy on DTC

[1] In term of technology, the Internet offers numerous opportunities for consumers to access product information at little or no cost (see, for example, Scott Morton, Zettlemeyer and Silva-Risso 2002, Brown and Goolsbee 2002, and Ellison and Ellison 2002). One example of new regulatory rules is restaurant hygiene grade cards implemented in Los Angeles County (Jin and Leslie 2002). In another example, Centers for Medicare & Medicaid Services disseminates health plan information through *Medicare & You* handbooks, toll-free phone services and online databases (Goldstein et al. 2001).

[2] According to the FDA guideline, DTC ads still have to include a "major statement" of the most important risks, and disclose four sources of product labeling information: (1) a toll-free phone number; (2) referral to a print advertisement in a concurrently running print publication; (3) referral to a healthcare provider; and (4) an Internet web page address.

advertising.[3]

In contrast to the intense policy debate, most published evidence is based on individual surveys. For example, FDA surveyed 1,081 consumers in 1999 and found that, among the 688 respondents who had seen a DTC ad and had been to a doctor in the previous three months, 27% asked for the first time about a condition or illness and 12% asked about a specific brand of drug. Among those who asked about any prescription drug, half got the requested drug.[4] As for the effect of DTC ads on patient-doctor communication, 81% of the patients who had seen DTC ads and discussed the drug with their doctors stated that their doctors welcomed the question (1999 FDA survey). However, in the 1998 IMS survey of 2,000 doctors, 64% of respondents said that they would like to see DTC advertising decrease or be discontinued. Because it is hard to interpret and compare survey results, both sides of the controversy end up citing the same surveys or even design their own surveys to support their positions.[5]

This paper studies both patient and doctor behaviors by merging 1996-1999 DTC advertising data with the annual National Ambulatory Medical Care Surveys (NAMCS). Specifically, we ask three questions: does DTC advertising encourage more outpatient office visits? Does DTC advertising encourage doctors to spend more time with patients? And if doctors prescribe any drug, does DTC advertising affect doctor choice of prescription?

For the first question, we find that DTC advertising increases physician office visits quite dramatically. After using instrumental variables (IV) to account for potential endogeneity of DTC advertising expenditure, we find that every $10 million extra DTC advertising in a typical drug class leads to 0.881 million or 14.8% increase in RX visits, where RX visits are defined as all non-hospital outpatient visits that result in any prescription. In contrast, visits that result in non-drug treatment or over-the-counter (OTC) drugs do not experience any significant increase. Thus, we cannot rule out the concern that DTC advertising may induce doctors to use prescription drugs over other treatment alternatives.

[3]Both sides of the controversies are well documented. See Holmer(1999) and Holmer(2002) for a summary of the proponents' position, and Hollon (1999) and Wolfe (2002) for a summary of the opponents' position. In response to these controversies, the FDA has announced that it will review its policy on DTC advertising (*the Wall Street Journal, March 28, 2001*).

[4]Similar results were found in the *Prevention Medicine* surveys of 1,200 people conducted annually since 1998. The *Prevention* surveys also found that consumer awareness of prescription drugs has increased substantially from 1998 to 2000.

[5]Consequently, institutions such as the National Health Council place a number of public calls for research in this area (NHC 2002).

Conditional on those visits that result in any drug use (referred to as drug visits), we find that a $100 million increase in DTC advertising prolongs the time spent with doctor by 1.08 minutes per visit. Interestingly, this modest increase concentrates on visits in which patients do not get the most advertised prescription drug(s) within the relevant drug class(es). For patients who got the most advertised drug(s), time spent is insensitive to DTC advertising. One explanation of this asymmetry is that doctors may spend extra time correcting misleading DTC ads or exchanging more information with patients when the most advertised drug is not the best choice. However, the results also suggest that consumer demand of the most advertised drugs, if it ever exists, does not hasten diagnosis and treatment choice.

As for the effect of DTC ads on doctor prescription choice, we investigate individual records in two of the most heavily advertised classes – cholesterol reducing and non-sedative allergy drugs. In both classes, we cannot find any significant, positive effect of DTC advertising on specific prescription choices. Instead, advertising directed to doctors, especially "detailing" has a much larger and significant effect on the choice of prescription. This rejects the view that DTC advertising may undermine the authority of physicians in choosing a prescription drug for their patients.

All together, our results suggest that the effect of DTC advertising is primarily market-expanding rather than business-stealing, and therefore DTC advertising is a public good for all drugs in the same therapeutic class. These results are consistent with the proponents' claim that DTC ads encourage patient visits but do not challenge doctors' authority in the specific choice of prescription drugs. From the drug companies' point of view, it is certainly worthwhile advertising towards consumers, because every $12 DTC advertising expenditure in a typical class will generate one extra RX visit and the average wholesale price per prescription far exceeds $12.[6] However, from the social planner's point of view, the welfare effect of DTC advertising remains unclear. Our results point out two possible negative impacts: DTC ads might have encouraged doctors to write more prescriptions in place of alternative treatments and might have forced doctors to waste valuable time in clarifying DTC ads.

Our paper complements a few recent academic studies on DTC advertising. On the demand side, the earliest paper examining the impact of DTC advertising on ethical drugs is Berndt et al. (1995). However, the authors used the data for 1977-1994, which precedes the surge of DTC advertising in the late 1990s. Two independent studies are conducted simultaneously with our paper, addressing the impact of DTC advertising after the FDA clarification in

[6] $10 million DTC ads / 0.881 million RX visits = $12 DTC ads per RX visit.

1997. Rosenthal et al. (2002a) investigate the effects of monthly DTC advertising and detailing on the sales of prescription drugs in six therapeutic classes. They find that DTC advertising have a significant effect on the aggregate sales at the class level but does not have any significant impact on market shares within each class. Wosinska (2002) examines individual prescription claim data from Blue Shield of California medical plans. Focusing on cholesterol reducing drugs, she finds that DTC advertising may affect the demand for an individual brand positively, but only if that brand is on the third party payer's formulary. Both papers discuss the possibility that DTC advertising may have a larger effect in market-expanding than in business-stealing. However, both admit that their data are not good enough to generate precise estimates of the two effects simultaneously. Our study complements both papers by investigating the effect of DTC advertising in three stages. In doing so, we provide more comprehensive evidence regarding market-expanding and business-stealing effects of DTC advertising.

On the supply side, Rosenthal et al. (2002b) and Iizuka (2002) documented the concentration of DTC advertising in newer drugs targeting chronic conditions, and the fluctuation of DTC advertising expenditure within and across therapeutic classes. As a complement, our results indicate that DTC advertising has positive externality within a therapeutic class. This may explain why DTC advertising tends to concentrate in classes that involve fewer competitors and why in these classes major drugs advertise more than minor drugs.

We recognize that the demand effect of detailing promotion has been examined in earlier literature. Hurwitz and Caves (1988) looked at a cross-section of fifty-six off-patent drugs and found that detailing promotion has a positive effect on the market shares between branded and generic drugs. Rizzo (1999) looked at the demand for antihypertensive drugs for 1988-1993 and found that detailing promotion lowers price sensitivity. However, none of these papers looked at the effect of advertising directed to consumers. To be sure, this is mainly because DTC advertising increased its significance only recently, after the FDA clarification in 1997.

This paper also contributes to the body of literature that empirically distinguishes market-expanding from business-stealing effect of advertising. An ad is viewed as market-expanding when it purely increases a total market size, and business-stealing when it solely shifts market share among brands. Typically, ads are viewed as welfare reducing unless they increase total market demand. For example, Gasmi, Laffont, and Vuong (1992) found that advertising in the carbonated soft-drink industry is primarily characterized as business-stealing. The effects of cigarette advertising are much more debatable. Roberts and Samuelson (1988) finds that low-tar cigarette advertising has a significant market expansion effect but not a business stealing effect.

In contrast, documents from the FTC litigation and the research developed afterwards suggest nearly the opposite.[7]

The rest of the paper is organized as follows. Section 2 describes the data sets. Sections 3, 4 and 5 conduct an empirical analysis for patient visits, time spent with doctors, and doctors' prescription choice respectively. Section 6 integrates results from the three stages and discusses their implications.

2 Data

We combine individual data from the National Ambulatory Medicare Care Survey (NAMCS) with advertising data from Competitive Media Reporting (CMR) and IMS Health. The NAMCS provides a national representative sample of individual visits to office-based physicians. For each office visit, it includes detailed information on patient demographics, insurance status, physician specialty, time spent with the patient, diagnoses, dispositions and prescription choices, if any. For example, in 1998, the NAMCS contains data on 23,339 patient visits to office-based physicians.[8] In comparison, the CMR & IMS data provides the total DTC advertising expenditure for every drug advertised via DTC channels, as well as detailing and professional journal advertising expenditures for cholesterol and allergy drugs. CMR monitors advertising outlays in units and dollars in several different media including network TV, cable TV, newspapers and magazines. Advertising dollars reflect the net costs of buying such elements as television time and print space. Detailing advertising expenditures are estimated based on the time that a pharmaceutical firm's salesperson spent with doctors to detail their brand name drugs. We also obtain price data for cholesterol and allergy drugs from Drug Topics Red Book. The Red Book reports average wholesale price for each prescription drug. Patient-day price for each drug is computed by using initial recommended volume shown in *Drug Facts and Comparisons*. All are annual data matched by drug names.[9] The data cover years of 1996-2000 for cholesterol drugs, and 1996-1999 for all other drugs.

Using NAMCS and advertising data, we decompose our empirical analysis in three stages: first, at the therapeutic class level, we examine the impact of DTC advertising on patient

[7] Based on conversation with FTC officials, Mulholland 1994 and Calfee 2000

[8] See Cherry et al. 2001 for more detailed description of the NAMCS.

[9] In rare cases, NAMCS may assign different drug class codes to the same drug across years. Because our DTC data is drug-specific, we merge DTC data with NAMCS drug class codes by the 1999 definition.

visits. Second, for each drug visit, we investigate how the total DTC advertising within relevant therapeutic classes affects the time spent with doctor. Note that both stages do not distinguish specific drugs within the same class. At the third stage, we focus on those drug visits that result in a single prescription of cholesterol or allergy drug. Conditional on these individual records, we ask whether doctors tend to prescribe heavily advertised drugs. Because each stage entails a different way to analyze the NAMCS data, we report summary statistics and regression results separately for each stage.

3 Effect of DTC advertising on patient visits

This section assesses the effect of DTC advertising on patient visits. Suppose all drugs in therapeutic class k treat disease k. If DTC advertising has raised consumer awareness of treatment options, then greater exposure to DTC ads in class k should encourage more consumers at the risk of disease k to visit doctors. However, it is quite possible that a DTC ad of a specific drug motivates an individual to visit a doctor, but he or she may end up getting a different drug within the same therapeutic class. Therefore, we look at the effects of DTC ads at the class level rather than the individual drug level. We will use therapeutic class and drug class interchangeably.

3.1 Empirical Model

Following this logic, an ideal model will link an individual's exposure to DTC ads in drug class k with his/her decision to visit a doctor's office for disease k. Unfortunately, our data on DTC advertising expenditure is in aggregate. Therefore, we focus our attention to the effect of DTC ads on aggregate demand.[10]

Specifically, consider:

$$V_{kt} = \alpha_k + \beta_t + \gamma \cdot DTC_{kt} + \epsilon_{kt}$$

$$ln(V_{kt}) = \alpha_k + \beta_t + \gamma \cdot DTC_{kt} + \epsilon_{kt}$$

[10] One potential drawback of this approach is that DTC advertising may affect different people differently. While we cannot address this issue completely, we have examined whether patient demographics have changed over time as DTC advertising increases. We do not find such a change, however, and this gives us confidence in looking at the average effect of DTC ads.

where V_{kt} stands for the total number of outpatient office visits related to drug class k at year t. V_{kt} is computed from the NAMCS data using the sampling weights associated with each observation. DTC_{kt} stands for the total DTC expenditure of drug class k at year t, α_k denotes class fixed effects and β_t denotes a time trend common to all classes. For each visit recorded in the NAMCS, a patient may receive treatment in one or more therapeutic classes. If it involves only one class, we count it as one visit no matter how many drugs or procedures were mentioned for that visit. If an NAMCS record results in treatment related to two or more drug classes, we count it as one visit for each relevant class. Defining class-year as unit of observation, we have 537 observations covering 137 drug classes over four years.

On the right hand side, we use linear DTC because linear DTC fits the data much better than $ln(DTC)$. Throughout this section, we will refer the first specification as linear-linear and the second specification as log-linear. If correctly identified, the coefficient γ in the linear-linear specification should tell us how much extra patient visits are generated by one unit increase in DTC advertising expenditure. In comparison, the log-linear coefficient γ should predict the percent increase in patient visits as a result of one unit extra spending on DTC ads.

3.2 Identification

Aggregate V_{kt} and DTC_{kt} raise several econometric concerns. For example, a class with a large number of potential patients naturally has more patient visits. In the meantime, drug companies also tend to allocate large advertising budgets to large drug classes. Therefore, a high correlation between DTC advertising and patient visits does not necessarily imply a causal effect. Moreover, as manifested by the concentration of DTC ads in a small number of drug classes, drug companies may have intentionally selected which classes to advertise. To address these concerns, we use class fixed effects α_k to control for time-invariant cross-class differences and year dummies β_t to account for time trend common for all drug classes.

Now the effect of DTC is mainly identified from over time variations within each drug class. There are still several reasons to suspect endogenous DTC_{kt}. First, if an advertising budget is proportional to sales revenue and somehow patient visits correlate with sales revenue, reverse causality will reinforce a positive correlation between V and DTC and therefore overestimate γ. Another possibility is that consumers may learn about new drug approvals or new research of drug effectiveness through channels other than DTC advertising. Given the fact that drug companies advertise more heavily on new and important drugs, this would imply an upward

bias on γ.[11]

Moreover, as the Pharmaceutical Manufacturing and Research Association claimed (Holmer 1999 and 2002), drug companies may devote a lot of DTC advertising to under-diagnosed classes. Although class fixed effects partially control for such selection bias, it is still possible that, for a specific drug class over time, drug companies commit to high DTC expenditure when the actual number of visits is relatively low. For example, Viagra may be advertised more heavily at its inception (i.e., when current visits are low) since the return from advertising is higher at the beginning. Overtime, as the number of patient visits increases, advertising expenditure may decrease since the marginal effect of ads declines. This negative correlation will imply a downward bias in γ.

To solve the endogenous problem, we use the same drug companies' DTC expenditures in other drug classes DTC_{-kt} as an instrument for DTC_{kt}. For example, cholesterol-reducing drugs involve four major drug companies – Bristol-Myers Squibb (for Pravachol), Merck (for Zocor), Pfizer (for Lipitor) and Novartis AG (for Lescol). These four companies also produce and advertise prescription drugs in other classes, for instance Novartis's Habitrol targets smoking, Bristol-Myer's Zerit targets HIV, Merck's Fosamax targets Osteoporosis and Pfizer's Viagra targets impotence. If class k refers to cholesterol reducing, DTC_{-kt} is defined as the sum of DTC advertising that these four drug companies spent on all the other classes at year t.

We argue that DTC advertising across classes is correlated within the same company, either because the company pursues a particular marketing strategy for all products or because different drugs are subject to a common constraint in the advertising budget. DTC advertising data supports this assumption: 90% of all the classes with positive DTC_{kt} also have positive DTC_{-kt}. Taking into account the dollar amount of DTC advertising, DTC_{-kt} is positively correlated with DTC_{kt} for all years and the correlation coefficient is as high as 0.66 in 1996 and 0.61 in 1999. These statistics suggest that DTC_{-kt} could be a strong instrument for DTC_{kt}.

On the other hand we assume, after controlling for drug class fixed effects and common time trend, unobserved factors that drive changes in patient visits are uncorrelated across classes. This assumption is based on the facts that drug companies often start researching a specific drug many years before its final FDA approval and the research progress is often subject to many scientific factors out of the control of drug companies. By this assumption, the only way for

[11] In an unreported analysis, we add in the basic specification the number of drugs that appeared in NAMCS by class year. Results are very similar.

DTC_{-kt} to influence DV_{kt} is through DTC_{kt}. The same identification strategy was pursued in Berndt et al. (1995).

3.3 Results

Due to several data cleaning issues elaborated below, we report separate results for three dependent variables: total number of RX visits, total number of OTC visits and total number of non-drug visits. The overall effect of DTC advertising on patient visits is the sum of the effects on these three types of visits. Specifically, a visit is counted as an RX visit of class k if it results in any prescription in class k. If a visit results in no prescription drug but at least one over-the-counter drug in class k, it is referred to as an OTC visit of class k. Because NAMCS may record up to six drug mentions for each visit, it is possible to double count one record as an RX visit in one class and an OTC visit in another class. However, conditional on the same class, RX and OTC are mutually exclusive. The sum of RX visits and OTC visits are referred to as drug visits. If a visit leads to no treatment or non-drug treatment, it is categorized as a non-drug visit.

RX and OTC visits are clearly defined, as NAMCS provides a class code for each drug mentioned in each drug visit. However, because the 1997 FDA clarification mainly applies to prescription drugs, it is reasonable to expect the DTC advertising of prescription drugs to have differential effects on RX and OTC visits. Estimating RX and OTC visits separately also avoids imposing any restriction on the coefficients of class dummies and year trends across the two types of visits.

The definition of non-drug visits involves a technical challenge: there is no therapeutic class code for non-drug visits. To address this issue, we propose the following procedure. Suppose a non-drug visit at year t was diagnosed as having disease x_t. In the same year, many other visits got the same diagnosis but received drug treatment, potentially in several drug classes. Among these classes, we allocate the most frequently used one as the class that is most likely applicable for disease x_t. Such inference allows us to associate each diagnosis with a specific drug class. Through diagnosis codes, we can link each non-drug visit with likely drug classes.[12] Note that the above procedure may generate a fair amount of noise[13], and therefore results on non-drug

[12] NAMCS provides up to three diagnosis codes for each visit. So a non-drug visit may be linked to at most three drug classes. Obviously, we cannot make such association for a small proportion of non-drug visits whose diagnosis codes are missing.

[13] NAMCS data not only record drug mentions that are directly related to diagnosis, but also include drug refills

visits are merely suggestive. We are reluctant to pool non-drug visits with drug visits as doing so may spread the potential data contamination to drug visits.

We now turn to report summary statistics of patient visits, followed by full regression results for each type of patient visits.

Figure 1 depicts the time trend of patient visits and DTC advertising from 1993 to 2000. Patient visits are weighted counts from annual NAMCS, grouped by RX, OTC and non-drug visits. DTC advertising expenditures are cited from Findley (2001).[14] During the eight years, DTC advertising skyrocketed more than 16-fold, from 151 million in 1993 to 2.5 billion in 2000. In comparison, the total number of RX, OTC and non-drug visits all fluctuate over time and do not follow the trend of DTC advertising in clear patterns. To clarify the correlation between DTC advertising and drug visits, we separate the top 10 advertised classes (defined by the 1999 DTC data) from the other classes (Figure 2 and Figure 3).[15] For the top 10 classes, RX visits grew much faster and tracked DTC advertising more closely than OTC and non-drug visits. For the non-top-10 classes, DTC advertising is not strongly correlated with any of the three types of visits. These figures suggest two possibilities: first, most actions take place in the RX visits of heavily advertised classes; and second, heavily advertised classes may follow a different time trend.

Table 1 presents regression results of RX, OTC and non-drug visits for the full sample. Because regressions allowing different time trends for different group of classes [16] generates similar results as those allowing a common time trend for all classes, here we only report results with a common time trend. According to the OLS results in column (1), \$10 million increase in DTC advertising in a typical drug class is associated with 0.305 million more RX visits, or a percentage increase as large as 4.7%. After using DTC_{-kt} as an instrument for DTC_{kt} in column (2), the actual effect of \$10 million DTC advertising increases to 0.881 million RX visits or a 14.8% growth. This suggests that OLS tends to underestimate the effect of DTC on drug

that may be irrelevant to current diagnosis.

[14] Data in Findley (2001) are based on the MIS Health analysis of CMR data.

[15] In Figure 1, the total counts of patient visits pool all classes together, so we do not make distinctions between visits related to single class and visits related to multiple classes. However, isolating the top 10 advertised classes entails visit counts by class. Since one visit may be linked to multiple classes, the sum of patient visits for top-10 and non-top-10 advertised classes are larger that the total number of visits reported in Figure 1.

[16] In an unreported analysis, we include a separate set of year dummies for classes that ever advertised in DTC. In another analysis, we restrict the sample to classes that have ever advertised in DTC and include a separate set of year dummies for classes with at least 5 million visits in 1996. In both analyses, results are similar to what we find in the basic specification.

visits, confirming the view that DTC ads may have targeted under-diagnosed diseases.

In contrast to the strong effect of DTC advertising on RX visits, we don't find any significant increase of OTC and non-drug visits as the result of DTC advertising (columns 3-4 and 7-8). In fact, after we apply the instrumental variable, $10 million DTC advertising in a typical class may even lead to a 0.215 million decrease in OTC visits with p-value 0.16. This suggests a potential substitution from OTC visits to RX visits.[17]

Columns 5 and 6 conduct similar regressions on drug visits in total, pooling RX and OTC visits. In all specifications, no matter linear-linear/log-linear or OLS/IV, the coefficients of DTC expenditure are positive and highly significant, suggesting that the potential substitution effect from OTC visits to RX visits, if it exists, cannot fully explain the strong growth in RX visits. Similarly, the close-to-zero effect of DTC advertising on non-drug visits suggests that the growth in drug visits cannot be attributed to substitution away from non-drug visits, either.

Overall, DTC advertising increases physician office visits quite dramatically, although most of the market expansion effect concentrates on RX visits. We can think of two explanations: first, DTC advertising encourages patients to conduct a pre-diagnosis by themselves. As a result, those patients who are more suitable for prescription treatment are more likely to visit doctors. By this explanation, it is the change in patient distribution that drives the growth in RX visits. For this theory to explain the negative effect of DTC advertising on OTC visits, one must believe that RX visits squeeze out some OTC visits, probably due to the capacity limit of doctors.

The second explanation casts doubts on doctor prescription behavior. Suppose the patient distribution does not change, either because patients do not have the ability to self-diagnose, or because a typical 30-second or 60-second DTC ad on TV does not provide enough information for self-diagnosis. Then the sharp rise in RX visits implies that, as a result of DTC ads, doctors are more likely to use prescription drugs than the other treatment alternatives. This explanation would be consistent with the opponents' claim that DTC ads distort doctor prescription behavior. Without more information on patient condition and drug-specific advertising targeting doctors, we cannot rule out this possibility.

To further understand the impact of DTC ads on the number of prescriptions, Table 1 columns (9) to (12) repeat the regressional analysis for total drug mentions and total prescrip-

[17] We confirm this finding in an unreported probit regression. For each drug visit, we estimate the probability of receiving any prescription drug (versus OTC drug(s)) in class k as a function of the total DTC adverting expenditure in class k. The coefficient of DTC is always positive and significant.

tions by class. Counts of drug mentions differ from counts of drug visits because one drug visit may receive more than one drug in the same therapeutic class. Similarly, counts of prescriptions are not necessarily equal to counts of drug mentions because the latter includes both prescription and over-the-counter drugs.

Throughout all specifications, DTC ads seem to have larger effects on total prescriptions than on drug mentions, both of which are greater than or comparable to the estimated effects on RX visits. This implies that DTC ads may not only prompt more patients to doctor visits, but may also increase the number of drug mentions per visit. Based on the IV estimates in the linear-linear specification, the marginal effect of DTC ads on RX visits accounts for 94.8%[18] of the growth in drug mentions, and 82.03%[19] of the growth in prescriptions. This confirms one of the opponents' concerns that DTC advertising may have accelerated the rapid growth of the number of prescriptions, thus the total expenditure on prescription drugs.[20]

3.4 Limitations

Before concluding this section, we would like to mention three limitations. First of all, even after we apply the instrumental variable, all estimates are identified from those classes that engaged in some DTC advertising during 1996 and 1999. Therefore, these estimates are only applicable to advertising classes, which explains why the effects of DTC advertising appear to be much stronger for the top 10 advertised classes.

Second, because patients do not observe any direct-to-doctor advertising, the sum of the effects of DTC advertising on RX, OTC and non-drug visits should generate a consistent estimate about the overall market-expanding effect of DTC advertising. However, a precise explanation of the *compositional* change among RX, OTC and non-drug visits would need controls for all relevant information flows observable to either patients or doctors. Unfortunately, we do not have any data on direct-to-consumer advertising of OTC drugs, nor do we observe detailing or professional journal advertising of prescription drugs. More importantly, our instrumental variable approach may not fully address the issue of omission, for different advertising categories may be correlated across classes within the same drug company. Bearing this caveat in mind,

[18]The ratio between the IV coefficient for drug visit (0.0881) and the IV coefficient for drug mentions (0.0929).

[19]The ratio between the IV coefficient for drug visit (0.0881) and the IV coefficient for prescriptions (0.1074).

[20]The total retail spending on prescription drugs has increased about 18% every year since 1997 (NIHCM 2002). Without detailed price data for all drugs, we cannot decompose the growth in drug expenditure into the growth of the number of prescriptions and the growth of drug prices. This certainly warrants future study.

readers should interpret our results as the direct effect of DTC advertising on patient visits, plus any indirect effect from those professional and OTC advertising expenditures that track DTC advertising changes over time.

Finally, table 1 assumes 100% depreciation of DTC advertising from one year to another. This is certainly an extreme assumption, but our panel is too short to identify the real depreciation rate. Alternatively, we use an estimate from Berndt et al. (1995) for a robustness check. Based on the 1977-1994 monthly data on the sales and advertising of anti-ulcer medicines, Berndt et al. (1995) found that DTC advertising depreciated 15% every month. This is equivalent to an annual depreciation rate of 85%. Using this estimate and assuming zero DTC advertising before 1996, we get very similar results in all regressions – the coefficient γ only differs slightly in the third digit.

Another strategy is to compare the 100% depreciation results with the other extreme case – 0% depreciation. Results based on 0% and 100% depreciation should give us the lower and upper bounds of the true effect.[21] Assuming 0% depreciation, we find that the signs and significant levels of coefficients are similar across all specifications (including IV regressions), although coefficient magnitudes are smaller. Finding significant coefficients of DTC in both 0% and 100% depreciation cases suggest that DTC advertising does indeed cause more office visits.

3.5 Summary

In summary, from 1996 to 1999, DTC advertising of prescription drugs led to an impressive growth in outpatient office visits, with most of the growth driven by RX visits. This finding provides mixed evidence regarding the ongoing debate about DTC ads. On one hand, it is consistent with the proponent's claim that DTC ads encourage more patients to seek treatment. On the other hand, we cannot rule out the possibility that DTC ads induce doctors to use prescription drugs over the other treatment alternatives.

[21] Although we do not observe DTC advertising before 1996, drug class fixed effects should fully control for the accumulated DTC advertising up to year 1996.

4 Effect of DTC advertising on time spent with doctor

This section assesses the effect of DTC advertising on time spent with doctor. Proponents claim that DTC advertising may facilitate the communication between patients and doctors, hence help doctors make better treatment choices. Although NAMCS provides no direct measure on the quality of patient-doctor communication, literature suggests that time spent with doctor may be a good proxy (Benham 1972 and Kwoka 1985).

DTC ads may affect the patient-doctor relationship in many ways, which may increase or decrease the time spent with the doctor. In one scenario, exposure to DTC ads may help a patient better recognize symptoms and therefore better articulate symptoms. This would improve patient-doctor communication and reduce the time spent for diagnosis. Alternatively, a patient exposed to a DTC ad may talk more about his/her health conditions and prolong the conversation with the doctor. In another scenario, the patient may simply ask for the advertised drug. If the doctor complies without thoroughly examining the patient, DTC ads will lead to a reduction in time spent and a worsened relationship between the patient and the doctor. If the doctor does not comply, the doctor may spend extra time explaining why the advertised drug is not the optimal choice for the patient.

4.1 Empirical Model

Without detailed information on the contents of patient-doctor conversation, it is impossible to distinguish one scenario from another. Instead, we estimate the total effect of all these potential scenarios on time spent with doctor. In doing so, we must associate time spent with doctor with the total DTC advertising of all relevant drug classes. Given the potentially noisy inference of drug class codes for non-drug visits, we limit the sample to drug visits only. Specifically, consider the following models for visit i at year t:

$$T_{it} = \sum_k (\alpha_k \cdot 1_{ikt}) + \beta_t + \gamma \cdot \sum_k (DTC_{kt} \cdot 1_{ikt}) + \delta \cdot X_{it} + \epsilon_{it}$$

$$ln(T_{it}) = \sum_k (\alpha_k \cdot 1_{ikt}) + \beta_t + \gamma \cdot \sum_k (DTC_{kt} \cdot 1_{ikt}) + \delta \cdot X_{it} + \epsilon_{it}.$$

T_{it} stands for the number of minutes patient i spent with doctor, excluding any time patient i spent in waiting or interacting with other health care providers. 1_{ikt} is a dummy variable equal to one if patient i received any drug treatment in drug class k, DTC_{kt} is the total DTC

advertising expenditure for all prescription drugs in drug class k at time t, and X_{it} denotes all observable patient or doctor characteristics that may affect the time spent. To elaborate, X_{it} includes payment methods (HMO/Medicare/Medicaid/self pay), physician incentive (capitated or not), whether the patient was seen before in the same establishment, whether the visit was referred by another doctor, whether the visit needs authorization, the major reason of visit (acute/chronic/injury-related/healthy checkup), physician specialty (15 groups following NAMCS definition), and patient demographics such as age, gender and race.

Table 2 presents summary statistics for all key variables used in the time-spent regressions. Among the 59,958 drug visits recorded in 1996-1999 NAMCS, the average time spent with doctor is 19 minutes per visit. In 6% of these visits, patients had zero contact with doctors (recorded as $T_{kt} = 0$), either because patients left before seeing any health care provider or because patients only encountered non-physician health providers. These zero time visits are included in the linear regression of T_{it} but are excluded in the log regression.

Interesting is that 51% of NAMCS drug visits involve more than one drug class. This may be because NAMCS recorded all types of drug mentions, including refills of old prescriptions. With no further information to isolate refills from new drug mentions, we have to treat all relevant drug classes equally. In particular, we define a dummy variable for each drug class. If visit i resulted in drug treatment in two drug classes, k and k', visit i will have two class dummies equal to one. In regressions, we allow separate intercept (α_k) for each drug class dummy. This implies that patients involved in multi-class visits spent more time with doctors. In the same spirit, we use the sum of DTC advertising expenditure for classes k and k' as a proxy for patient i's exposure to relevant DTC ads.[22]

4.2 Identification

As detailed in Section 3, DTC expenditure is potentially correlated with some unobserved factors driving aggregated counts of patient visits, for example, the overall distribution of patient health insurance status, patient demographics, patient health, doctor incentives and doctor specialties. For regressions of time spent, we use individual level data and therefore are able to control for most of these factors. Even for factors with no direct measures, say patient health, we have

[22]To further account for potential economy of scope in time spent in multiple-class drug visits, one may use the total number of classes involved in each individual visit as a separate independent variable. Including or excluding this variable generates identical results.

multiple proxies – age, gender, reason of visits, whether the patient was seen before, and whether the patient was referred by another doctor. With all these controls plus drug class dummies and year dummies, we argue that the DTC variable in the time-spent regressions is unlikely to correlate with the error term. This assumption is confirmed in the real data. When we follow the instrument definition in Section 3 and apply the instrument to all time spent regressions[23], Hausman tests always suggest no need of instrument.

As with the visit regressions, we have tried $ln(DTC)$ instead of linear DTC for both specifications and always found better fits with linear DTC. Also, applying 85% annual depreciation rate on DTC generates very similar results as 100% depreciation, so we assume a 100% depreciation rate and only report results with linear DTC. Furthermore, since different patients may visit the same doctor in NAMCS, their time spent with doctor can be correlated. All regressions are clustered by doctor-year to account for this data structure. To generate national representative estimates, all regressions use sample weights.

4.3 Results

Table 3 reports regression results of time spent for all drug visits in 1996-1999 NAMCS. Conditioned on the full sample, column (1) finds that, for a typical drug visit, a $100 million increase in the total DTC advertising expenditure of all relevant classes prolongs the time spent with the doctor by 1.08 minutes or 4%. Compared to the average 19-minute encounter, this increase, although statistically significant, is very modest. When we restrict the sample to single-class visits, results become clearer and stronger. Column (2) suggests that, for each single-class visit, $100 million more DTC advertising would lead to 2.07 more minutes spent with doctor. Similarly, in the log-linear specification, $100 million increase in DTC advertising implies an 8% increase in time spent.

Next, we examine whether the time spent with doctor may vary depending on whether the patient received the most advertised drug in the class or otherwise. We speculate a few possibilities. First, if DTC ads correctly inform patients of the attributes of the drug, this may encourage a pre-matching between the patient and the drug. In turn, better pre-matching

[23]Since a drug visit may involve more than one drug class, the instrument definition is more complicated than in Section 3. For a specific drug visit i, we know all the drug companies who produced at least one drug in one relevant drug class. The instrument is defined as the total DTC advertising that these companies spent in all classes that are irrelevant to visit i.

may lead to a shorter time spent with doctor for heavily advertised drugs. For those drugs not heavily advertised, we may expect to see no change in time-spent with doctor since there is no self-matching in that case. Second, DTC ads may encourage patients to talk about DTC ads with their doctors. If such conversation does not challenge the doctor's prescription authority but makes patients more involved in the decision process, doctors may need extra time to explain their decisions, especially if they choose not to prescribe the most advertised drug. On the other hand, if DTC ads undermine doctor authority in diagnosis and prescription, doctors may simply comply with patient requests. In that case, we should observe shorter time spent for those visits who got the most advertised drug. .

To test these speculations, we focus our attention on D classes (D stands for "diverse") in which some patients got the most advertised drugs and some patients did not. There are 51 D classes in our data set. Columns (3), (4) and (5) of Table 3 confine the single-class sample to D classes only. In particular, column (3) reports results for this confined sample as a whole, and columns (4) and (5) divide the confined sample by whether a patient got the most advertised drug in his drug class. Results for D classes only (column 3) are quite similar to what we find for all single-class visits (column 2), which suggests little concern in sample selection. Comparing column (4) with column (5), it is obvious that the modest increase in the average time spent with the doctor is mostly driven by those visits that did not get the most advertised drug in the relevant class. For those who got the most advertised drugs, their time spent is insensitive to DTC ads.

This pattern goes beyond single class visits. In an unreported table, we extend the analysis to the full sample of drug visits and isolate visits that led to at least one most advertised drug in at least one drug class. Similar to the single-class results, the effect of DTC advertising on time spent concentrates on those visits that did not get most advertised drugs in any class. This finding has two implications: first, consumer demand for the most advertised drugs, if it ever exists, does not hasten doctor diagnosis and treatment choice. Second, doctors only spend more time with patients when the most advertised drug is not the best choice. One explanation of this asymmetry is that doctors may spend extra time correcting misleading DTC ads. Another explanation is that doctors exchange more information with patients when the most advertised drug is not the best choice.

So far we find that DTC advertising leads to a sharp rise in the number of drug visits and a moderate increase in time spent with doctor per drug visit. If the total capacity of doctor time is limited, these two facts combined may imply less doctor time for non-drug visits or for drug

visits in less advertised classes. To address the concern of negative externality, we adopt the following procedure. For each of the 15 physician specialties defined in the NAMCS data, we calculate the total DTC advertising of all drug classes that are related to drug visits occurring for that specialty. This variable, referred to as $TOTALDTC_{st}$, denotes the intensity of DTC advertising that may potentially influence doctors of specialty s.

To capture the potential externality of DTC advertising on the time spent of non-drug visits, we regress the time spent of each non-drug visit on $TOTALDTC_{st}$ and all the other controls on individual and physician characteristics. For each drug visit, we add one variable $OTHERDTC_{st}$ in the above specification to capture the difference between all the DTC advertising related to that visit and $TOTALDTC_{st}$. If negative externality exists, we should find a negative coefficient of $TOTALDTC_{st}$ on the time spent of non-drug visits and a negative coefficient of $OTHERDTC_{st}$ on the time spent of drug visits. While not reported in a table, these coefficients are indeed of the expected signs, but never statistically significant. Moreover, adding $OTHERDTC_{st}$ in the regressions of drug visits does not generate any significant change in the coefficient of DTC. Therefore, we conclude that the moderate increase in the time spent of visits related to heavily advertised classes does not motivate doctors to shorten the time spent of non-drug visits or less advertised drug visits. It is possible that doctors work longer hours or more doctors join the profession to accommodate more and longer patient visits.

Proponents of DTC advertising also speculate that DTC advertising may be especially beneficial for certain types of patients. They argue insurance companies, especially managed care, have used payment incentives and drug formularies to influence doctors' prescription choices. Since doctors are double agents for patients and insurers, DTC advertising may help overcome the agency problem of managed care doctors (Holmes 2002, and Rubin & Schrag 1999). If managed care incentives make managed care patients less attractive to doctors, doctors may spend fewer efforts and thus less time with managed care patients (Melichar 2002). Should DTC advertising help reverse this trend, the effect of DTC advertising on time spent would differ by whether the patient is insured by an HMO and whether the doctor is capitated.[24]

To test this hypothesis, for each drug visit, we interact HMO dummy and capitation dummy with the total DTC spending related to that visit. [25] To avoid potential confounding factors, we also include interactions of DTC spending with other major visit/patient charac-

[24]NAMCS since 1997 does report whether a mentioned drug is on- or off-formulary, but this variable has a lot of missing values and we suspect health plans may adjust drug formulary status by the intensity of DTC advertising.

[25]Since NAMCS does not provide capitation status until 1997, we control for a dummy variable indicating missing capitation. Results are robust if we exclude 1996 observations.

teristics. While not reported in table form, our linear-linear specification finds that every $100 million DTC advertising makes doctors spend 1.04 minutes more with HMO patients than with non-HMO patients, but 0.99 minutes less with capitated patients than with non-capitated patients, both significant at the 95% level. If we take time spent with doctor as a proxy for the service quality of doctor, this finding suggests that DTC advertising does not help correct the distorted relationship between doctors and capitated patients. It may improve doctor interaction with non-capitated HMO patients, if extra time implies better communication.

4.4 Summary

DTC advertising leads to a modest increase of the time spent with doctor. This effect is mainly driven by the visits in which patients did not get the most advertised drug(s) in the relevant drug class(es). For those who got the most advertised drugs, DTC advertising had no significant effect on time spent. One explanation of this asymmetry is that doctors may spend extra time correcting misleading DTC ads or exchanging more information with patients when the most advertised drug is not the best choice. However, the results also suggest that consumer demand of the most advertised drugs, if it ever exists, does not hasten doctor diagnosis and treatment choice. When comparing HMO vs. non-HMO and capitated vs. non-capitated patients, we find that DTC advertising does not help restore the potentially distorted relationship between doctors and capitated patients. If anything, DTC advertising may help improve doctor communications with non-capitated HMO patients.

5 Effect of DTC advertising on prescription choice

The main interest of this section is to analyze the effect of DTC advertising on the choice of prescription drugs, i.e. brand switching effects. If physicians maintain their authority to choose a drug, then DTC advertising may encourage people "to seek medical help," but may not affect brand choice. On the other hand, if DTC advertising enables patients to "persuade" physicians to prescribe what they want, DTC advertising may have a significant effect on brand choice. Of course, opponents are concerned about the latter as a consequence of the surge in DTC advertising.

5.1 Empirical Model

To distinguish these two arguments, we estimate demand for prescription drugs using a multinomial logit model. A discrete choice model is useful for our purpose because of the short panel data we have. We assume that a physician k chooses a drug j for patient i at time t, among J alternatives, which maximizes the objective function represented by V_{ijkt}:

$$\max_{j \in J} \; V_{ijkt} = f(X_{jt}, A_{jt}, P_{jt}, Y_{it}, H_{kt})$$

where, X_{jt} is a vector of product characteristics of drug j at t, A_{jt} is a vector of advertising expenditures of drug j at t, P_{jt} is the price of drug j at t, Y_{it} is a vector of patient i's attributes and H_{kt} is a vector of physician k's attributes at time t. We observe three different types of advertising expenditures in A_{jt}: DTC advertising, detailing advertising and professional journal advertising.[26] This allows us to examine whether the impact of these advertisements may be different in promoting prescription drugs. Product characteristics X_{jt} include both product specific dummies and time varying attributes, i.e., age of drug.

In the simplest form, we can specify the objective function V as a linear function of X, A, and P and error term μ:

$$V_{ijkt} = X_{jt} \cdot \beta + A_{jt} \cdot \gamma + \alpha \cdot P_{jt} + \mu_{ijkt}$$

If we assume the error term is distributed as Type I extreme value, we can estimate the model by the multinomial logit model. A number of interaction terms between physician/patient characteristics and drug characteristics are also added to the above model as controls (discussed in the next session).

5.2 Identification

The main identification assumption in this section is that the right-hand side variables, in particular price and advertisement variables, are not correlated with the error term. The assumption is not likely to hold, however, if the error term contains aggregate components common among consumers. One such candidate is some product attribute that is observed by market participants but not by the econometrician. As shown in Berry et al. (1995), this often becomes a

[26] We do not have data on the number of free samples that drug companies gave to doctors. However, Wosinska (2002) finds that including or excluding data of free samples for cholestrol-reducing drugs generate very similar results.

problem if aggregate level data are used. In our case, however, we can include drug specific dummies on the right-hand side because of the micro-level data we have. This in turn alleviates the above concern.

Another potential problem is that aggregate demand shocks such as the change in demographics may bias the coefficients of our interest if they are left as error components common across consumers. Again, the micro-level data, which allow us to include various interaction terms, alleviate the problem. Specifically, we include interaction terms between price and patient/doctor characteristics and a full set of interaction terms between drug fixed effects and patient demographics. Patient characteristics include insurance status (i.e., Medicare, Medicaid, and self-pay), HMO membership, and demographics (i.e., age group, gender, and race). Doctor characteristics include doctor specialties, i.e., family practice, internal medicine, and cardiovascular specialist (for cholesterol reducers. Since the Hausman tests in Section 4.2 suggest no need of instrument for the DTC variable when individual data are used, we believe the error term in this section is also less likely to be correlated with the price and advertising variables.

Another identification assumption is that doctors do not gain additional information from DTC advertising regarding drug attributes. This allows us to interpret the effects of DTC advertising as the influence of patients on physician prescriptions. If the assumption does not hold and physicians also gain information from DTC advertising, then the estimated coefficients would confound the effects of DTC advertising both on patients and physicians. We believe the assumption is reasonable, however, given the timing that DTC advertising was adopted in these drug classes. As shown in Table 4, most of the drugs entered the market before the second half of the 1990s. By 1996, these drugs were already popular and frequently prescribed by physicians. Moreover, detailing advertising has been extensively used to promote these drugs and drug information is readily available from various professional references, such as *Drug Facts and Comparisons* and *Physician's Desk Reference*. Given that DTC advertising transmits only limited information to viewers, it is less likely that DTC advertising affected the physician's knowledge on these drugs. In the case of Lipitor, the most popular Statin drug that entered the market in 1997, the firm did not spend much money on DTC advertising until 1999 and instead focused on promoting the drug using detailing advertising. Thus, physicians were quite familiar with the drug when its DTC advertising campaign picked up in 1999.

5.3 Two Drug Classes

5.3.1 Cholesterol Drugs (Statins)

The first drug class we examine is Statin drugs (HMG CoA Reductase Inhibitors). Statin is the most popular therapeutic class used to lower elevated cholesterol.[27]. Statins gained enormous popularity with the introduction of Mevacor (lovastatin) in 1987 and has dominated the market. Statin drugs share similar mechanisms of actions and have similar chemical structure; thus they are close substitutes for each other. Within the class, patient health conditions are relatively homogeneous, which reduces the difficulty to control for the heterogeneity of patients. However, advertising level varies across drugs and over time. This allows us to identify the effects of advertising on the choice of prescription drugs. There are six Statin drugs available on the market in 2000. No generic version of the Statin drugs is yet available on the market. In the NAMCS, we observe a total of 3,095 patient-visits between 1996 and 2000, which resulted in the prescription of one of those Statin drugs.[28]

Between 1996 and 2000, the Statin market has grown substantially. Figure 4 shows the increase of prescriptions during this period. Figure 5 shows the change in DTC advertising for major Statin drugs. A few observations are worth mentioning. First, notice that Lipitor became the number one drug in the class in just two years since its inception in 1997. However, Pfizer didn't use DTC advertising for Lipitor aggressively until 1999. Thus, it is unlikely that DTC advertising contributed to its initial success. Second, Bristol-Myers Squibb suddenly stopped using DTC advertising for Pravochol in 1999, although it has continuously spent more than $30 million per year since 1996. Interestingly, even with the drastic cut in DTC advertising, Pravachol's prescriptions increased (and market share didn't change) in 1999. These observations suggest that DTC advertising may not have a strong impact on the physician's prescription choice in this market.

[27] Other classes include bile Acid binding resins, fibric Acid derivatives and nicotinic Acid derivatives (*Mosby's GenRx* 1999)

[28] In rare occasions, multiple Statin drugs are prescribed in one visit. We dropped these observations from our sample.

5.3.2 Allergy Drugs (Non-sedating antihistamine)

The second therapeutic class we examine is the non-sedating antihistamine. Non-sedating antihistamine has gained popularity because it relieves the symptoms of seasonal allergy without causing drowsiness. The first drug marketed was Seldane in 1985, followed by Hismanal, Claritin, Zyrtec and Allegra. No generic versions of these drugs were available during the time period of our data. In the NAMCS, we observe a total of 1,883 patient-visits between 1996 and 1999, which resulted in the prescription of one of the allergy drugs.[29]

Prescription of non-sedating antihistamine has increased dramatically between 1996 and 1999 (see Figure 6). Among the five drugs, Claritin has clearly dominated the therapeutic class. More recently, however, newer drugs especially Allegra have gained market shares. During the same period, we have observed extensive DTC campaigns to promote these drugs (see Figure 7). While Claritin is also the leader in DTC advertising expenditure, this does not appear to have helped increase its market share. In fact regardless of the large amount of DTC advertising, Claritin's market share has declined since 1997. This suggests, once again, that DTC advertising may not have strong effects on physician prescription.

5.4 Results

5.4.1 Cholesterol Drugs

Table 5 Model 1 shows the multinomial logit results for cholesterol reducers using the data for 1996-2000. We focus our discussion on the coefficients for the three types of advertising, our main interests. However, as noted before, extensive interactions are included in the estimation as controls (not reported.) Following previous literature, advertising expenditures are expressed in natural logarithm forms in order to incorporate decreasing returns to scale of advertising.[30]

First of all, note that the coefficient for DTC advertising is negative and significant, suggesting that, regardless of the massive DTC advertising campaign on cholesterol reducers, DTC advertising had no positive impact on physicians' prescription choices. This contrasts with the

[29] In January 1997, the Food and Drug Administration (FDA) announced its intention to withdraw Seldane because it has been associated with a potentially fatal heart condition, ventricular arrhythmia. For this reason, Seldane was dropped from the estimation after 1996. Similarly, Hismanal was withdrawn from the market in June 1999, and thus included in the choice set only up to 1998.)

[30] We used a transformation of ln (adv. expenditure +1) because some of the advertising expenditures are zero.

results in Section 3 that DTC advertising increases visits to physicians substantially. Interestingly, however, the coefficient for detailing promotion expenditure is positive and significant, suggesting that doctor decisions are highly influenced by the promotional efforts of pharmaceutical salespersons. These results suggest that DTC advertising and detailing promotion – the two major forms of promotion in ethical drugs – play quite different roles in promoting ethical drugs; while DTC advertising increases physician office visits, detailing promotion affects a physician's prescription choice.

The minimal effect of DTC advertising on prescription choice is also consistent with the observations by industry experts. It is noted that "even a $60 million consumer ad budget couldn't prevent Pravachol, an anti-cholesterol drug made by Bristol-Myers Squibb Co., from losing ground to Lipitor, sold by Pfizer . . . And analysts say the Pravachol ads probably encouraged people to see their doctors for help in lowering cholesterol. But the doctors picked Pfizer's drug Lipitor as the champion over Pravachol ."[31]

The third type of advertising, i.e. professional journal advertising, also affects brand choice significantly, but to a lesser extent. The coefficient for price is not significantly different from zero, suggesting that physicians are not sensitive to prices when choosing among Statin drugs. [32] The coefficient for time from entry (in a natural log form) is positive and significant, suggesting that older drugs are more likely to be prescribed than younger ones.

While these initial results provide some interesting perspectives on the role of advertising in this market, we are concerned with why the estimated coefficient for DTC advertising is negative and significant. We suspect that the drastic change in DTC advertising of Pravachol between 1998 and 2000 might have produced the negative coefficient. As noted before, our data show that Bristol-Myers Squibb drastically reduced DTC advertising for Pravacol from over $50 million in 1998 to $0 in 1999, and increased once again to more than $50 million in 2000.[33] Nonetheless, Pravachol's market share didn't change in 1999 and decreased in 2000.[34] While we do not have a good explanation why Pravachol's market share didn't decline in 1999, we suspect that the outlier in 1999 might drive the entire results and produce the negative coefficient for DTC advertising.[35]

[31] *Modern Healthcare*, August 23, 1999.

[32] This may not be a big surprise, however, because no generics for the Statins are available on the market. It may be difficult for physicians to identify price differences among those similar brand-name drugs.

[33] These drastic changes in Pravachol's DTC advertising have also been recognized by industry observers (see, for example, Hensley, "Prescription costs become harder to swallow," *Modern Healthcare*, August 23, 1999.)

[34] Pravachol's detailing promotion and professional journal advertising in 1999 were also lower than that of 1998.

[35] Wosinska (2002) finds small positive effect of DTC advertising on formulary drugs. In her data, Pravachol is

To address the above concern, we re-estimate the model by dropping all observations for 1999. If the previous results are driven by the outlier as we suspect, the negative coefficient should disappear after dropping the 1999 observations. Table 5 Model 2 shows the results. First, note that the coefficient for DTC advertising is now positive but not statistically significant. In contrast, detailing and professional journal advertising continue to show positive and significant effects on prescription choice and the estimated coefficients are comparable to the previous model.[36] These results provide additional support for the previous conclusion that DTC advertising has little effect on the choice of prescription, while promotional efforts targeted to physicians do indeed affect choice.[37]

Opponents of DTC advertising have argued that DTC advertising would lead to the increase of prescriptions of expensive drugs even if equally effective and cheaper drugs may be available. This is possible if DTC advertising reduces consumer's price sensitivity by creating loyalty or "prestige effects" to the advertised drugs. We examine this claim by including the interaction term between price and DTC advertising in the previous model. If the claim is true, we should observe a positive coefficient for the interaction term. Table 5 Model 3 shows the results using the data excluding the 1999 observations. The coefficient for $P \cdot DTC$ is positive and weakly significant, providing some support for the claim that DTC advertising reduces price elasticity.

Table 5 Model 4 reports the results when DTC advertising expenditure is lagged by one year. This specification is motivated by the observation that Pravachol's market share appears to follow the previous year's DTC advertising rather than the current one. The model can be justified to the extent that there is time lag between when patients see an advertisement and when they visit doctors and talk about the drug. Once again, the coefficient for DTC advertising is positive but not statistically significant. In contrast, detailing continues to have a positive and significant coefficient. Thus, this model also supports the previous conclusion that DTC advertising has little effect on the prescription choice but detailing promotion does.

So far, advertising expenditures are treated as flow variables. That is, we assumed that the effect of advertising lasts only one year. This may not be the case, however, if, for example,

never on formulary, and this may explain the difference between this paper and her result.

[36]The coefficients for other variables (except DTC advertising) are also comparable to the previous results.

[37]We also estimated the model including various interaction terms between advertising variables and patient/doctor characteristics (not reported). We find some evidence that DTC advertising affects patients differently. In particular, it appears that DTC advertising is more effective for female patients than male and less effective for white population than minorities.

physicians form a "habit" in prescribing drugs. In this case, advertising should be treated as capital that may or may not depreciate over time. Ideally, one would like to estimate the rate of depreciation for different types of advertising capital using time series data. Unfortunately, this was not possible for us given the short panel data we have. As an alternative, we estimated the other extreme case – perpetual advertising capital – by accumulating advertising expenditures since 1996. Under this assumption, drug fixed effects will capture the effect of cumulative advertising prior to 1996. As shown in Model 5 in Table 5, the results are similar to the previous ones. In particular, among the three advertisements used to promote prescription drugs, only detailing promotion appears to have positive and significant impact on the choice of prescription. This result confirms the previous conclusion that DTC advertising has little effect on the physician's prescription choice. Note that the estimated coefficient for detailing is larger than the previous results. This may be either because cumulative detailing has a larger impact on physician's choice than current detailing or cumulative detailing picks up a part of the time effect.[38]

5.4.2 Allergy Drugs

Table 6 presents the results for allergy drugs. Due to the smaller number of drugs in the therapeutic class and shorter time period we cover (i.e., 1996-1999), the results are less significant than those of cholesterol reducers. Nonetheless, the effect of advertising variables is found similar across the two classes. Model 1 shows the results when we treat advertising as a flow variable. Here, the coefficient for detailing promotion is positive and significant, suggesting positive effects of detailing promotion on prescription choice. In contrast, the coefficients for DTC advertising and professional journal advertising are not significant, indicating these advertisements have little effect on doctors' prescription choices. Again, these results are consistent with the previous conclusion that detailing promotion and DTC advertising appears to play different roles in promoting ethical drugs.

Model 2 adds the interaction term between price and log of DTC advertising to Model 1. The coefficient for the interaction term is positive as in the case of cholesterol drugs but not

[38] Additionally we estimate the model by using the depreciation rates found in Berndt et al. (1995), i.e., DTC depreciates 85% each year and detailing and professional journal advertising does not depreciate at all. The results are similar to the previous models and not reported here. We are concerned, however, that the results may not be reliable since we do not have advertising data prior to 1996, thus cannot accurately account for the depreciation of historical advertising.

statistically significant. Thus, we do no have clear evidence for the claim that DTC advertising reduces the price sensitivity. Model 3 estimates the model using cumulative advertising expenditure since 1996. Unlike the case of cholesterol reducers, cumulative detailing promotion does not appear to have much impact on the choice of prescription. One explanation of this is that detailing promotion may be short-lived in this market. Throughout the models, the coefficient for price is negative and significant, suggesting that demand is sensitive to drug prices. This may be because non-sedating antihistamines have many substitutes, including sedating histamines and over-the-counter (OTC) drugs. The coefficient for time since entry is positive and significant, indicating that drugs that entered the market earlier are more likely to be prescribed than more recent drugs.

5.5 Summary

In this section, we analyzed the effects of direct-to-consumer advertising on the choice of prescription drugs. Results from cholesterol reducers and allergy drugs show that DTC advertising has little effect on the choice of prescription drugs. This is particularly true in comparison with the effects of detailing advertising directed to physician. For most of the specifications we examine, detailing promotion has positive and significant effects on the choice of drugs, while DTC advertising does not show any positive effect on the choice of prescription. These results suggest that the two forms of advertising play quite different roles in promoting ethical drugs. In particular, DTC advertising seems effective in increasing aggregate demand and detailing advertising is to affect brand choice. In fact, the results are consistent with the argument that DTC advertising may encourage patients to seek medical help but does not interfere with the patient-physician relationship. It appears that, regardless of the massive DTC advertising by pharmaceutical firms, prescription choice is still determined by physicians once patients visit doctors' offices.

6 Conclusions

Above all, we present three pieces of demand-side evidence regarding the effects of DTC advertising for prescription drugs: DTC advertising has a large, positive and significant effect on the number of outpatient office visits; a modest, positive effect on the time spent with doctors; but no effect on doctors' choice of prescription drugs. These results appear to be consistent with the

proponents' claim that DTC ads encourage patients to seek medical help but do not challenge doctors' authority in the specific choice of prescription drugs.

However, two phenomena in patient visits and time spent make us hesitate to reach a positive conclusion about the welfare impact of DTC advertising. First, because most increases in patient visits are driven by the visits that result in at least one prescription, we cannot rule out the possibility that DTC ads induce doctors to use prescription drugs over the other alternatives (i.e. over-the-counter drugs or non-drug treatments). Second, patients only spend more time with doctors when they do not get the most advertised drug(s) in the relevant class(es). This is consistent with the opponents' conjecture that DTC ads may provide misleading information to patients and doctors may spend extra time to correct patients' misbeliefs about drug choice. Of course, there are more optimistic explanations for these two phenomena: DTC ads may have helped patients conduct an effective pre-match between their own health condition and the choice of prescription/non-prescription treatments; and DTC ads may have facilitated patients' communication with doctors when the most advertised drugs are not the best choices. Future research is certainly needed to distinguish these explanations.

Despite the ambiguity in welfare, our study does generate a supply-side implication that has been omitted in the existing debates. Because all the significant effects we find are at the therapeutic class level, DTC advertising appears to be a public good for all prescription drugs within the same therapeutic class. This positive externality implies that the observed DTC expenditure, despite its strong growth in recent years, may still represent an under-provision of DTC ads from the pharmaceutical industry's perspective. The public good nature of DTC ads also suggests that even before 1997 drug companies could have used "generic advertising" – which only mentions the availability of a drug treatment but not a brand name – and achieved similar effects as do current DTC ads. We suspect that drug companies substantially increased DTC ads recently without fully recognizing that the externality effects of DTC ads may not change substantially before and after the FDA clarification.

7 References

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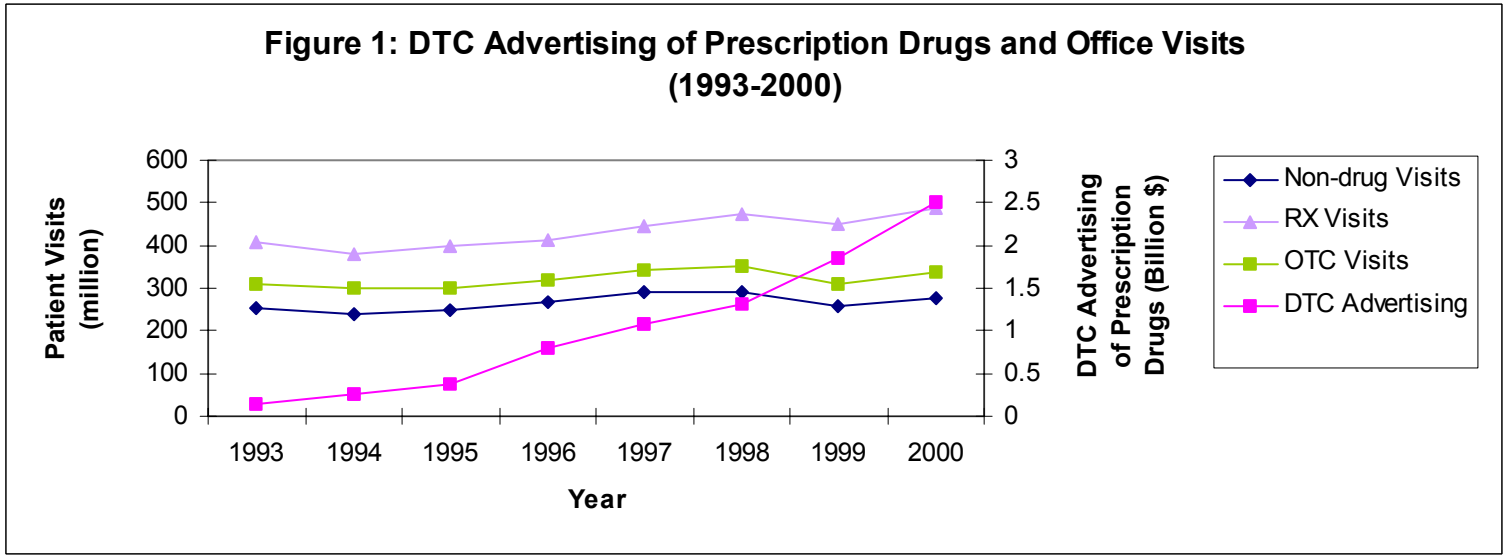
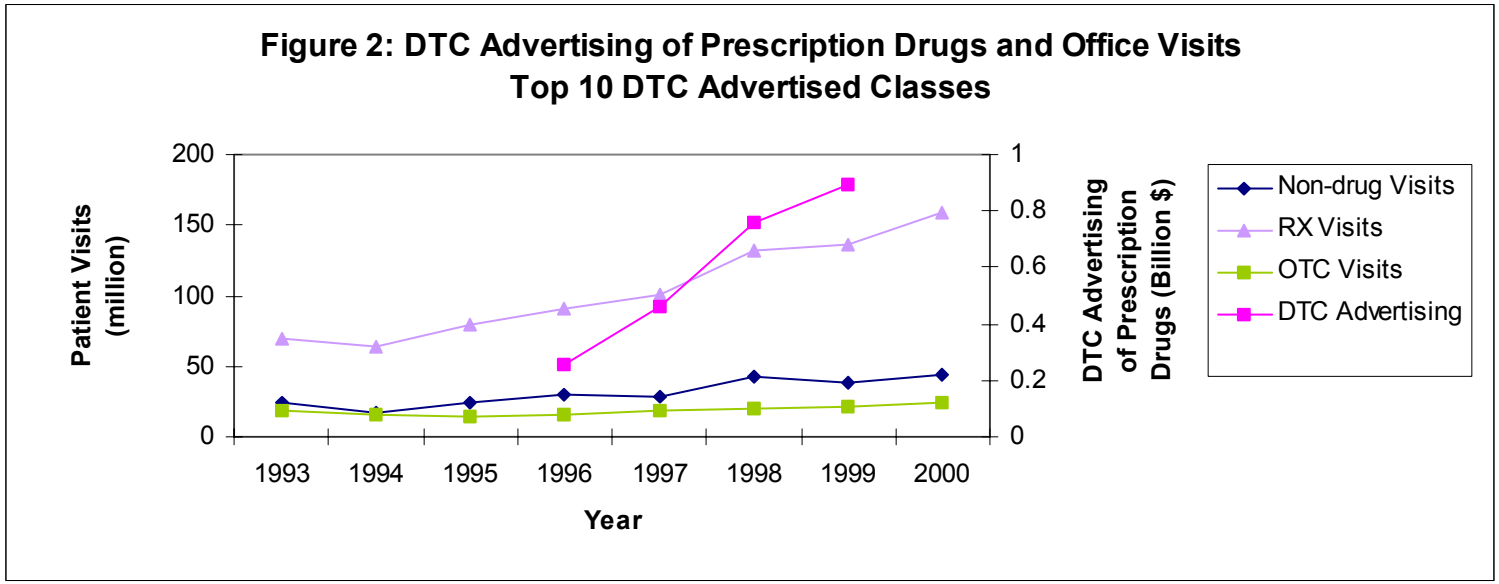
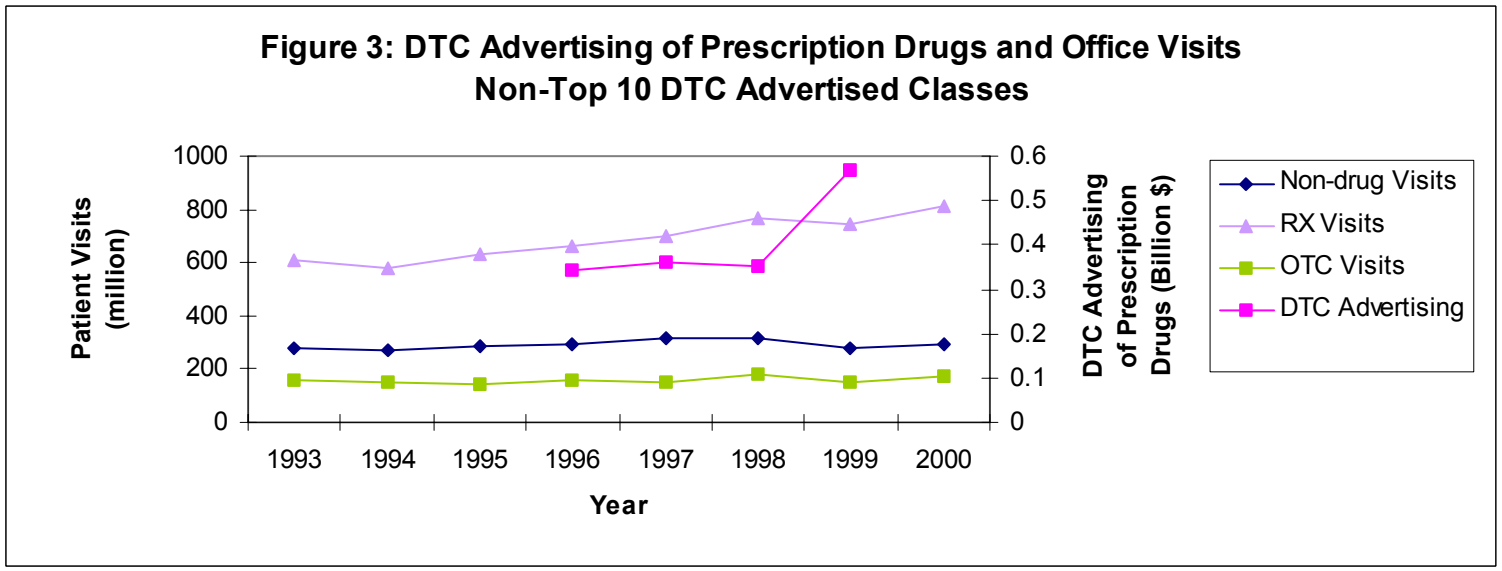


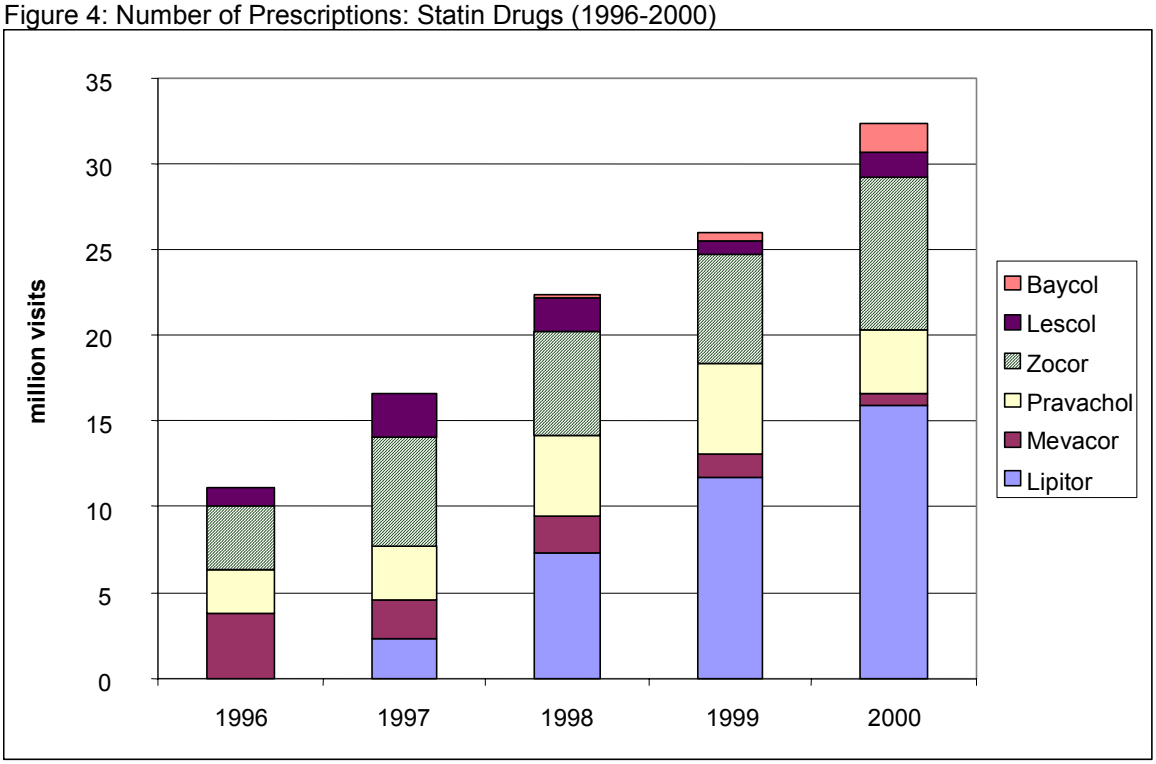
Source: 1993-2000 non-drug specific DTC advertising spending is cited from Findlay (2001) on the basis of MIN Health analysis of data from Competitive Media Reporting. 1996-1999 drug specific DTC advertising data is directly from Competitive Media Reporting. Patient visits are estimated from annual NAMCS.





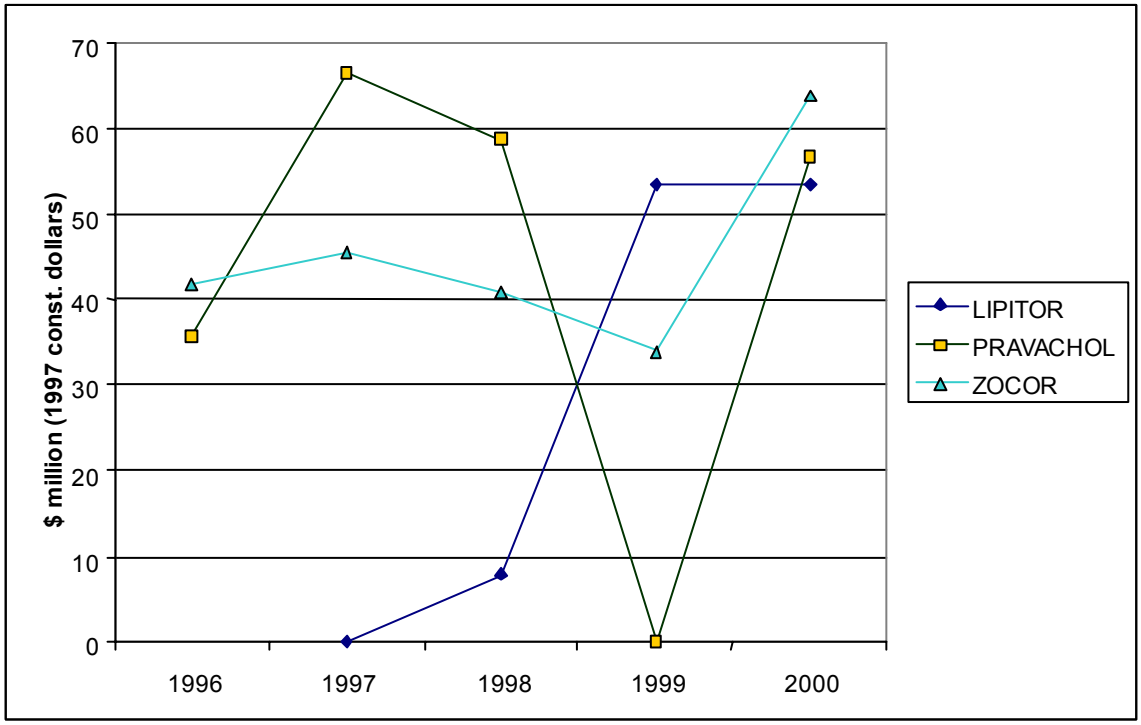
Source: 1996-1999 drug specific DTC advertising data are directly from Competitive Media Reporting. Patient visits are weighted estimates from annual NAMCS. Top 10 DTC advertised classes are defined by 1999 DTC data.

Figure 4: Number of Prescriptions: Statin Drugs (1996-2000)



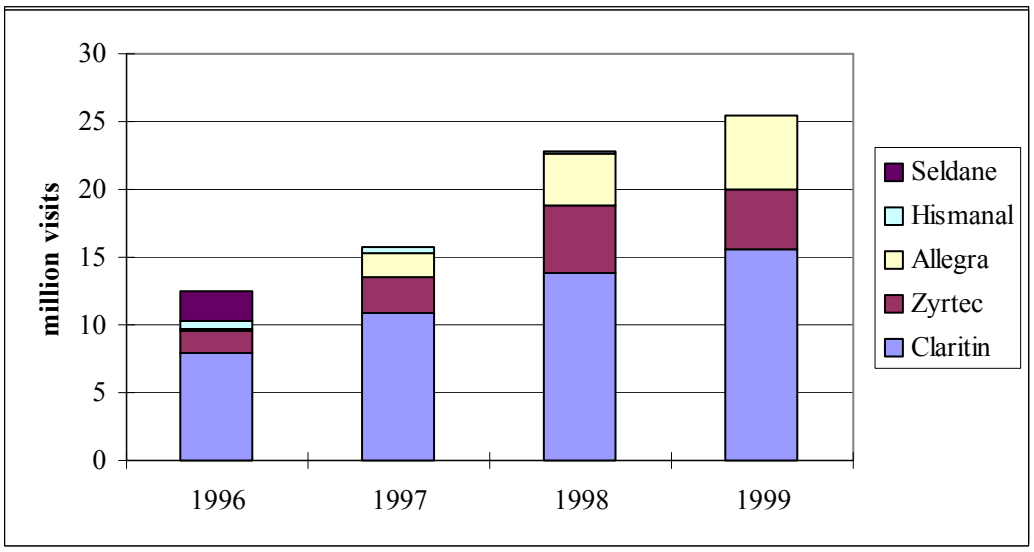
Source: Computed from NAMCS using visit weights.

Figure 5: DTC Advertising Expenditures for Major Statin Drugs (1996-2000)



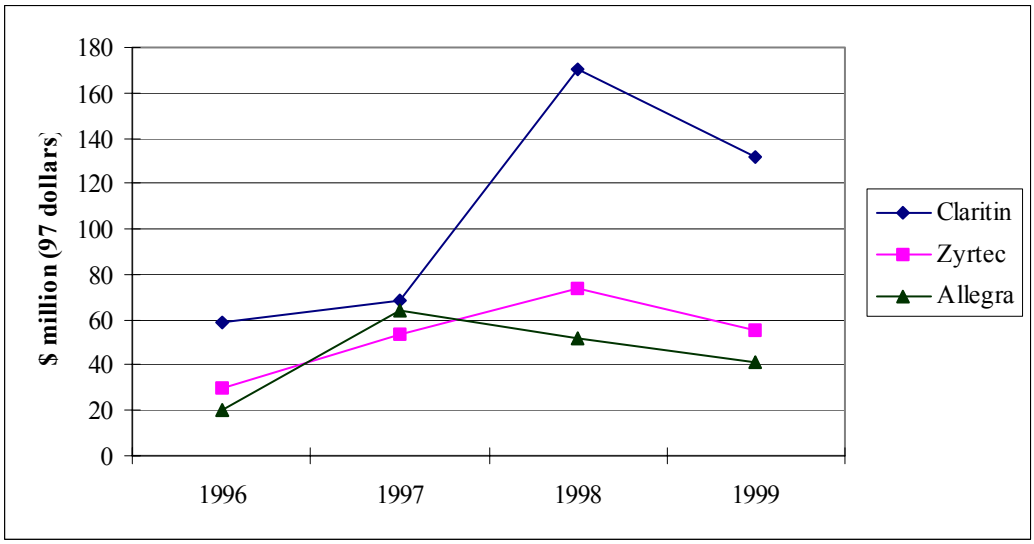
Source: CMR & IMS Health

Figure 7: Number of Prescriptions: Non-Sedating Antihistamines (1996-1999)



Source: Computed from NAMCS using visit weights.

Figure 8: DTC Advertising Expenditures for Major Allergy Drugs (1996-1999)



Source: CMR and IMS Health

Table 1: Effects of DTC advertising on visits, drug mentions and prescriptions

Model	Independent Variable	Dependent Variables (million) Drug Visits					
		RX Visits		OTC Visits		RX + OTC	
		(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Linear-Linear	DTC expenditure (million)	0.0305***	0.0881**	0.0011	-0.0215(p=0.16)	0.0311***	0.0736**
		(0.0072)	(0.0394)	(0.0051)	(0.0153)	(0.0076)	(0.0359)
	R2	0.9672		0.9597		0.9695	
	First stage R2		0.7869		0.7977		0.7826
Log -linear	DTC expenditure (million)	0.0047**	0.0148**	-0.0027	-0.0128	0.0037*	0.0119**
		(0.0020)	(0.0065)	(0.0033)	(0.0126)	(0.0021)	(0.0055)
	R2	0.953		0.882		0.9453	
	First stage R2		0.7869		0.7977		0.7826
OBS		499		309		537	
# of Classes		139		95		147	

Model	Independent Variable	Non-Drug Visits		Total drug mentions		Total Prescriptions	
		(7) OLS	(8) IV	(9) OLS	(10) IV	(11) OLS	(12) IV
Linear-Linear	DTC expenditure (million)	0.0077	0.0375	0.0327***	0.0929***	0.0319***	0.1074**
		(0.0096)	(0.0357)	(0.0083)	(0.0405)	(0.0079)	(0.0445)
	R2	0.8363		0.969		0.9669	
	First stage R2		0.7826		0.7826		0.7869
Log -linear	DTC expenditure (million)	0.0012	0.0069	0.0036*	0.0126**	0.0046**	0.0156**
		(0.1343)	(0.0097)	(0.0021)	(0.0055)	(0.0020)	(0.0066)
	R2	0.8091		0.9459		0.9539	
	First stage R2		0.7826		0.7826		0.8769
OBS		420		537		499	
# of Classes		125		147		139	

Notes: Unit of observation is year-class. Standard errors in parentheses. * <0.1 **<0.05 ***<0.01. Each cell represents a separate regression. All regressions control for year dummies and drug class fixed effects.

Table 2: Summary statistics for NAMCS drug visits

Variables	Obs	Mean	Std. Dev.	Min	Max
Key variables					
Time spent with doctor (minute)	59958	19.045	14.212	0	240
DTC advertising in all relevant classes (million $)	59958	31.127	56.893	0	502
Visit characteristics					
# of relevant classes	59958	1.992	1.313	1	6
=1 if the visit is capitated	59958	0.079	0.270	0	1
=1 if capitation status is missing	59958	0.291	0.454	0	1
=1 if seen in the same establishment before	59958	0.864	0.343	0	1
=1 if referred by another doctor	59958	0.174	0.379	0	1
=1 if need authorization	59958	0.081	0.273	0	1
Major reason of visit					
=1 if for acute disease 1997-1999	42532	0.354	0.229	0	1
=1 if for chronic (routine) 1997-1999	42532	0.351	0.228	0	1
=1 if for chronic (flare up) 1997-1999	42532	0.109	0.097	0	1
=1 if for healthy check up 1997-1999	42532	0.115	0.101	0	1
=1 if unknown 1997-1999	42532	0.015	0.015	0	1
=1 if major reason not coded	59958	0.291	0.454	0	1
Insurance status					
=1 if insured by Medicare	59958	0.240	0.427	0	1
=1 if insured by Medicaid	59958	0.092	0.289	0	1
=1 if the visit is subject to self payment	59958	0.053	0.224	0	1
=1 if belong to HMO	59958	0.259	0.438	0	1
Demographics					
=1 if white	59958	0.687	0.464	0	1
=1 if female	59958	0.584	0.493	0	1
=1 if age < 18	59958	0.172	0.377	0	1
=1 if age >=18 but <40	59958	0.218	0.413	0	1
=1 if age >=40 but <65	59958	0.332	0.471	0	1
=1 if age >=65	59958	0.278	0.448	0	1
Doctor specialty					
General and Family Practice	59958	0.209	0.406	0	1
Internal Medicine	59958	0.127	0.333	0	1
Pediatrics	59958	0.094	0.292	0	1
General Surgery	59958	0.030	0.172	0	1
Obsetetrics and Gynecology	59958	0.056	0.231	0	1
Orthopedic Surgery	59958	0.033	0.179	0	1
Cardiovascular diseases	59958	0.061	0.239	0	1
Dermatology	59958	0.071	0.258	0	1
Urology	59958	0.033	0.179	0	1
Psychiatry	59958	0.063	0.243	0	1
Neurology	59958	0.037	0.189	0	1
Ophthalmology	59958	0.056	0.230	0	1
Otolaryngology	59958	0.042	0.200	0	1
All Other	59958	0.087	0.282	0	1

Table 3: Effects of DTC advertising on time spent with doctor

Dep. Var.	Indep. Var.	Sample				
		All Drug Visits	Single Class Drug Visits	Single D Class Drug Visits	Single D Class Drug visits that did not get the most advertised drug	Single D Class Drug visits that got the most advertised drug
Time Spent with Doctor (minute)	DTC expenditure (million)	0.0108**	0.0207**	0.0174*	0.0141*	0.0078
		(0.0052)	(0.0092)	(0.0094)	(0.0075)	(0.0129)
(Linear-linear)	Hausman Statistics	0.3310	0.2680	0.5077	0.3463	0.1560
	R2	0.1537	0.1679	0.2122	0.2748	0.2985
	OBS	59958	29569	13789	11446	2343
Ln (Time Spent with Doctor)	DTC expenditure (million)	0.0004**	0.0008**	0.0008**	0.0007**	0.0002
		(0.0002)	(0.0003)	(0.0004)	(0.0003)	(0.0006)
	Hausman Statistics	0.2975	0.1975	0.1453	0.1107	0.0861
(Log-linear)	R2	0.1716	0.1788	0.2224	0.2753	0.2755
	OBS	56347	27548	13088	10833	2255

Notes: Unit of observation is per NAMCS visit. Standard errors in parentheses. * <0.1 **<0.05 ***<0.01. All regressions control for visit characteristics, insurance status, major reason of visit, demographics, doctor specialty and drug class dummies (see table 2 for a complete list). Sample weights apply. Hausman statistics are based on the comparison of the reported DTC coefficients and the DTC coefficients from unreported instrumental variable regressions, where the instrument of DTC is defined as the total DTC advertising the relevant drug companies spent on irrelevant classes.

Table 4: Cholesterol Reducers and Allergy Drugs Included in the Data Set

Brand name	Generic name	Entry	Is generic available?
Cholesterol Reducers (Statins)			
Lipitor	Atorvastatin	01/97	NO
Baycor	Cerivastatin	12/97	NO
Lescol	Fluvastatin	04/94	NO
Mevacor	Lovastatin	08/87	NO
Pravacol	Pravastatin	10/91	NO
Zocor	Simvastatin	01/92	NO
Allergy Drugs (Non-sedating Antihistamines)			
Claritin	Loratadine	08/93	NO
Allegra	Fexofenadine	08/96	NO
Zyrtec	Cetirizine	01/96	NO
Hismanal	Astemizole	01/89	NO
Seldane	Terfenadine	05/85	NO

Note: A generic version of Seldane was not approved for marketing until January 1997.

Table 5: Multinomial Logit Results for Statin Drugs

	Model 1 Full Sample		Model 2 Excluding 1999		Model 3 Excluding 1999 w/ price interaction		Model 4 Lagged DTC		Model 5 Cum Ads	
P	1.108		1.165		-0.032		1.333		0.883	
	(1.520)		(1.629)		(1.749)		(1.504)		(1.515)	
Log_T	2.283	***	1.560	***	1.138	***	1.567	***	1.011	**
	(0.223)		(0.304)		(0.382)		0.220		0.406)	
LOG_DTC	-0.061	***	0.009		-0.162	*	0.013		-0.027	
	(0.012)		(0.021)		(0.098)		(0.009)		(0.036)	
LOG_DTL	0.190	***	0.204	***	0.210	***	0.243	***	2.545	***
	(0.040)		(0.040)		(0.040)		(0.041)		(0.739)	
LOG_JNL	0.049	***	0.083	***	0.084	***	-0.002		-0.608	
	(0.016)		(0.018)		(0.018)		(0.013)		(0.450)	
P*LOG_DTC					0.115	*				
					(0.064)					
Log likelihood	-4316.0		-3302.7		-3301.1		-4327.9		-4318.4	
Obs.	3095		2450		2450		3095		3095	

Standard errors in parenthesis
* 10% ** 5% *** 1% confidence level

All models include interaction terms between price and patient/doctor characteristics, drug fixed effects, and a full set of interaction terms between drug fixed effects and patient demographics. Patient characteristics include insurance status (i.e., Medicare, Medicaid, and self-pay), HMO membership and demographics (i.e., age group, gender, and race). Doctor characteristics include doctor specialties, i.e., family practice, internal medicine, and cardiovascular specialist (for cholesterol reducers).

Table 6: Multinomial Logit Results for Allergy Drugs

	Model 1 Full Sample		Model 2 Full Sample w/ price interaction		Model 3 Cum Ads	
P	-9.160	**	-12.557	**	-8.909	**
	(3.717)		(5.758)		(4.091)	
Log_T	1.754	***	1.897	***	2.390	***
	(0.325)		(0.371)		(0.534)	
LOG_DTC	-0.047		-0.764		-0.197	
	(0.071)		(0.915)		(0.465)	
LOG_DTL	0.644	**	0.362		0.157	
	(0.293)		(0.459)		(0.815)	
LOG_JNL	-0.075		0.050		0.852	
	(0.179)		(0.240)		(0.630)	
P*LOG_DTC			0.358			
			(0.455)			
Log likelihood	-1753.2		-1752.9		-1752.4	
Obs.	1883		1883		1883	

Standard errors in parenthesis
* 10% ** 5% *** 1% confidence level

All models include interaction terms between price and patient/doctor characteristics, drug fixed effects, and a full set of interaction terms between drug fixed effects and patient demographics. Patient characteristics include insurance status (i.e., Medicare, Medicaid, and self-pay), HMO membership and demographics (i.e., age group, gender, and race). Doctor characteristics include doctor specialties, i.e., family practice, internal medicine, and cardiovascular specialist (for cholesterol reducers).