The Effect of Prescription Drug Advertising on Doctor Visits

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The dramatic increase of direct-to-consumer advertising (DTCA) of prescription drugs created intensive debates on its effects on patient and doctor behaviors. Combining 1994–2000 DTCA data with the 1995–2000 National Ambulatory Medical Care Surveys, we examine the effect of DTCA on doctor visits. Consistent with the proponents' claim, we find that higher DTCA expenditures are associated with increased doctor visits, especially after the Food and Drug Administration clarified DTCA rules in August 1997. After 1997, every $28 increase in DTCA leads to one drug visit within 12 months. We also find that the market-expanding effect is similar across demographic groups.

1. Introduction

The year 1997 witnessed an important change in direct-to-consumer advertising (DTCA) of prescription drugs. Prior to 1997, any DTCA that contained both brand name and medical claims must disclose a "brief summary" of drug effectiveness, side effects, and contraindications. Consequently, TV advertising was prohibitively expensive, and DTCA was largely limited to newspapers and magazines. A small number

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of the prescription drug ads that aired on TV included only brand names without describing their indications. This tradition changed drastically after August 1997, when the Food and Drug Administration (FDA) clarified that pharmaceutical firms can use DTCA on TV that contain both brand name and indications without a "brief summary."[1] Following the clarification, DTCA expenditures increased from $800 million in 1996 to $2.5 billion in 2000. As of 2000, DTCA accounted for 2.5% of the overall mass media ad spending in the United States. The top promoted drug—Vioxx—spent $146 million in DTCA, beating Pepsi Cola, Budweiser Beer, and most automobile manufacturers (NIHCM, 2001).

The effects of prescription drug advertising are controversial. Proponents argue that DTCA primarily has a market-expanding effect: the ads inform consumers of new treatment options and, therefore, generate new doctor visits. If true, this could improve patient welfare, because many diseases are underdiagnosed. Opponents argue, however, that DTCA has a business-stealing effect that misleads patients into demanding heavily advertised drugs, leading to inappropriate drug use and the unnecessary purchase of expensive drugs. Not surprisingly, pharmaceutical firms support the former position, while insurers and medical providers generally agree with the latter view.[2] Clearly, the heart of the debate is the distinction between the market-expanding versus business-stealing effects of advertising, a familiar issue in economics literature (e.g., Roberts and Samuelson, 1988; Gasmi et al., 1992).

This paper contributes to the growing literature that investigates the effects of DTCA on the demand for prescription drugs.[3] We focus our analysis on one type of market-expanding effect, namely, the extent to which DTCA affects patients' visits to the doctor. For this study, we use nationally representative, patient-level data that cover all classes, which allows us to generalize the effect of DTCA beyond specific categories studied by previous papers (e.g., Berndt et al., 1995; Calfee et al., 2002; Wosinska 2002; Rosenthal et al., 2003).[4] In addition, we exploit a rich,

1. DTCA still needs to include a "major statement" of the most important risks and refer consumers to other sources for more comprehensive information.

2. Both sides of the debates are well documented. See Holmer (1999, 2002) for a summary of the proponents' position, and Hollon (1999) and Wolfe (2002) for a summary of the opponents' position. See, also, the debate on the role of DTCA by several authors published in the February 26, 2003, issue of *Health Affairs*. In response to these debates, the FDA held a public hearing in September 2003 to review its policy on DTCA.

3. In addition to the economics literature we discuss here, a number of surveys have been conducted in order to understand consumer and doctor responses to DTCA. For example, the FDA conducted surveys on DTCA in 1999 and 2002. *Prevention Magazine* (1998–2000) has also conducted surveys on DTCA annually since 1998. Gonul et al. (2000) analyze one of those surveys conducted by Scott-Levin, a pharmaceutical information company, and find that consumers and doctors value DTCA differently depending on ongoing needs for health care, degree of experience, and exposure to DTCA.

4. We discuss these papers in more detail in the next section.

patient-level dataset and provide new insights into the heterogeneous responses to DTCA. The question of whether DTCA has a business-stealing effect is addressed in a companion paper (Iizuka and Jin, 2004).

Combining 1994–2000 monthly DTCA data with the 1995–2000 National Ambulatory Medical Care Surveys (NAMCS), we estimate the effect of DTCA on doctor visits using a nonlinear least-squares regression with drug-class-fixed effects and allow DTCA to depreciate over time. We find that higher DTCA expenditures are associated with increased doctor visits and that this relationship is stronger after the 1997 clarification. Specifically, after the clarification, every $28 increase in monthly DTCA expenditures leads to one patient visit within 12 months, and the effect concentrates on the visits that result in prescription drugs. In terms of heterogeneous responses to DTCA, we find that the market-expanding effect does not vary across demographic groups.

The rest of the paper is organized as follows. Section 2 discusses the background and reviews the literature. After a data description in Section 3, we set up the empirical model in Section 4 and report estimation results in Section 5. Our conclusion is offered in Section 6.

2. Background and Related Literature

The large increase of DTCA after the 1997 FDA clarification has created a controversy over the effects of DTCA. From a social planner's perspective, DTCA will improve consumer welfare if its benefits outweigh the costs. One benefit that proponents suggest is the market-expanding effect of DTCA. For example, DTCA may inform untreated patients of existing or new drug treatments and encourage them to seek medical help via office visits. This effect could be substantial because a number of leading diseases, such as diabetes, high cholesterol, and high blood pressure, are underdiagnosed and undertreated (Holmer, 1999). Holmer, who represents the pharmaceutical industry, further asserts, "DTCA merely motivates patients to learn more about medical conditions and treatment options and to consult their physicians, but once the dialogue is started, the physician's role is preeminent" (p. 381).

On the other hand, most opponents of DTCA worry about the business-stealing effects of DTCA. They are concerned that, once underinformed patients watch DTCA, they may demand inappropriate therapies from doctors and increase the cost of treatment. For example, Hollon (1999), who provides a doctor's perspective, argues that "by creating consumer demand, [DTCA] undermine the protection that is a result of requiring a physician to certify a patient's need for a prescription drug" (p.382). Cohen (1990) also argues that DTCA may encourage people to try more expensive drugs though cheaper, but equally effective, drugs may be available.

This paper contributes to the debate by providing a detailed analysis of the market-expanding effects of DTCA in outpatient office visits. We not only examine an aggregate market-expanding effect, but also examine the distribution of this effect among patient groups. Understanding the heterogeneous effects of DTCA is important because not all market-expanding effects are welfare improving. For example, moral hazard may encourage insured patients who watched DTCA to visit doctors "too often," because they do not bear all the costs of the visit (and the costs of resulting treatment). In such cases, DTCA may or may not improve welfare even if DTCA has a market-expanding effect.

Our paper complements the few academic studies on DTCA. On the demand side, the earliest paper examining the effect of DTCA on prescription drugs is Berndt et al. (1995). They used the data for antiulcer drugs for 1977–1994, which precedes the surge of DTCA in the late 1990s.[5] Calfee et al. (2002) estimated a monthly time-series regression of total statin drug prescriptions on advertising expenditures during 1995 and 2000. They found that advertising had no statistically significant effect on new statin prescriptions or renewals, but television advertising increased the proportion of cholesterol patients who had been successfully treated. Rosenthal et al. (2003) investigated the effects of DTCA and detailing on the aggregate sales of prescription drugs, using monthly data for five therapeutic classes between August 1996 and December 1999. They found that DTCA has a significant effect on total class sales, but does not have any significant impact on market shares within each class. Our study builds upon these studies by using nationally representative, patient-level data that cover substantially larger number of therapeutic classes. Because of the advantage of the data, the conclusion of our paper is more applicable to a broader class of prescription drugs.

Wosinska (2002) also examined the effect of DTCA on the demand for cholesterol-reducing drugs, using individual prescription claim data between 1996 and 1999. She finds that DTCA may affect the demand for an individual brand positively, but only if that brand is on the third-party payer's formulary. Similarly, using the NAMCS data as in the current paper, Iizuka and Jin (2004) examined the business-stealing effect of DTCA in nonsedating antihistamines. This paper is different from those papers because, while the above references are concerned about the

5. In related research, Ling et al. (2002) examined the spillover of DTCA between prescription and over-the-counter (OTC) segments. Using data for antiulcer drugs, many of which switched from prescription to the OTC market in the late 1990s, they found small but significant spillovers from prescription to the OTC market for some brands, but not vice versa.

effect of advertising once patients arrived at doctor offices, that is, the business-stealing effect of DTCA, this paper examines whether DTCA brings potential patients to doctor offices, that is, the market-expanding effect of DTCA.

On the supply side, Rosenthal et al. (2002) analyzed the industry-wide trends for DTCA and found that DTCA is highly concentrated on a subgroup of products and the spending fluctuates over time. Iizuka (2004) examined the determinants of DTCA and found that DTCA tends to concentrate in classes that involve fewer competitors. He also found that drugs that are new, of high quality, and for undertreated diseases are more frequently advertised. Our finding that DTCA of prescription drugs has a market-expanding effect on the demand side complements their findings.

This paper also contributes to the body of literature that empirically distinguishes the market-expanding effect from the business-stealing effect of advertising [see Bagwell (2001) for a broad overview of classic papers on the economics of advertising, and King (2003) for a study on the disagglomeration and growth of the US advertising-agency industry]. An ad is viewed as market expanding when it purely increases total market size and business-stealing when it solely shifts market share among brands. Roberts and Samuelson (1988), for example, found that cigarette advertising has a significant market-expanding effect, but not a business-stealing effect. In contrast, Gasmi et al. (1992) found that advertising in the carbonated soft-drink industry is primarily characterized as business stealing.

Finally, we recognize that the demand effect of direct-to-doctor advertising (i.e., detailing promotion) has been examined in earlier literature. Hurwitz and Caves (1988) looked at a cross-section of 56 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 antihypertension drugs for 1988–1993 and found that detailing promotion lowers price sensitivity. Gonul et al. (2001) showed that detailing and free samples affect physician prescription behavior for an undisclosed therapeutic class. Azoulay (2002) found that, in addition to detailing promotion, scientific evidence from medical literature affected the diffusion pattern of antiulcer drugs. However, none of these papers looked at the effect of advertising directed to consumers. To be sure, this is mainly because DTCA increased its significance only recently, after the FDA clarification in 1997. Moreover, because we are interested in the patient's decision to visit a doctor rather than the doctor's decision to choose a specific drug, it is natural to focus on drug advertising that is oriented toward consumers.

3. Data

We combine individual-level data from the 1995–2000 NAMCS with the 1994–2000 monthly DTCA data from the TNS Media Intelligence/Competitive Media Reporting (CMR). Each year since 1993, NAMCS has collected a national representative sample of individual visits to office-based physicians. For each office visit, NAMCS provides patient demographics, insurance status, physician specialty, time spent with the patient, diagnoses, dispositions, and prescription choices, if any.[6] Although NAMCS has been constructed by stratified sampling each year, the Centers for Disease Control and Prevention only provide detailed sampling information for 1995 and beyond. To make sure the aggregate counts of office visits are nationally representative, we focus on 1995–2000.

In comparison, the DTCA data provides the total DTCA expenditures for every prescription drug advertised via direct-to-consumer channels. Specifically, CMR monitors advertising outlays in units and dollars for several different media, including network TV, cable TV, newspapers, and magazines. The DTCA dollars reflect the typical costs of buying such elements as television time and print space.[7] Our DTCA data covers 1 year longer than the period covered by the NAMCS data, so we can estimate the long-lasting effect of DTCA on patient visits. The DTCA and NAMCS data are matched by drug names and the month during which the advertising and physician office visits took place.[8]

Our unbalanced panel data contain a total of 7,824 observations covering 151 drug classes over 72 months. Defining class-month as the unit of observation, we include a class-month in the sample if at least one visit (either drug or nondrug) occurred in that class and that month. To keep the sample stable, this sample construction applies to all regressions.[9] A drug class is defined by the four-digit National Drug Code (NDC).[10] Some classes do not appear in all months because some diseases are seasonal, and the NDC has added or deleted a few four-digit class codes between 1995 and 2000.

6. See Cherry et al. (2001) and Burt (2002) for more detailed description of NAMCS.

7. However, they may not reflect the discounts typically given to large buyers who bundle various products' ads with one advertising agency.

8. In rare cases where NAMCS assigns different drug class codes to the same drug across years, we use the 2000 NDC definition.

9. As a result, some class-months may have zero drug visits in our sample, because we only observe nondrug visits in that class-month and vice versa.

10. For example, hyperlipidemia (which includes cholesterol reducing drugs), ace inhibitors, and calcium channel blockers belong to separate four-digit NDC categories.

4. Empirical Model

4.1 Specification

Suppose all drugs in therapeutic class k treat disease k. If DTCA has raised consumer awareness of treatment options, greater exposure to DTCA in class k should encourage more consumers at the risk of disease k to visit doctors. However, it is quite possible that a DTCA of a specific drug motivates an individual to visit the doctor, but he or she ends up getting a different drug within the same therapeutic class. Therefore, we look at the effects of DTCA at the class level rather than at the individual drug level. We use therapeutic class and drug class interchangeably.

Following this logic, the ideal model will link an individual's exposure to DTCA in drug class k with his or her decision to visit the doctor's office for disease k. Unfortunately, the DTCA data are not individual specific, and the NAMCS data only record those patients who choose to visit doctors. To overcome these difficulties, we use NAMCS' sampling weights to calculate the total number of patient visits by class and time. Specifically, we estimate the following model:

$$\begin{aligned} VISIT_{kt} = {} & \alpha_k + \beta_t + \theta_K T + \lambda_{K,qtr} \\ & + \gamma_b SUMDTCA_{kt}(1 - AFTER_t) \\ & + \gamma_a SUMDTCA_{kt} \times AFTER_t \\ & + \epsilon_{kt}, \end{aligned}$$

where $VISIT_{kt}$ stands for the number of outpatient office visits related to drug class k at month t, and $SUMDTCA_{kt}$ stands for the discounted sum of DTCA of class k up to month t. $AFTER_t$ is a dummy equal to 1 if month t is after the FDA clarification (August, 1997), 0 otherwise. The key coefficients, γ_b and γ_a, denote the marginal effect of *SUMDTCA* on *VISIT* before and after the clarification. α_k and β_t are drug-class and time-fixed effects, respectively. The other terms, $\theta_K T$ and $\lambda_{K,qtr}$, further control time trends and are discussed in Section 4.2. ϵ_{kt} is the error term.

The definition of *SUMDTCA* and *VISIT* requires more discussion. First, it may be reasonable to expect that the effect of DTCA would last for more than 1 month but depreciate over time. To capture the long-lasting effect of advertising, we define *SUMDTCA* in the following way:

$$SUMDTCA_{kt} = \sum_{i=0}^{t} \delta^{t-i} DTCA_{kt},$$

where δ denotes the monthly depreciation rate to be estimated in the empirical analysis, and $DTCA_{kt}$ is the total DTCA expenditures reported for class k in month t. Because our DTCA data starts in January 1994,

we treat all the DTCA before January 1994 as zero. Although this treatment is motivated by our limited data, given the small amount of DTCA before 1994, the omission of the data prior to 1994 is unlikely to affect estimation results. In fact, results do not change if we impute the before-1994 DTCA from the aggregate DTCA amount reported by CMR.[11] The discount factor δ enters the model nonlinearly, so we estimate the whole model by nonlinear least squares.

Second, we define our dependent variable, *VISIT*, in five different ways: drug visits, RX visits, OTC visits, nondrug visits, and all visits. 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. Drug visits are the sum of RX and OTC visits. If a visit leads to no treatment or nondrug treatment, it is categorized as a nondrug visit. All visits are the sum of drug visits and nondrug visits. If a visit involves more than one class, we count it as one visit for each relevant class.

Drug visits, RX visits, and OTC visits are well defined as NAMCS provides a drug class code for each drug that was prescribed or mentioned by a doctor during each visit. In contrast, the definition of nondrug visits (and all visits, accordingly) involves a technical challenge: no therapeutic class code exists for nondrug visits. To address this issue, using drug visits observations, we create a mapping between a diagnosis and the most common drug class associated with the diagnosis. Specifically, we construct the mapping in the following way. First, we create a subsample of NAMCS visits that have a single diagnosis and at least one prescription or OTC drug. We focus on single-diagnosis visits to ensure that we can establish the link from a specific diagnosis to drug classes. Then, using the subsample, we identify the most common drug class for each diagnosis. This is done for each year separately, allowing drug treatment of specific disease to change over time. After this procedure, we are able to associate each diagnosis with a specific drug class and count the number of nondrug visits by drug class.[12]

Because the purpose of this paper is to examine the effect of DTCA on physician office visits, it is theoretically correct to use all visits (i.e., drug visits + nondrug visits) as the dependent variable. However, the nondrug visit definition as described above generates a fair amount of

11. The imputation is implemented in the following way: if drug class k advertised x dollars in a specific month of 1994, we define the $DTCA_k$ in the corresponding month of 1993 as $x \cdot TOTALDTC_{93}/TOTALDTC_{94}$. The same imputation applies to any year between 1989 and 1993. The aggregate DTCA numbers are taken from "Prescription Drug Advertising Soars through Third Quarter; Expected to Top $1 Billion in 1998," *PR Newswire*, December 30, 1998.

12. NAMCS provides up to three diagnosis codes for each visit, so a nondrug visit may be linked to, at most, three drug classes.

noise and, therefore, results for nondrug visits are merely suggestive.[13] For this reason, we report the results of drug visits as our main results. Nonetheless, main results stay the same even when all visits are used as the dependent variable. We show these results in Section 5.4.

Finally, note that both *VISIT* and *SUMDTCA* enter the specification linearly. We choose the linear–linear specification over alternatives due to the following reasons. First, as we show in Section 5.4, the linear–linear specification dominates the linear–log specification. Similarly, the log–linear specification dominates the log–log specification (by a small margin). Second, we prefer linear–linear over log–linear because log–linear forces us to drop or artificially modify visit counts when these numbers are zero. This happens frequently when we break down the visits by nondrug, RX, and OTC, or by patient groups. To avoid the sample selection problem, we use the linear–linear specification as our primary specification. To further address the concern of zero advertising, we rerun the linear–linear regression on advertising classes only. As a robustness check for the nonlinear estimate of depreciation, we also rerun the linear-linear regression using the depreciation rate estimated in Berndt et al. (1995). As showed in Section 5.4, basic results are robust regardless of specification.

4.2 Identification

Aggregate $VISIT_{kt}$ and $SUMDTCA_{kt}$ 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 may also allocate large advertising budgets to large drug classes. Therefore, a high correlation between DTCA and patient visits would not necessarily imply a causal effect. Moreover, as manifested by the concentration of DTCA in a small number of drug classes, drug companies may intentionally select which classes to advertise. To address these concerns, we use class-fixed effect α_k to control for time-invariant cross-class differences, a full set of month dummies β_t to account for over-time fluctuation common for all drug classes, $\theta_K T$ for class-specific time trends, where T denotes the number of months between the visit month and January 1994, and $\lambda_{K,qtr}$ for class-specific seasonality. θ and λ are specific to an aggregated drug class K, defined by two-digit NDC classes.[14]

13. NAMCS data not only record drug mentions that are directly related to diagnosis, but also include drug refills that may be irrelevant to the current diagnosis. To minimize the noise, we restrict the reference group to patients with a single diagnosis in the same calendar year.

14. There are 21 two-digit NDC classes, such as "cardiovascular–renal drugs" and "gastrointestinal agents." In theory, the model is still implementable if we define θ and λ by four-digit NDC class. In reality, the model with four-digit trends yields qualitatively similar results in the coefficients of *SUMDTCA*, but the depreciation rate δ becomes

After all these controls, the effect of DTCA is mainly identified from over-time variations within each drug class. Still two reasons to suspect endogenous $SUMDTCA_{kt}$ exist. First, if the advertising budget is proportional to sales revenue and somehow patient visits correlate with sales revenue, reverse causality will reinforce a positive correlation between *VISIT* and *SUMDTCA* and, therefore, overestimate γ. Second, as the Pharmaceutical Manufacturing and Research Association claimed (Holmer, 1999, 2002), drug companies may devote much DTCA to underdiagnosed 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 DTCA expenditures when the actual number of visits is relatively low. This negative correlation will imply a downward bias in γ.

To address the endogeneity problem, we use the same drug companies' DTCA expenditures in other "unrelated" drug classes $DTCA_{-kt}$ as an instrument for $DTCA_{kt}$. We define class $-k$ "unrelated" to class k if (1) k and $-k$ do not belong to the same two-digit NDC class and (2) the correlation of patients getting any drug (including over the counter) in the two-digit NDC classes K and $-K$ at the same time is small.[15] The latter ensures that we do not include the DTCA of complementary drugs in the instrument.

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 erectile dysfunction. If class k refers to cholesterol reducing, $DTCA_{-kt}$ is defined as the sum of DTCA that these four drug companies spent on all the other classes excluding those under the same two-digit NDC class (metabolic/nutrients) or under related two-digit NDC classes (e.g., cardiovascular–renal drugs).

We argue that DTCA 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. After controlling for drug-class-fixed effects and time trends, we assume unobserved factors that drive changes in patient visits are uncorrelated across two classes, unless both belong to the same two-digit NDC class or they are under different two-digit NDC classes but often used on the same patients. By this

unstable, often reaching the boundary of 1 or 0. We suspect this is because the four-digit trends absorb too many variations.

15. After examining the distribution of correlation across two-digit classes, we use correlation = 0.1 as the cut-off point.

assumption, the only way for $DTCA_{-kt}$ to influence $VISIT_{kt}$ is through $DTCA_{kt}$. Berndt et al. (1995) pursued a similar identification strategy.

To further justify the validity of the instrument, we note that 90% of all the classes with positive $DTCA_{kt}$ also have positive $DTCA_{-kt}$. Moreover, the correlation of $DTCA_{kt}$ and $DTCA_{-kt}$ are significant and positive in all years. If we regress $DTCA_{kt}$ on class-fixed effects and time trend (i.e., all exogenous variables), including $DTCA_{-kt}$ on the right-hand side would improve the within-class R^2 from 11% to 14%. The coefficient of $DTCA_{-kt}$ is also positive and highly significant in the first stage regression.[16] These statistics suggest that $DTCA_{-kt}$ is a valid instrument for $DTCA_{kt}$. Because *SUMDTCA* is defined as a discounted sum of current and past DTCA, we use $DTCA_{-kt}$ as instrument for $DTCA_{kt}$, $DTCA_{-k(t-1)}$ as instrument for $DTCA_{k(t-1)}$, and so on.

The extent to which our instrument solves the endogeneity problem depends on the validity of assumptions. Should one of the assumptions fail, our results are better interpreted as a statistical association rather than a causal relationship between doctor visits and DTCA. Bearing this in mind, we proceed to the next section, which reports our results.

5. Results

We start this section by describing the data and showing the results for drug visits. Then, we report the effect of DTCA on drug visits by patient groups. The final subsection conducts robustness checks and provides additional estimation results.

5.1 Descriptive Statistics

Table I summarizes the dataset. As noted before, we have an unbalanced panel dataset with 7,824 observations covering 151 classes over 72 months between 1995 and 2000. A unit of observation is drug class-month. The first block of Table I summarizes DTCA data. As Rosenthal et al. (2003) and Iizuka (2004) showed, DTCA often concentrates in a few drug classes. In our data, on average, only 20.8% of classes advertise in a typical month.[17] Conditional on positive advertising, the average DTCA expenditures are $3.84 million per class per month.

The second block of Table I shows the number of visits by different visit definitions. By far the majority of NAMCS visits are drug visits, especially RX visits. Nondrug visits and OTC visits account for smaller

16. *F*-statistics is 236.00, with *p*-value equal to 0.

17. This number has increased over time. In 1995, only 10 classes advertised via DTC channels. This number increased to 30–35 in 2000. During the 6 years from 1995 to 2000, 67 classes have ever advertised through DTC channel(s).

Table I.
Summary Statistics

	Mean	Std. Dev.
DTCA data		
Dummy =1 if DTCA>0	0.208	0.406
DTCA ($ million)	0.799	2.960
DTCA ($ million) conditional on DTCA>0	3.836	5.516
Visit data		
Drug visits (million)—visits that lead to any drug mention(s)	0.778	0.984
RX visits (million)—visits that lead to any prescription drug (RX) mention(s)	0.641	0.875
OTC visits (million)—visits that lead to any otc drug mention(s) and no RX	0.137	0.406
Nondrug visits (million)—visits that lead to no drug mention	0.226	0.417
All visits (million) (= drug visits + nondrug visits)	1.004	1.275
Drug visits by demographics and doctor types		
Drug visits (million)—belongs to an HMO?	0.202	0.296
Drug visits (million)—patient age≥65?	0.258	0.390
Drug visits (million)—who pays for the visit?		
Self	0.051	0.104
Government-sponsored program	0.293	0.413
Private insurer	0.433	0.593
Total OBS	7,824	
Total number of classes	151	

Note: A unit of observation is four-digit NDC class-month. For each observation, the count of visits takes into account the NAMCS sampling weights. The data in an unbalanced panel show some classes do not exist in all years due to seasonality or definition changes in the NDC.

percentages of NAMCS visits. In the third block of the table, we provide a breakdown of drug visits by patient demographics. This shows that the majority of patients are non-HMO members, younger than 65 years old, and insured (either by the government or privately).

Table II shows the top 10 advertising classes in 1996 and 2000 and the corresponding number of doctor visits in each class. In both years, antihistamines and hyperlipidemia are ranked number 1 and 2, respectively, in DTCA expenditures.[18] At the same time, we also notice many changes in the top 10 advertised classes between 1996 and 2000. For example, drugs used for hypertension (i.e., calcium channel blockers and alpha blockers) were among the top 10 classes in 1996, but disappeared from the list in 2000. Although DTCA expenditures are highly concentrated in the top 10 classes in both years, the extent of concentration has declined from 77% in 1996 to 68% in 2000. Interestingly, the number of doctor visits for each class does not necessarily

18. Antihistamines include allergy drugs such as Claritin and Allegra. Hyperlipidemia includes cholesterol-reducing drugs such as Lipitor and Zocor.

Table II.
Distribution of DTCA and NAMCS Visits

Rank by DTCA	Drug Class Code	Drug Class Name	DTCA ($million) (% in total)	NAMCS Visits (million) (% in total)
Top 10 DTC advertised classes in 1996				
1	1944	Antihistamines	108.17	18.86
			19.28%	2.03%
2	912	Hyperlipidemia	69.33	13.70
			12.36%	1.48%
3	1265	Dermatologics, misc.	57.00	12.66
			10.16%	1.37%
4	1860	Antiprotozoals	47.92	1.77
			8.54%	0.19%
5	1947	Corticosteroid-inhalation/nasal	36.88	12.50
			6.57%	1.35%
6	1034	Estrogens/progestins	28.60	19.85
			5.10%	2.14%
7	510	Calcium channel blockers	25.56	28.67
			4.56%	3.09%
8	916	Calcium metabolism	22.28	1.19
			3.97%	0.13%
9	1723	Antimigraine/other headaches	18.90	2.09
			3.37%	0.23%
10	513	Alpha agonist/alpha blockers	18.25	12.63
			3.25%	1.36%
Total of Top 10			432.89	123.93
			77.16%	13.37%
Top 10 DTC advertised classes in 2000				
1	1944	Antihistamines	238.51	35.35
			10.84%	3.05%
2	912	Hyperlipidemia	209.80	35.86
			9.54%	3.09%
3	1947	Corticosteroid-inhalation/nasal	206.90	19.88
			9.41%	1.71%
4	1727	NSAID	158.83	11.80
			7.22%	1.02%
5	874	Disorders, acid/peptic	140.54	37.78
			6.39%	3.26%
6	630	Antidepressants	128.50	48.88
			5.84%	4.21%
7	388	Antiviral agnets	111.10	4.91
			5.05%	0.42%
8	1724	Antiarthritics	110.03	51.28
			5.00%	4.42%
9	631	Anorexiants/CNS stimulants	98.93	8.38
			4.50%	0.72%
10	504	Vascular disorders, cerebral/peripheral	89.19	4.04
			4.06%	0.35%
Total of Top 10			1492.34	258.15
			67.86%	22.25%

Note: Drug class code and name are based on the List of National Drug Code Directory Drug Classes published in the NAMCS 2000 documentation. Both Vioxx and Celebrex were classified in the drugclass 1727 (NSAID) in 1999. But in 2000, Celebrex was reclassified in drug class 1724 (Antiarthritics) while Vioxx classification remains unchanged. We use the 2000 definition.

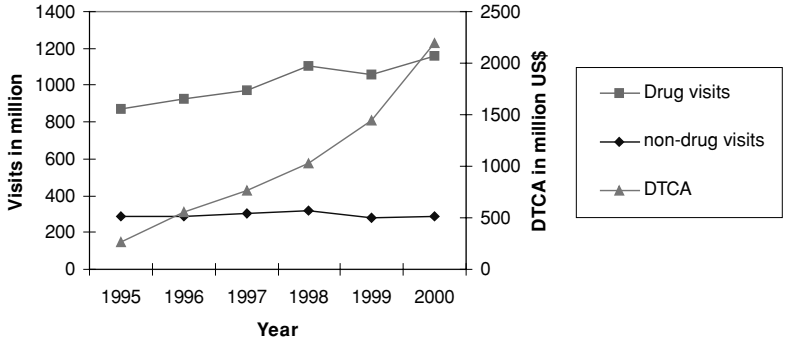

FIGURE 1. DTCA vs. NAMCS Visits

correspond to the dollar amount spent for DTCA. This is consistent with the finding of Iizuka (2004) that the amount of DTCA reflects the size of the untreated patient population rather than the currently treated population.

To draw a rough association between patient visits and DTCA, we plot the annual trends (1995–2000) in Figure 1. Patient visits are weighted counts from annual NAMCS, pooling all classes and decomposed into drug and nondrug visits. DTCA is the total DTCA expenditures within a calendar year, excluding the amount of DTCA spent on drugs that never occur in NAMCS. During a 6-year period, DTCA grew steadily from $257 million in 1995 to $2.3 billion in 2000. In comparison, patient visits fluctuate across years. Drug visits indicate an upward trend, whereas nondrug visits follow no obvious pattern.

In Figures 2 and 3, we differentiate the top 10 most DTC-advertised classes (as of 2000) from the other classes. Again, the trend is more conspicuous for drug visits. More importantly, drug visits of the top 10 classes grow much faster and track DTCA more closely than those of the non-top-ten classes. This suggests that most actions take place in drug visits, especially in the heavily advertised classes.

5.2 DTCA and Doctor Visits Where Drugs Are Prescribed

As discussed in Section 4.1, we report drug visits using the linear–linear specification as our main results. Table III, Model 1, shows these results. Given the endogeneity concern for *SUMDTCA*, we report estimates with and without instruments. Although the results with and without instruments are generally similar, the Hausman test does not reject the null hypothesis that *SUMDTCA* is exogenous.[19] For this reason,

19. The test statistics are reported in Table III.

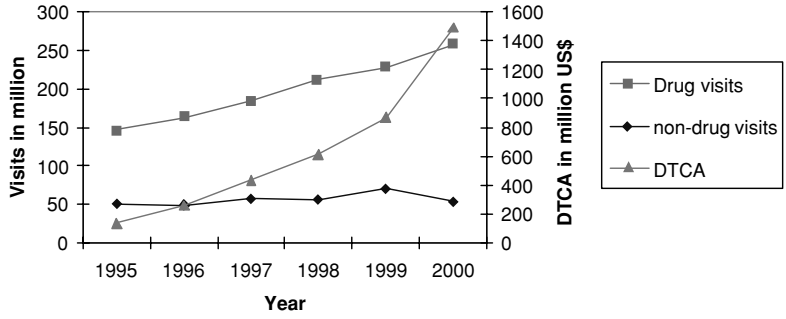

FIGURE 2. DTCA vs. NAMCS Visits—top 10 advertised classes

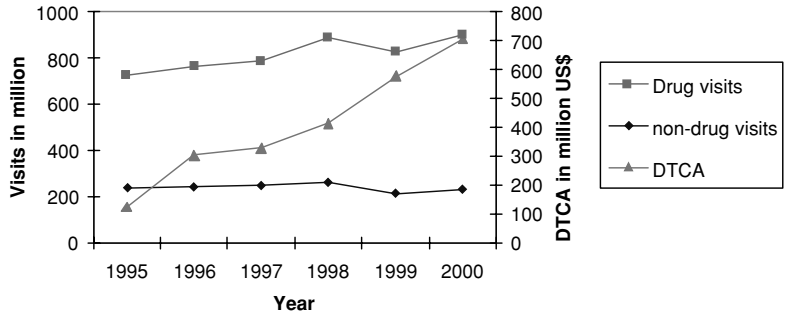

FIGURE 3. DTCA vs. NAMCS Visits—non-top 10 classes

we focus our discussion on the OLS results. We note, however, that because we have neither a structural model of doctor visits and DTCA expenditures, nor a strong natural experiment, our results establish a statistical association between visits and DTCA, but do not necessarily prove a causal relationship.

The OLS results in Model 1 suggest that DTCA is positively associated with drug visits before and after the clarification. The after coefficient is statistically larger than the before coefficient at the 5% confidence level. This may not be surprising, given the fact that the clarification allows pharmaceutical companies to mention both drug names and drug indications. Compared to mentioning drug names alone, this is likely to deliver a clearer message so that consumers can associate their own symptoms with the drug indication and remember the drug brands more effectively. Another possibility is that the clarification had the biggest impact in DTCA via television, and television is more effective in reaching consumers than are newspapers and magazines.

Table III.
Results of Drug Visits Regressions

	Model 1 Linear–Linear Dep. var = drug visits		Model 2 Linear–Log Dep. var = drug visits	Model 3 Log—Linear Dep. var = ln (drug visits)	Model 4 Log–Log Dep. var = ln (drug visits)
	OLS	IV	OLS	OLS	OLS
SUMDTCA, before FDA clarification	0.1747**	0.4097*	−0.0029	0.8076**	0.0143***
	(0.0815)	(0.2393)	(0.0020)	(0.3886)	(0.0042)
SUMDTCA, after FDA clarification	0.3489***	0.2414***	0.011***	1.1184***	0.0244***
	(0.0592)	(0.0345)	(0.0018)	(0.3014)	(0.0035)
Monthly depreciation rate	0.9672***	1	0.8926***	0.7421***	0.5494***
	(0.0112)	Boundary binding	(0.0769)	(0.0841)	(0.1189)
Test before=after	4.21**	0.59	51.05***	0.7	6.63***
OBS	7824	7824	7824	7619	7619
R^2	0.8049	0.804	0.8008	0.8065	0.8063

Note: Visits are in millions, DTCA in $100 millions. All regressions include a full set of year-month dummy, four-digit drug class fixed effects, as well as time trend and seasonality specific to first two-digit of drug class codes. In linear–log and log–log, the right hand side variables are ln(SUMDTCA) instead of SUMDTCA, and we impute zero DTCA as 1E-06. Standard errors in parentheses. Hausman test for model 1 is 93.51 with degrees of freedom 257 and p-value 1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Not only is the effect of DTCA positive and significant, it is also long lasting. The monthly discount factor is estimated as 96.72%, which means that 96.72% of the DTCA spent in month t would continue to take effect in the next month. Put another way, the effect of $DTCA_t$ will diminish to 67.02% in a year and 44.91% in 2 years. This implies that, for a typical class with one million drug visits per month, a one-million-dollar increase in month t's DTCA is associated with an increase in 35,082 drug visits in a year. In other words, every additional 28 dollars in DTCA is associated with one drug visit within 12 months.[20] This is a substantial market expanding effect, considering the fact that most prescription drugs cost much more than $28 per prescription, and one drug visit for a chronic disease could generate a stream of drug use in the future.

Models 2–4 show the results for the alternative specifications, that is, linear–log, log–log, and log–linear. When a log applies, we recode DTCA as DTCA $+ \epsilon$ to maintain the log validity.[21] However, if one class has zero drug visits at month t, we cannot define log(*VISIT*) and, therefore, have to drop the observation. As noted before, this is one shortcoming of using log(*VISIT*) as the dependent variable.

We compare the four specifications by focusing on the OLS results. We do so because, in all regressions, the Hausman test does not reject the hypothesis that SUMDTCA is exogenous.[22] From R^2, linear–linear is better than linear–log, and log–linear is better than log–log, but by a smaller margin. In all four specifications, *SUMDTCA* has a significant, positive effect on drug visits after the clarification. The before-clarification coefficient is also positive and significant except for the linear–log case. As for the relative magnitude, the after coefficient is always larger than the before coefficient, and the difference is statistically significant at least at the 5% confidence level except for log–linear. We take this as evidence for robustness. Because log specifications force us to drop or artificially modify visit counts and/or advertising expenditures when these numbers are zero, we hereby focus on the linear–linear specification.

5.3 Does the Effect of DTCA Differ Across Patient Subgroups?

This section further examines whether the relationship between DTCA and doctor visits vary across the population. The ongoing debate of

20. The 95% confidence interval is (21.76, 35.24).
21. $\epsilon = \$1$.
22. We were unable to compute the statistics for the original Hausman tests for the log–log and log–linear cases. We instead conducted the coefficient-based Hausman test. Wooldridge (2002, p. 119) discusses these issues in detail.

DTCA not only questions the existence of the market-expanding effect, but also concerns how that effect distributes among patient groups and what consequences the effect may have on prescription drug expenditure. For example, if underdiagnosis is more prevalent among the nonelderly and the main effect of DTCA is to target the underdiagnosed population as proponents claim, we should observe a greater market-expanding effect for the nonelderly. While our analysis here does not provide conclusive evidence to answer such welfare questions,[23] we hope our results constitute the first step to motivate more research.

We consider three ways to group patients: (1) whether the patient belongs to an HMO, (2) whether the patient is 65 or older, and (3) whether the visit is expected to be primarily paid by government insurance, private insurance, or the patient himself. Insurance status and HMO status are different measures, as both government and private insurances could be HMO or non-HMO. Because NAMCS is based on stratified sampling, counting patient visits by detailed demographic tabulates may substantially reduce the number of raw records in each cell, thus making the count of patient visits per cell unreliable. In light of this limitation, we examine the three dimensions one by one. For each dimension, we regress the visits count by each patient group and compare the regression results across groups.

Table IV reports the results. Following Table III, all regressions use drug visits as the dependent variable and are based on the linear–linear specification without instruments. In most cases, the coefficient for SUMDTCA is significant, positive, and larger after the clarification. This confirms our main findings reported in Table III.

In order to compare the *relative* market-expanding effect of DTCA across groups, we also report the DTCA dollar amount associated with a 1% increase in doctor visits within 12 months. We compute these numbers because the coefficients of the linear–linear specification only indicates the *absolute* market-expansion effect of DTCA, which does not take into account the population share of each group.[24] For example, given the fact that there are more nonelderly than elderly in the overall population, we would expect to see a higher impact of DTCA on nonelderly in absolute terms, even when the relative effectiveness of DTCA is the same between the two groups. Thus, we believe it is more sensible to compare relative DTCA effects by taking into account the composition of each group. This discussion also suggests that, to

23. For example, we cannot tell from our data whether the heterogeneous responses to DTCA come from a difference in response or a difference in exposure to DTCA.

24. The 1% increase before the clarification is based on the average monthly visit counts during January 1994 and December 1994. The 1% increase after the clarification is based on the average monthly visit counts during August 1996 and July 1997.

Table IV.
Effects of DTCA on Drug Visits by Patient Groups

Dep. Var: drug visits by	HMO = 1	HMO = 0	Elderly	Nonelderly	Self-Paid	Governm't Insured	Privately Insured
Coefficients reflecting absolute market-expanding effect							
SUMDTCA (in $100 million) before FDA clarification	0.0429	0.1371*	0.0241	0.146**	−0.0643**	−0.1698	0.0977**
	(0.0279)	(0.0706)	(0.0479)	(0.0585)	(0.0280)	(0.1824)	(0.0472)
SUMDTCA (in $100 million) after FDA clarification	0.0861***	0.2819***	0.1500***	0.2279***	0.0197*	0.5916***	0.2010***
	(0.0196)	(0.0527)	(0.0371)	(0.0416)	(0.0116)	(0.1277)	(0.0333)
Monthly depreciation rate	0.9795***	0.9567***	0.9324***	0.9731***	0.9472***	0.5166***	0.9777***
	(0.0126)	(0.0142)	(0.0252)	(0.0110)	(0.0478)	(0.1160)	(0.0094)
Wald test before=after?	2.32	3.68*	4.59**	2.04	5.51**	10.92***	44.57**
Relative market-expanding effect							
Predicted effect ($1000 needed to generate 1% more drug visits in 12 month before clarification)	274.86	371.35*	937.03	278.14***	−129.87	−651.30	304.04**
	(178.46)	(192.68)	(1890.89)	(110.64)	(83.89)	(673.14)	(146.75)
Predicted effect ($1000 needed to generate 1% more drug visits in 12 month after clarification)	196.64***	204.78***	179.88***	211.62***	288.58***	222.77***	188.62***
	(33.43)	(25.58)	(26.56)	(28.03)	(115.63)	(30.20)	(23.19)
Differ across groups (after clarification)?	−8.13		−31.74		65.81	34.15	99.95
	(42.10)		(38.61)		(119.51)	(38.08)	(117.93)
	HMO vs. non-HMO		elderly vc. non-elderly		Self-paid vs. gov insured	Gov vs. privately insured	Self-paid vs. privately insured
OBS	7824	7824	7824	7824	7824	7824	7824
R^2	0.678	0.78	0.7588	0.7974	0.4193	0.7268	0.779

Note: Visits are in millions, DTCA in $100 millions. All regressions are nonlinear OLS, including a full set of year-month dummy, four-digit drug class fixed effects, as well as time trend and seasonality specific to first two-digit of drug class codes. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

observe differences in relative impacts, the same DTCA intensity must affect patient groups differently in the likelihood of seeing the ads and/or visiting the doctor after seeing the ads.

We can think of three reasons for expecting different DTCA impacts on HMO and non-HMO patients. On the one hand, HMO patients may be healthier than non-HMO patients and thus less attentive to drug advertising that informs of the existence of treatments. Similarly, knowing that HMOs often don't include the newest brand name drugs in their formularies, HMO patients may pay less attention to DTCA. If so, DTCA may be relatively less effective in bringing HMO patients to doctors. On the other hand, HMO patients may think they are generally underdiagnosed and undertreated because of the cost-cutting incentive that HMOs face. In this case, HMO patients may pay more attention to DTCA to learn about potential treatments, which in turn may increase HMO visits relative to non-HMO patients.

Estimates in columns 1 and 2 show that the coefficient for SUMDTCA is substantially larger for non-HMO members. This means that, in absolute terms, DTCA has a larger impact on non-HMO visits than on HMO visits. However, after taking into account the population share of each group, we find the relative effect of DTCA is not statistically different between the two groups (e.g., 196.64 vs. 204.78 after the clarification).[25] Thus, the effect of DTCA does not appear to vary with HMO membership.

We note two factors that could potentially drive differential effects between elderly and nonelderly patients. On the one hand, if age is a good proxy of health and sicker people are more attentive to DTCA, we would expect DTCA to be more effective on the elderly. On the other hand, if DTCA mainly targets underdiagnosed diseases and the degree of underdiagnosis is more severe for the young, DTCA should be more effective on nonelderly patients. Results suggest that the former exceeds the latter—an additional \$179.88K (\$211.62K) DTCA dollars are associated with a 1% increase in the elderly (nonelderly) visits, but the difference is not statistically significant. If underdiagnosis concentrates in the nonelderly population, this finding is not consistent with the proponent's claim that DTCA results in significant improvement over underdiagnosis.

Our final comparison focuses on insurance status. Compared with self-paying patients, the insured do not bear the full financial cost of the office visit or the full cost of subsequent treatment expenditure. This moral hazard argument explains the huge absolute differences in the

25. As shown in Table I, HMO members constitute only 20% of the population in our sample.

SUMDTCA coefficients, but not necessarily the relative differences after considering the skewed composition of self-paid and insured visits. A relative difference may occur, for example, if self-paying patients are more underdiagnosed and undertreated. In this case, DTCA that informs the potential patients of the existence of treatments would have a relatively bigger impact for self-paying patients. On the other hand, DTCA may be more effective among the insured if the insured pay more attention to available medical information including DTCA.

After taking into account the composition of each group, we find that an additional \$288.58K is associated with a 1% increase in self-paid visits, which is higher than the corresponding amount for the government insured (\$222.77K) or the privately insured (\$188.62K). The results appear to suggest that the insured are relatively more responsive to DTCA in visiting physician offices than the noninsured, although the difference is not statistically significant.

Overall, we find that the effect of DTCA is similar across patient demographics. Although the *absolute* impact of DTCA often differs across demographic categories, we did not find a statistically different *relative* effect of DTCA across demographic groups.

5.4 Robustness Check and Additional Results

In this section, we report four sets of additional results that further support our main findings.

5.4.1 All Visits

As mentioned before, the ideal study of a patient's decision to visit a doctor should encompass all types of visits, no matter whether the visit leads to drug or nondrug treatment. So far, we have used drug visits as the dependent variable because the counts of nondrug visits are likely to contain substantial noise (see Section 4.1 for determining the number of nondrug visits). In this section, we show that the results don't change even if we use all visits (drug visits + nondrug visits) as the dependent variable.

The second column of Table V presents the estimation results for all visits, using the linear–linear specification without instruments. We also report the results for drug visits (previously reported in Table III) in the first column as a reference. Column 2 shows that the results for all visits are very similar to what we have for drug visits. The coefficients for DTCA are still positive and significant before and after the clarification. All estimates are comparable to that of drug visits. The only exception is that the coefficient for DTCA after the clarification is no longer significantly bigger than that of before clarification. Although

Table V.
Effects of DTCA, by Visit Type

Dep. Var	Drug visits (Copied from Model 1 in Table 3)	All Visits	Nondrug Visits	RX Visits	OTC Visits
Coefficients reflecting absolute market-expanding effects					
SUMDTCA (in $100 million) before FDA clarification	0.1747**	0.2326***	0.0655*	0.1726**	0.1025
	(0.0815)	(0.0886)	(0.0360)	(0.0705)	(0.2295)
SUMDTCA (in $100 million) after FDA clarification	0.3489***	0.3440***	0.0365*	0.3276***	0.1554
	(0.0592)	(0.0619)	(0.0207)	(0.0506)	(0.0936)
Monthly depreciation rate	0.9672***	0.9782***	0.9946***	0.9711***	0
	(0.0112)	(0.0101)	(0.0247)	(0.0096)	bound binding
Wald test before=after	4.21**	1.68	1.22	4.59**	0.06
Relative market-expanding effect					
Predicted effect ($1000 needed to generate 1% more drug visits in 12 month before clarification)	442.89***	404.89***	296.17**	361.79***	1336.59
	(207.30)	(152.46)	(145.37)	(147.82)	(2992.53)
Predicted effect ($1000 needed to generate 1% more drug visits in 12 month before clarification)	221.76***	273.77***	531.49***	190.62***	881.60
	(26.73)	(36.52)	(237.43)	(21.00)	(531.16)
OBS	7824	7824	7824	7824	7824
R^2	0.8049	0.8332	0.7236	0.8013	0.8176

Note: Visits are in millions, DTCA in $100 millions. All regressions are non linear OLS, including a full set of year-month dummy, four-digit drug class fixed effects, as well as time trend and seasonality specific to first two-digit of drug class codes. Standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

not reported, we also reproduced Table IV for all visits and find similar distributional effects. These robustness results confirm that DTCA does have a similar aggregate and distributional effect on doctor visits.

5.4.2 RX Visits, OTC Visits, Nondrug Visits

In this section, we report additional results when we break down all visits into RX visits, OTC visits, and nondrug visits. These results are reported in the remaining three columns in Table V. Unlike the results for all visits discussed above, these results are only suggestive because we do not observe some variables, such as detailing promotion, that may affect the doctor's choice between RX, OTC, or nondrug treatment after patients visited physician offices. This was not a problem in the "all visits" regression because we can safely assume that a consumer's decision to visit a physician may be affected by DTCA, but not by promotion efforts directed to doctors such as detailing.[26]

With this caveat in mind, we report the results. The third column in Table V shows that DTCA has a positive but only weakly significant effect on nondrug visits before and after the clarification. The magnitude of the DTCA coefficients is one order smaller than the previous results, suggesting that DTCA has little effect on nondrug visits. The fourth and fifth columns suggest that, if we decompose drug visits into RX or OTC visits, most of the market-expanding effect concentrates on RX visits. DTCA has essentially no impact on OTC visits.

At least two explanations occur for these results. First, DTCA encourages patients to prediagnose themselves. As a result, those patients who are more suitable for prescription treatment are more likely to visit doctors. According to this explanation, it is the change in patient distribution that drives stronger growth in RX visits versus OTC and nondrug visits. The second explanation casts doubts on doctors' 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- or 60-second DTCA on TV does not provide enough information for self-diagnosis. Then the sharp rise in RX visits implies that, as a result of DTCA, doctors are more likely to use prescription drugs than other treatment alternatives. This explanation would be consistent with the opponents' claim that DTCA distorts doctors' prescription behavior. Unfortunately, without a more explicit model of doctor behavior and more information on patient condition and drug-specific advertising targeting doctors, we cannot rule out

26. We realize that a similar concern may be raised for our drug visit results because, for example, detailing promotion, which we don't observe, may affect this choice. As we discussed before, however, nondrug visits contain a lot of noise due to the difficulty in assigning a drug class for each nondrug visits. Facing this trade-off, we choose to use more clearly defined drug visits as our main specification. We showed, however, that the results are similar even when we use all visits as the dependent variable.

either of these explanations. Certainly, these important issues must be explored in future research.

5.4.3 Results for the Therapeutic Classes Where DTCA is Concentrated

As noted before, DTCA is concentrated in a small number of therapeutic classes, and thus there are many therapeutic classes, especially earlier in the data, that do not use DTCA at all. This creates a potential difficulty in interpreting results. This section repeats our main analysis by focusing only on the advertised classes.

We report two results in Table VI. The second column shows the results when we include all therapeutic classes that used DTCA at least once during the 1995–2000 period. As shown at the bottom of the table, the dataset is smaller than before, containing only 67 classes as opposed to 151 in our main analysis. By contrast, the third column reports the results when we further narrow down the sample to the "heavily advertised classes," which include the top 50% most advertised classes (i.e., 34 classes) in terms of cumulative DTCA between 1995 and 2000.

The estimation results change little even when we focus on "advertised at least once" and "heavily advertised" classes. The coefficients for SUMDTCA after 1997 are very similar regardless of the sample used and continue to be positive and significant. The estimated depreciation rates are also very similar to our previous results. Predicted market-expanding effects are comparable across the three models. The only difference we notice is that the before 1997 coefficient is no longer significant for the smaller samples, although the difference between the before and after 1997 coefficient is still statistically significant.

5.4.4 Results for Fixed Depreciation Rate In the remaining three columns in Table VI, we report the results when we fix the depreciation rate of DTCA, using the estimate found in a previous study. This exercise is motivated by the concern that, without a detailed structural model of DTCA spending and doctor visits, it may be difficult to separately estimate the coefficient on SUMDTCA from the depreciation rate. We set the monthly depreciation rate of DTCA equal to 0.85, which was found in the previous study by Berndt et al. (1995).

We find that the estimated coefficients for SUMDTCA after the 1997 clarification are positive and significant for the three models estimated. As before, the effect of SUMDTCA is larger after the 1997 clarification than before the clarification. As expected, because we force DTCA to depreciate faster in these models than in our main analysis, the estimated coefficients are larger in magnitude than the previous results. However, the predicted market-expanding effects of DTCA are

Table VI.

Robustness Check Using Advertised Classes Only and Fixing Depreciation Rate

	Estimate Depreciation Rate			Set Depreciation Rate = 0.85		
Dep. Var = Drug Visits	Full Sample (Copied from Model 1, Table 3)	DTC Advertised at Least Once	Heavily DTC Advertised	Full Sample	DTC Advertised at Least Once	Heavily DTC Advertised
Coefficients reflecting absolute market expanding effects						
SUMDTCA (in $100 million) before FDA clarification	0.1747**	0.121	0.0975	0.0721	−0.0464	−0.067
	(0.0815)	(0.0946)	(0.1187)	(0.1621)	(0.1871)	(0.2121)
SUMDTCA (in $100 million) after FDA clarification	0.3489***	0.3239***	0.3453***	0.8298***	0.7350***	0.6821***
	(0.0592)	(0.0673)	(0.0828)	(0.0636)	(0.0793)	(0.0945)
monthly depreciation rate	0.9672***	0.9677***	0.9579***	0.85	0.85	0.85
	(0.0112)	(0.0136)	(0.0180)			
Wald test before=after	4.21**	4.06**	3.63*	28.92***	22.08***	15.18***
Predicted absolute market expanding effects						
Predicted effect before clarification ($ needed to generate one drug visit in 12 months)	56.93***	81.97	107.10	242.54	−376.88	−261.01
	(26.65)	(64.30)	(132.05)	(545.30)	(1519.72)	(826.26)
Predicted effect after clarification ($ needed to generate one drug visit in 12 months)	28.50***	30.62***	30.24***	21.07***	23.79***	25.64***
	(3.44)	(4.59)	(5.18)	(1.62)	(2.57)	(3.55)
OBS	7824	4556	2395	7824	4556	2395
Number of four-digit drug classes	151	67	34	151	67	34
R^2	0.8049	0.8020	0.8037	0.8046	0.8016	0.8034

Note: Visits in millions, DTCA in $100 millions. "DTC advertised at least once" refers to the classes that have ever advertised in DTC during 1995–2000. "Heavily DTC advertised" refers to the classes whose total DTCA during 1995–2000 is no less than the median of total DTCA among ever advertised classes. All columns use nonlinear OLS, but the latter three constrains the depreciation rate equal to Berndt's estimate (i.e., 0.85). All regressions include a full set of year-month dummy, four-digit drug class fixed effects, as well as time trend and seasonality specific to first two-digit of drug class codes. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

comparable whether we directly estimate the depreciation rate or use the estimate from previous work.

6. Conclusion

This paper examined the effect of DTCA of prescription drugs on outpatient office visits between 1995 and 2000. We found that higher DTCA expenditures are associated with increased doctor visits, and this relationship is stronger after the 1997 FDA clarification. This finding is consistent with the proponents' claim that DTCA encourages more patients to seek medical treatment. We also examined heterogeneous responses to DTCA and found the market-expanding effect is similar across demographic groups. We note, however, that because we have neither a natural identifying experiment, nor a structural model of DTCA spending and doctor visits, we cannot rule out the possibility that we have omitted some variable affecting both DTCA and doctors visits.

It is also important to note that although our results suggest that DTCA has a market-expanding effect, the welfare effects of DTCA are far reaching. For one thing, we do not model the substitution of prescription drugs against outside goods, including OTC drugs and nondrug treatment. In fact, because most increases in patient visits are driven by the visits that result in prescription drugs, we cannot rule out the possibility that DTCA induces doctors to use prescription drugs over the other alternatives. Moreover, we do not observe the price of prescription drugs as well as outside goods, which makes it difficult to discuss welfare conclusions. Therefore, our study constitutes only the first step in understanding the overall effects of DTCA. Any further studies on this issue would complement our findings and improve our understanding of the welfare effects of DTCA.

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