Informing the Uninformed:
How Drug Advertising Affects Check-up Visits

Daniel Hosken
Brett Wendling
Federal Trade Commission[1]
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Abstract

Direct-to-consumer drug advertising has recently become an important and controversial component of drug marketing. In this paper we examine one of the claimed benefits of drug advertising: encouraging the undiagnosed to seek out medical treatment. Using detailed person-level panel data on more than 30,000 individuals from the Medical Care Expenditure Panel Survey, we measure how advertising affects an undiagnosed individual's decision to visit a physician for a check-up. We find drug advertising is an important determinant of an individual's decision to get a check-up and that the estimated effect varies by demographic group. The highly educated and women, in particular women with Medicaid insurance, are the most responsive to drug advertising while Hispanics are the least responsive to advertising.

JEL: I11, I18, L65, L15
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[1] The opinions expressed here are those of the authors and not necessarily those of the Federal Trade Commission or any of its Commissioners. We thank Pauline Ippolito, David Schmidt, Steven Tenn, Catherine Tucker, and Matthew Weinberg for helpful comments.

I. Introduction

Quickly diagnosing serious medical conditions, such as hypertension, high cholesterol or diabetes, can enhance welfare directly by avoiding or delaying catastrophic health outcomes, and indirectly by lowering future medical care expenditures. Unfortunately, many individuals are unaware that they may have a serious medical condition and subsequently do not receive timely medical treatment. For example, the undiagnosed fraction of the population with hypertension, diabetes and high cholesterol populations are estimated to be 28%, 27%, and 22%, respectively (PhRMA 2008). Some, including the pharmaceutical industry, have suggested that direct-to-consumer (DTC) advertising for prescription drugs can play an important role in encouraging those at risk of serious medical conditions to seek out professional screening.

Despite the potentially large social benefits associated with advertising to the uninformed, the efficacy of drug advertising in informing consumers about health conditions and treatment options remains a controversial topic. Pharmaceutical companies advertise their product to maximize profits, not to provide consumers with information to make optimal health care decisions. Thus, drug manufacturers may face incentives to provide consumers with biased or incomplete information. As a result of these agency concerns, the U.S. Food and Drug Administration (FDA) extensively regulates the content of drug advertisements. Until quite recently the FDA required extensive disclosures of efficacy and risks in all drug advertisements that severely limited the efficacy of some forms of advertising, such as television. In 1997 the FDA issued a significant change in its regulatory guidance that modified the types of statements required in specific advertisements. Following the change in regulation, drug advertising increased dramatically from roughly 764 million dollars in 1997 to 4.1 billion dollars in 2004. The increase in DTC drug advertising has occurred alongside substantial growth in prescription drug expenditures which have grown as fraction of medical expenditures from 11% to 19.8% over the same period.[2] Coincident with the increase in prescription drug advertising and expenditures, there has been a growing concern that the FDA has not adequately regulated the content of DTC drug advertisements. A recent study by the

[2] Source: Author calculations using the Medical Care Expenditure Survey.

U.S. Government Accountability Office (GAO) found that "The effectiveness of the FDA's regulatory letters as halting the dissemination of violative DTC materials has been limited (GAO 2006)." These concerns regarding the content and effect of drug advertising have led to calls for additional limitations on drug advertising such as banning drug advertising for the first two years a drug is on the market.[3]

To help aid this policy debate, our paper examines one of the key potential benefits of drug advertising: encouraging individuals who are currently undiagnosed with a medical condition to see a physician for a check-up. Check-up visits are an important outcome to study because they are typically an individual's first contact with the medical care system, and are largely responsible for chronic disease diagnoses. In addition, using check-up visits as the outcome of interest captures important advertising spillovers that have not been addressed by previous research. Although drug advertising is intended to generate drug sales, the resulting physician visits necessary to receive prescribed medicines will likely involve screenings for both advertised and unadvertised medical conditions. For example, while an advertisement for a cholesterol-reducing medication may lead an individual to visit their physician, the check-up may result in the patient being diagnosed with high-blood pressure (rather than high cholesterol). Empirically, these types of spillovers have a potential to be important. Hypertension (high blood pressure) and hypothyroidism (underactive thyroid) are among the ten most prevalent chronic conditions in our data while neither is among the top 10 advertised conditions.[4] To better capture these spillovers we measure how all drug advertisements relevant to a person affects the likelihood of scheduling a check-up.[5]

Our analysis uses individual level data from the 1997-2004 Medical Expenditure Panel Survey (MEPS). A key advantage to the MEPS relative to other data used to study the effects of drug advertising for our study is the detail provided for those who choose

[3] Bart Stupak, Chairman of the House Energy and Commerce Subcommittee on Oversight and Investigations states, "Two years will give the FDA and doctors time to see what safety issues arise once a drug is approved. It will also allow adequate time to educate doctors on how to use the drug." *Time*, February 4, 2009.

[4] See Appendix Table 1 for a list of the top advertised conditions in the United States.

[5] We define "relevant" advertising as advertising corresponding to conditions that would affect a person of a given sex and age. For example, advertisements for conditions affecting men (enlarged prostate) should only affect men's behavior, and drugs affecting the relatively young (birth control) should not affect an older women's decision to see a doctor for a check-up.

not to consume medical care services. This information is particularly valuable when considering the decision to initiate medical care consumption. We examine how drug advertising affects the likelihood that those over thirty-five years of age with no previously diagnosed medical condition visit a physician's office for a "check-up" visit. We interpret a positive relationship between advertisements and check-up visits as the "informative" effect of advertising; consumers begin consuming health care services in response to drug advertising. Our direct-to-consumer (DTC) advertising data comes from TNS Media Intelligence, which allows us to construct bi-annual measures of national DTC advertising expenditures in the U.S. during our sample period (1997-2004). Our combined data provide a rich set of health, demographic, labor market, insurance, and advertising data that allow us to measure the differential impact of DTC advertising on many important subgroups of the U.S. including women, minorities and the uninsured.

Our results suggest that direct-to-consumer advertising plays an informative role in affecting consumers' health care decision-making. Overall drug advertising has a statistically significant and positive effect on the likelihood that consumers visit a physician for a check-up. We find that if drug advertising were to increase by 10%, an individual is predicted to increase their likelihood of visiting a physician for a check-up by about 7.5%. The effect of drug advertising varies substantially by gender, race, and education. We find that women, particularly women with Medicaid insurance, and the highly educated are the most responsive to drug advertising. Responsiveness also varies by ethnicity. Although Whites and Blacks appear more likely to see a physician for a check-up, the estimated effect for Hispanics is much smaller, and essentially zero for Hispanic men.

The remainder of the paper is structured as follows. Section II provides an overview of important institutional details of prescription drug markets and a brief review of the existing literature on DTC drug advertising. Section III presents our empirical specifications, and Section IV describes the data, variable construction, and construction of the estimation sample. Section V presents the results, and Section VI concludes.

II. Institutional Background and Literature Review

Advertising in prescription drug markets differs from other consumer goods because consumers cannot purchase drugs directly. Instead, a physician must authorize the purchase of a drug for every consumer. While the physician may prescribe an appropriate drug for an individual, it is not clear that a consumer's preference for a drug will result in a purchase of that drug. Because of this market structure, drug manufacturers must convince both consumers and physicians of the value of their treatment. Consequently, drug companies have incentives to develop advertisements directed at both consumers and physicians. The advertisements directed at consumers attempt to convince the consumer to visit their physician to ask about conditions treated by their drugs. Advertisements directed at physicians convince them (the physicians) to prescribe the relevant product.

Because physicians make the ultimate prescription writing decisions, a large fraction of the marketing expense for pharmaceuticals is targeted at physicians. The various forms of marketing activities directed at physicians are referred to as "detailing" in both the academic literature and the pharmaceutical industry. The primary detailing expense is incurred through the employment of a large sales force that markets drugs by directly contacting individual physicians. Drug detailers often provide physicians free samples for the doctor's patients and literature discussing the efficacy of their firm's products. Other detailing expenses include advertisements in professional journals and the sponsorship of professional events such as medical conferences. Detailing is the primary method pharmaceutical firms use to inform physicians of the availability and efficacy of the prescription medications they sell.[6]

The importance of drug detailing can complicate any analysis that estimates the effect of drug advertising on drug demand.[7] Detailing can provide general information to physicians about the efficacy and availability of products to physicians, but is also used

[6] Instead of modeling the informative role of drug marketing to physicians to consumers, Coscelli (2000), Coscelli and Shum (2004), and Crawford and Shum (2005) estimate empirical of physician learning resulting from previous prescribing experience. In related work Azoulay (2002) examines how information in the scientific literature regarding drug efficacy affects physician prescribing behavior.
[7] Brekke and Kuhn (2006), for example, develop an interesting model of drug marketing which predicts that DTC drug advertising and drug detailing are complementary.

to encourage physicians to "switch" patients from one drug to another. Identifying the informative versus persuasive effects of detailing is a difficult exercise, but is an important distinction for the welfare effects attributed to this form of marketing. While detailing is an economically important phenomenon, it is unlikely to play an important role in the outcome we are studying. Our paper examines the decision to have a check-up, which is a decision made by patients *prior to* the decision made by physicians to prescribe a specific product. In all likelihood, the consumer may be completely unaware of any detailing that has occurred when making the decision to visit a physician for a check-up, and is therefore influenced only by DTC drug advertising.

The goal of drug advertising is to increase sales of that drug by either encouraging untreated patients to begin taking the drug, or to encourage patients taking other drugs to switch therapies. The economics literature has viewed these two aspects of advertising as having two (not mutually exclusive) components: informative and persuasive.[8] Informative advertising provides consumers with information that increases demand generally, and is typically viewed as efficiency enhancing. For example, advertising the health benefits of the early detection of breast cancer is informative because it increases demand for cancer screening. In contrast, persuasive advertising is typically modeled as affecting the relative position of products within a market without increasing overall market demand. Cola advertising is a classic example. Advertising for colas likely does not increase consumers' awareness of colas, but probably does affect the demand for Pepsi relative to Coke. Persuasive advertising may or may not be welfare enhancing. For example, persuasive advertising can be beneficial by better matching consumers and products. However, the social gain resulting from the better matches may be smaller than the resource costs associated with the gain from better matching. Hence, the effect of advertising on consumer welfare is theoretically ambiguous.

The information content of drug advertising likely varies systematically depending on the nature of the condition treated by the drug. A number of important medical conditions often generate no visible symptoms to the individual until a more severe outcome occurs. For example, an individual cannot ascertain if he or she has high cholesterol without a blood test or hypertension without measuring blood pressure. For

[8] See Bagwell (2007) for a comprehensive review of the advertising literature.

these types of conditions advertising informs consumers of those characteristics which place them at risk of a medical condition (family history, weight, diet, and race), and can provide consumers with information about treatment options including the advertised medication. Other conditions present more easily recognizable symptoms to the patient. For example, arthritis patients often have joint pain. The pain might indicate that something is wrong, but a patient may still not know what is causing the pain or if treatments are available. For such conditions, advertisements inform consumers of viable treatments options and may be more persuasive in content. Conditions such as depression or attention deficit disorder are more ambiguous. Patients with these conditions are likely aware of the symptoms but may not know if their symptoms are severe enough to merit professional treatment. Advertisements for drugs treating these medical conditions may encourage individuals to seek out medical advice while suggesting treatment (prescription drug) options.

Existing empirical work finds evidence that DTC advertising is both persuasive and informative. Consistent with the persuasive hypothesis, a number of studies find that increases in DTC advertising decrease the own-price elasticity of demand (Rizzo (1999) and Meyerhoefer and Zuvekas (2008)). The literature also finds that the number of consumers receiving treatment for a condition increases in response to DTC drug advertising for that condition (Rizzo (1999), Wosinska (2002), Ling, Berndt, and Kyle (2002), Rosenthal et al. (2005), Iizuka and Jin (2005, 2007), and Meyerhoefer and Zuvekas (2008)). This latter effect suggests that there is a public good component to drug advertising. Demand for both advertised and unadvertised products treating a condition increases in response to DTC advertising for drugs treating a condition. This spillover is likely exacerbated by the fact that physicians—not consumers—make the final prescription decision. Finally, a number of studies having access to both DTC and detailing data find that direct physician contacts are much more likely to result in the sale of a specific product than DTC advertising (Wosinska (2002) and Iizuka and Jin (2005, 2007)). This work suggests that DTC advertising is successful in increasing patients' awareness of a medical condition, but not successful in generating a sale of the advertised product.

Our study complements a growing drug advertising literature that largely focuses on the relationship between drug advertising and drug demand. We differ from much of the literature in that we have chosen to focus on the relationship between drug advertising and check-up visits for the undiagnosed rather than the relationship between advertising and drug demand.[9] Although the relationship between advertising and drug demand is a natural starting point, and is especially important to drug manufacturers trying to maximize profits, our focus on check-up visits for the undiagnosed population provides us with several advantages. First, the informative (demand increasing) content of advertising is implicitly isolated by choosing to consider check-up visits for the undiagnosed. The undiagnosed represent the "untreated" population, who are much less likely to receive regular medical attention and are therefore the group most likely to be uninformed about potential health conditions. Check-up visits for this population are often the entry point into the medical system and begin the process of disease diagnosis. Consequently, check-up visits are often the type of visit where patients become informed of their medical conditions, whether or not the condition has been advertised. Second, our focus on check-up visits better captures potential advertising spillovers than either specific drug purchases or office visits for specific conditions. Advertising of any type may lead an individual to choose to visit a physician for a check-up, which may, in turn, lead to diagnoses of any condition. These types of spillovers are analogous to those found in previous work. For example, advertisements for one drug increase the consumption of other drugs that treat the same condition. However, our measure captures a broader set of spillover effects. In addition to capturing spillovers across drugs within a therapeutic class, we also capture spillovers across medical conditions (e.g., advertising for high cholesterol leads to a diagnosis of high blood pressure), and non-drug therapies (e.g., a diagnosis leads to a diet change or a recommendation for surgery rather than a drug).

The final major distinction between our study and that of the previous literature is the nature of our data. Most previous work uses either aggregate drug consumption data, data that is not representative of the general population (for example, from a single

[9] In related work (Iizuka and Jin (2005)) focus on the relationship between advertising and demand for office visits used to treat the advertised medical condition.

insurer), or contains only a cross section for an individual.[10] The MEPS data we use contains a rich person-level panel data set that is nationally representative. This allows us to directly control for individual heterogeneity through the inclusion of detailed control variables and/or individual specific fixed-effects. In addition, we are able to separately estimate the effect of advertising on visiting a physician for a check-up for different racial, gender, and education subgroups.

III. Empirical Model

The goal of this paper is to provide a measure of the informative content of DTC drug advertising. We estimate a simple relationship between advertisements and physician check-up visits that is motivated by an economic model of uninformed agents learning from advertisements. We assume that a mass of consumers are uninformed about their medical condition, and that these consumers may observe the symptoms of a medical condition but cannot directly diagnose the medical condition. In order to resolve diagnosis uncertainty they must visit a physician.[11] However, visiting a physician is costly, and consumers are hesitant to incur the cost unless they believe the visit could potentially result in a treatable diagnosis. DTC drug advertising provides information to consumers about the likelihood of having a treatable medical condition. The advertisements provide information about the symptoms and the demographic characteristics that place consumers at a greater risk of having the condition treated by the drug. The advertisement may also provide information about the consequences of leaving the condition untreated. For example, advertisements may warn patients with heart palpitations that they may have a medical condition that, left untreated, could lead to continuous pain. After viewing advertisements, a consumer who believes she matches the demographic profile of those with the condition, but is uninformed about whether she has the condition, decides whether she should visit a physician to learn more about her diagnosis. A physician visit resolves the uncertainty: the consumer is either diagnosed as

[10] The one exception we are aware of is Meyerhoefer and Zuvekas (2008) who also use the MEPS data.
[11] Consumers may be unaware that certain conditions are asymptomatic and require medical tests to determine a diagnosis.

being ill or receives a clean bill of health. In this way, advertisements encourage consumers to see a physician to learn about potential medical conditions.

Our empirical model measures how contemporaneous aggregate DTC drug advertising expenditures increases the likelihood that an individual without any diagnoses visits a physician for a check-up. We model the likelihood that an individual has a check-up visit in a period using the standard discrete choice model presented in equation (1) below.

$$\text{(1)} \quad \text{Prob}(\text{Visit}_{it}=1) = F(a + \beta x_i + \delta z_{it} + \theta \log(\text{DTC}_{it}) + \sum_{k=1997}^{k=2004} \gamma_k Y_{it}^k + \lambda \text{Month1\_6}_{it})$$

In equation (1), we model whether person i visits a physician (Visit=1) in period t, which is defined as a six month period corresponding to either the first or the last six months of a calendar year. Our data span the years 1997 through 2004, which represents a total of 16 time periods. The vector x_i includes time invariant person characteristics including race and sex. The vector z_{it} includes time varying characteristics such as individual's age, income, self-reported health limitations, education, and type of health insurance. Table 1 contains a complete list of controls included in the estimating equations.

Direct-to-consumer drug advertising is defined as aggregate advertising expenditures in the U.S. for all prescription drugs relevant to the consumer in period t. Variation in our measure of DTC drug advertising occurs over time and across "relevant" demographic groups. For example, we assume that advertisement expenditures for enlarged prostate medications (e.g., Avodart) are irrelevant for women, and that birth control advertisements (e.g., Seasonique) are irrelevant for men.[12] While there is some localized television and newspaper advertising for drugs, this fraction of spending is small (4% in our data). Furthermore, the public use MEPS data that we use contains very limited information on an individual's residence (census region and an indication of living in an MSA). For all of these reasons, we choose to aggregate advertising to the national level. While our direct-to-consumer advertising variable varies across both time and demographic group, advertising increased significantly during our sample period. To control for a spurious correlation between advertising and check-ups, which may be the result of trending, we control for time effects by including separate year indicators (Y_{it}^k).

[12] See Data Section for a more detailed discussion of condition relevance.

We control for seasonality in check-ups by including an indicator for observations occurring during the first 6 months of the year ($Month1\_6_{it}$).[13]

We limit our sample to those older than 35 and without *any* previously diagnosed chronic medical condition. Individuals over age 35 are the most likely targets of chronic condition drug advertisements, which represent more than 90% of total drug advertisement expenditures.[14] Figures 1-2 demonstrate the importance of age in becoming diagnosed with one of a number of heavily advertised conditions in the United States. The figures plot the proportion of adults in the MEPS data of a given age with each condition. Note how older individuals are the most at risk of developing a chronic condition, and that most chronic conditions disproportionately affect older adults. For most of these conditions, the group younger than 35 is much less likely to have the medical conditions relative to those older than 35. For the heavily advertised conditions of bladder control, menopause, and osteoporosis, those consumers younger than 35 report having less than a 1% chance of contracting the condition. Figures 1 and 2 suggest that age 35 is an age where the transition from "healthy" states to "unhealthy" states begins to occur. Consequently, we choose to focus our analysis on those older than 35 years of age.

We limit our attention to those without any previous disease diagnosis because these individuals should be, on average, relatively uninformed about their health status and should be the population most likely to benefit from the informative content of drug advertising. The effect of drug advertising on visiting a physician for a check-up can be viewed as a purely informative effect for this group. In response to an advertisement they consume a medical product not previously consumed. For consumers with one or more diagnoses the interpretation of the effect of advertising on check-ups is more difficult to determine. Individuals that have already been diagnosed with a chronic medical condition are much more likely to be receiving regular medical care. For example, individuals with diagnosed medical conditions visit the doctor, on average, more than five times as often as those without medical conditions. Further, the previously diagnosed receive regular follow-up care for their medical conditions. For example, nearly half of

[13] We also perform two tests which address the potential problem of spurious correlation (see Results section). In addition, we estimate the check-up equations using a linear time trend rather than separate year effects and find qualitatively similar results.
[14] Appendix Table 1 presents the share of drug advertising for the top 30 advertised conditions in the U.S. during our sample period.

patients with some diagnosis have more than one doctor visit in a six month period while less than 15% of patients without a diagnosis have greater than one office visit. Follow-up care is problematic to our study for several reasons. First, those receiving medical attention for one condition are potentially being monitored for other medical conditions. Consequently, individuals with at least one diagnosis are more likely to be aware of other diagnoses. In addition, identification of the advertising effect on physician visits is more difficult when considering a population with other medical conditions. For example, a patient that is being treated for hypertension may, in response to an advertisement, request a cholesterol test during a follow-up visit monitoring the patient's hypertension.[15] Separately identifying whether the visit is a hypertension diagnosis that occurred as a result of advertising or a follow-up visit treating high cholesterol is a difficult exercise.

Unfortunately, limiting the sample to the undiagnosed may cause selection into our sample that may be systematically different along the dimension of age. As people age, they are more likely to develop and learn about long lasting chronic conditions. For example, as can be seen in Figure 1, the likelihood of becoming diagnosed with a single medical condition, hypertension, increases dramatically with age. In fact, by age 65 more than 40% of all individuals are diagnosed with hypertension. For this reason, the type of individual in our sample will differ systematically with the age of the individual. Older individuals left in our sample are more likely to be a "low risk" of developing any disease than the younger consumers in our sample. The change in sample composition may be substantial. Figure 3 plots the fraction of individuals with no medical diagnosis by age in our MEPS sample for men and women. The figure shows that at all ages women are much more likely than men to have a medical diagnosis. At age 40 roughly half of men have no diagnosed medical condition compared to 35% of women. By age 60 these fractions have shrunk substantially to 25%, and 18% of men and women, respectively. Individuals who are of retirement age and have no diagnosed medical condition are likely very different from the rest of the senior population. For this reason, there may be significant unobserved person-specific factors that affect the likelihood that an individual becomes ill. However, we choose to look at this sample because this group is the most

[15] It is common practice for a physician to check a patient's blood pressure in an office visit.

likely to be uninformed about their condition; that is the group that would benefit most from informative advertising.

One major advantage of the MEPS data is that it contains short (two year) panels on individuals that can be used to control for this unobserved heterogeneity. Specifically, we estimate how drug advertising affects the likelihood that individuals visit the type of doctor visits that are most likely caused by drug advertisements: check-ups. We are not examining how advertising affects those medical visits generated by acute conditions (colds) or visits to treat previously diagnosed chronic medical conditions. We control for an individual's heterogeneity by estimating the probability that a consumer visits a physician for a check-up in a period by estimating models that include a full set of individual characteristics (both time invariant and time varying) and by estimating models with person-specific fixed-effects and time varying demographic characteristics (e.g. age, self-reported health status).

In estimating a discrete, yes/no, outcome like ours, researchers typically prefer to use a probit or logit model. While it is possible to estimate a fixed-effect logit model, the parameter estimates from a probit model that includes fixed-effects are inconsistent.[16] In addition, while we can obtain coefficients corresponding to the time-varying variables for the logit model we cannot calculate the implied marginal effects because they depend on the person fixed-effects which are not explicitly estimated in the fixed-effects logit procedure. For this reason, when estimating fixed-effects models we rely on the results of a linear probability model to make economic statements, but support our conclusions with the estimates from the fixed-effects logit coefficients.

Healthcare consumption and healthcare outcomes differ dramatically across the U.S. population, suggesting that the response to drug advertising may vary across population groups. For example, in Figure 4 we plot the likelihood that men and women see a doctor for a check-up by age group. The figure shows that when parents are making health care decisions for their children (ages 0-18), males and females have nearly identical propensities to visit a physician for a check-up. Upon becoming adults, however, the profiles of men and women shift dramatically with women being much

[16] It is not possible to estimate the probit model where the coefficients of interest can be estimated separately from the person fixed-effects (the incidental parameter problem), see, for example, Hsiao (1991).

more likely to see a physician. The relative reluctance of adult men to see doctors may suggest that men's response to drug advertising may differ from women. Individuals with different levels of education or racial background may also respond differently to advertising. Ippolito and Mathios (1990) found evidence that advertising the health benefits of high fiber cereals increased demand by informing groups that were relatively unaware of the health benefits of a high fiber diet including Non-Whites. Finally, because health insurance typically subsidizes the cost of prescription drugs and doctor visits, those with health insurance may respond differently to drug advertising than the uninsured. For these reasons, we estimate the effect of drug advertising on an individual's check-up probability separately by sex, education, race and insurance type.

IV. Data and Sample Construction

In this section of the paper we describe the two different data sources we use in this study, variable creation, and the details involved in constructing the estimation sample.

Direct-To-Consumer Advertising

The direct-to-consumer advertising data is provided by TNS Media Intelligence. TNS conducts periodic surveys of advertising in major media markets (local newspaper, national and local magazines, radio, network and local television, cable and internet) to estimate media advertising for prescription drugs. TNS reports advertising expenditures quarterly for a specific media outlet and drug. For example, one observation represents the expenditures for Zocor (a cholesterol drug) on the cable network TNT in the first quarter of 2002. Over 90% of advertising expenditures during our sample are for national advertisements. Most advertising expenditures are for traditional media: network television, national magazines, and cable television account for 35%, 32%, and 13% of drug advertising expenditures. Not surprisingly, advertising appears to be targeted at the audiences most likely to respond. The top two prescription drugs (accounting for 60% of drug advertising revenue) on MTV, which presumably reaches a youth audience, are Valtrex (a herpes drug) and Differin (an acne drug). In contrast, the top advertised drugs on the Golf channel treat impotence, allergy, and high cholesterol. Because most drug advertising revenues are for national advertising all of our DTC drug advertising expenditures are measured at that level. We aggregate DTC drug advertising expenditures across all media, regions, and drugs in a time period for all model specifications.

We define the drug advertising corresponding to a person in a time period as the advertising that would be relevant to that person's health care decision making. We use two pieces of information about the conditions treated by drugs to map relevant advertising to a person. First, a handful of heavily advertised drug are for conditions that are sex specific. Drugs treating impotence and contraceptive drugs are the seventh and eight largest categories of drug advertising expenditures in our data accounting for roughly 5% and 4% of total drug advertising, respectively. Second, while the most heavily advertised drugs affect virtually all adults (allergy, ulcer/heartburn, depression and asthma), some are associated with different age groups. Using data from various sources (including the MEPS data informing us of the fraction of individuals diagnosed with a condition at a given age) we have associated diseases with certain age groupings. For example, we assume all adults over age 35 are at risk of developing high cholesterol, and that all adults may respond to that advertising. Advertising for osteoporosis drugs is assumed to be relevant for women over age 45. Appendix Table 1 provides the categorization of drug categories for the top 30 drug categories accounting for more than 96% of drug advertising.[17]

The MEPS

Information on agent behavior is obtained from the 1997-2004 Medical Expenditure Panel Surveys (MEPS). The MEPS is a household survey that collects demographic, insurance, health and medical care utilization information from a nationally

[17] As a robustness check, we also constructed a measure of drug advertising which was a simple aggregation of all drug advertising in a period. Obviously, this measure of advertising only varies over time (not across demographic groups). Our results using this measure of advertising were qualitatively the same as those obtained using the measure that varied by both time and demographic group. Results obtained using this measure are available on request.

representative sample of approximately 30,000 individuals per year.[18] The expressed purpose of the MEPS is to associate every individual in the sample with detailed records of their medical care utilization. Information reported in the survey is collected, initially, by interviewing all survey participants five times over a 2.5-year period. During that period, the survey collects most of the demographic, health and medical care information. However, the survey performs a follow-up survey of medical care providers, such as physicians, hospitals and pharmacists, in order to verify utilization and expenditure information that occurs over a two-year calendar period. The survey classifies all interactions with medical care providers into eight categories, and labels each interaction as an “event”. The nature of an event depends on the service provider. Examples of events include hospital stays, filled prescriptions, and physician office visits. The MEPS reports all utilization and expenditure information for each event, separately. Expenditure information includes and distinguishes between all payments to providers including third-party insurance payments. The reported utilization information includes an array of details describing the event and the services provided during the event, including the date of occurrence.[19] The resultant panel reports all utilization and expenditure information for every medical event made beginning on January 1 of the first interview year and ending on December 31 of the following year for everyone in the survey. Note that the reported utilization information spans a two-year calendar period rather than the 2.5 years over which the survey participants are interviewed. We therefore limit our analysis to the two-year period. Some time information depends on the date of the interview round for the survey itself, and is associated with the relevant period of analysis.

The insurance plan information reported in the MEPS distinguishes between all private and public insurance plans that cover an individual. Medical care insurance information includes whether an individual is privately insured, uninsured, or publicly insured through Medicaid, Medicare, veteran's insurance, or other public insurance. The survey reports additional details about the characteristics of private insurance such as whether the participant is part of a managed care or an indemnity plan. The MEPS

[18] Specifically, the sample sizes are 1996: 22,601; 1997: 34,551; 1998: 24,072; 1999: 24,618; 2000: 25,096; 2001: 33,556; 2002: 39,165; 2003: 34,215.

[19] Filled prescriptions only report the survey round, not the actual date the prescription was filled. All other events report the actual date of the event.

allows an individual to be simultaneously covered by several insurance types, both public and private. Using the insurance information, we assign individuals to one of five mutually exclusive insurance types using a hierarchical algorithm. Patients are first assigned to Medicare, then to private managed care, private indemnity, Medicaid and finally the uninsured.

The health information reported in the MEPS includes both objective and subjective measures of health. For example, every survey participant is asked to subjectively rate their mental and overall health from 1-5 during every survey round. In addition, survey participants are often asked whether their medical conditions cause functional limitations including limitations of cognition, social functioning and certain physical activities. All years of the survey also include three-digit International Classification of Disease version 9 (ICD-9) code indicators that are not only associated with each individual, but also with each medical event.

In addition to insurance, expenditure and health information, the MEPS also reports labor supply and demographic information for each individual. This information includes geographic region, educational attainment, marital status, age, sex, race, ethnicity, employment status, wages and total income. Finally, relationships between individuals in the survey are also provided in order to construct household and family structures. Using the demographic information reported in the MEPS we construct a 4-period panel for every individual in the sample.[20] Each panel represents a 6-month period that begins in either January or July, and ends in June or December, respectively.[21] The advertising information is associated with individuals by matching the period of the survey with the period of the relevant advertisement spending.

Our dependent variable is a discrete indicator that is equal to one if a patient visits a physician for a "check-up", and equal to zero if the patient did not. Check-up visits are visits that patients with few observable (to the patient) symptoms use to diagnose conditions that they may be unaware of having. Check-ups are responsible for over 40%

[20] There is some attrition in the survey resulting in an unbalanced panel where some individuals are followed for fewer than four-periods.

[21] Information that varies by round (instead of date) is associated with the period in which the round occurs. Rounds that span periods are associated with the period of the midpoint. Health information with more than one response during a period is associated with the healthiest response. For example, if a person reports a SRHS of "Good" in round 2 and "Excellent" in round 3 and both are associated with the same 6-month period, then the SRHS is reported as "Excellent".

of newly diagnosed chronic medical conditions, and nearly half of women's chronic condition diagnoses. Individuals having check-ups in the previous period are up to 15% more likely to become diagnosed with a new medical condition than individuals without check-ups.[22] Consequently, if an advertisement for a drug used to treat one condition (e.g., high cholesterol) leads to a patient visiting a physician for a check-up, the result may be that the patient becomes diagnosed with an entirely different medical condition (e.g. hypertension). In this way, the check-up can generate a "spillover" diagnosis.

The check-up variable is constructed using office-based visit information reported in the MEPS. Office-based visit information is reported separately by event (visit), for every interaction that each patient has with an office-based provider. Every event is categorized into one of ten event types. These event types include check-ups, treatment/diagnosis, and emergency care.[23] We limit our focus to physician "check-up" visits, which can be interpreted as "well-visits". These visits are rarely generated by medical conditions (they are rarely associated with any ICD9 code) and are interpreted as the first stage in seeking a diagnosis for an unknown condition. The survey also identifies the date at which the event occurred and whether the provider is a physician or a non-physician (such as nurse practitioners and chiropractors). The existence of an event, the date of a reported event, the medical provider type and visit type information are all used to identify the number of times a patient chose to visit a physician for a check-up during the period.

Table 1 presents summary statistics for all of the variables included in our analysis. We have calculated these statistics for the overall sample and separately by gender because men's and women's check-up propensity is so different. For example, the average woman in our sample is nearly twice as likely to visit a physician for a check-up as a man (.15 versus .079) in the same six-month period. Our sample is also disproportionately male. This likely stems from the fact that men are much less likely to visit a physician for check-ups than women (as shown in Figure 4) and as a result are less likely to be diagnosed with a medical condition at any given age. Similarly, the

[22] Again, this description is for undiagnosed patients over the age of 35.
[23] The complete list of visit types in the MEPS data are: check-up, treatment/diagnosis, immunization/shots, maternity, psychotherapy, emergency care, post-operative/follow-up care, well-child visit, vision, vision surgery, and other.

uninsured are over-represented in our sample (21.4%) because they are less likely to see physicians and consequently are less likely to have a medical diagnosis. The women in our sample are also more likely to be poor, Black, and have Medicaid insurance than men.

We include self-reported health metrics and activity limitation variables in all of our estimating equations. These variables are used as metrics of health symptoms that are revealed to the patient. Not only will our results control for person-level heterogeneity, but they also control for changes in these health metrics that may lead a person to see a physician.

V. Results

Table 2 presents the full set of parameter estimates for four specifications of the check-up equation. The specifications are a linear probability model (LPM) and a logit model. Both specifications are estimated with and without person-level fixed-effects. Standard errors are clustered at the person-level. Each model includes a large set of controls for region, income, type of insurance, self-reported health status, age, marital status, and education. The random-effects models also include time invariant controls such as race and sex. The variable of interest is the coefficient on direct-to-consumer drug advertising. In the LPM fixed-effect model, the estimated coefficient is .084. In each specification the estimated effect of drug advertising on check-up probability is positive and economically and statistically significant (the smallest p-value is .002). The magnitude of this effect implies that a 10% increase in DTC advertising for the average person in our dataset would increase their check-up propensity from .1110 annual check-ups to .1194 – a change of more than 7.5%.

We next examine the importance of controlling for person-level fixed-effects in estimating an individual's likelihood of scheduling a check-up. First, we note that the coefficient of interest varies systematically with the inclusion of person-level fixed-effects. The fixed-effect models' estimated coefficients on DTC advertising are larger than the coefficients in their random-effects model counterparts (.084 vs .056, and 1.152

vs .588, for the LPM and logit models, respectively).[24] Hausman specification tests reject the hypothesis that random-effects coefficients are the same as fixed-effects coefficients with a high degree of confidence (p-values of .014 and .001 in the LPM and logit models, respectively). The results of the Hausman test are consistent with our expectation that person-level heterogeneity is important in determining who visits a physician for a check-up. In the remainder of the paper we will only present results from these specifications.

The results from the LPM and the logit models are qualitatively very similar. In both specifications the drug advertising increases the likelihood an individual visits a physician for a check-up. However, because the coefficient estimates in the linear model are equivalent to marginal effects and are easier to interpret we focus our discussion on the results from the linear probability model.[25]

The effect of advertising on the likelihood that an individual visits a physician for a check-up may vary by demographic group. For example, as shown in Figure 4, adult women of virtually every age are much more likely to see a physician for a check-up than are men. Given the large differences in check-up probabilities by gender, we might expect to see a different effect of advertising on check-up probability. It is well known that health outcomes vary dramatically across racial groups and with an individual's education level. Smokers are much more likely to be less educated (see, e.g., Currie and Moretti (2003) and Chaloupka and Warner (2000)), and Blacks have a life expectancy 5.1 years less than Whites (U.S. Census Bureau, 2009). Given these differences in health related outcomes and health related behavior by race and education groups, it is plausible that the effect of health advertising, e.g. drug advertising, may also vary with race and education. Table 3 presents the estimated effect of advertising on check-up probability for models estimated separately by sex, race, and education groups. Each estimating equation contains all of the time varying control variables reported in Table 2. However, for brevity we only report the coefficient estimate for the advertising variable. The first

[24] We have estimated all specifications of the check-ups equation reported in the paper using random-effects models and find the same result: the coefficient corresponding to DTC advertising is always larger in the fixed-effect specifications.
[25] Calculating marginal effects in the fixed-effect logit model is infeasible because the marginal effects depend on the (unknown) person-effects. We have, however, estimated each specification of the check-up equation reported in the paper using the fixed-effect logit models and find qualitatively similar results.

column of table 3 shows the estimated effect of drug advertising on check-up probability for men and women. The estimated effect of drug advertising is nearly three times larger for women (.147) than men (.055). The coefficients are statistically different from each other with a p-value of .06. Because both the level of check-up propensity and the estimated responsiveness to advertising is so different between men and women, we estimate all remaining specifications of the check-up equation separately by gender.

The remaining columns of Table 3 estimate the effect of DTC drug advertising separately for different levels of educational attainment and different races. We begin by dividing the sample into three mutually exclusive and jointly exhaustive racial groups: Blacks, Hispanics, and "Whites and all other races".[26] The check-up equation is then estimated separately for each group. This approach allows for different responses by group at the cost of less precise estimates. We find that the estimated effect of advertising for Blacks and Whites is economically important and statistically different from zero at least at the 10% level. For both men and women, Hispanics are estimated to be much less responsive to advertising. However, because the parameter estimates are so imprecisely estimated we cannot reject the null hypothesis that the estimated coefficients are different from one another.

Similarly to the analysis of race, we consider the differential effects of advertising by education group by dividing the samples into three mutually exclusive and completely exhaustive groups: those with at least a college education, those with a high school education (both GED and traditional high school diploma) and those with less than a high school diploma. The results are shown in the final three columns of Table 3. College graduates are the only male educational group who respond to drug advertising by visiting a physician for a check-up. A similar pattern is seen for women. Female college graduates are estimated to be the most responsive to advertising while those with less than a high school degree are the least responsive (although, in contrast to men, the estimates for both female college and high school graduates are statistically different from zero).

Ideally, we would like to determine if the impact of advertising on an individual's check-up probability varies separately for each gender, race, and education group; that is,

[26] The group "Whites and all other races" is primarily composed of Whites (90.35%).

to estimate the check-up equations separately by race, sex, and education. Unfortunately, some of the races do not comprise a large subset of our data, and we therefore do not have enough data to do this for each racial group. We have, however, re-estimated the check-up equation separately by education group for the largest racial group, Whites and others, and find the same pattern shown in Table 3. Specifically, we find that only college educated men are predicted to increase their likelihood of having a check-up in response to DTC drug advertising.[27] For women, college graduates have the highest estimated effect followed by high school graduates and those who did not complete high school.[28] We interpret these findings as evidence that the observed pattern by education group seen in Table 3 is likely robust across racial groups.

We also consider how an individual's medical insurance type interacts with the role that drug advertising has in the decision to visit a physician for a check-up. Insurance plans vary in the prices that patients pay for drugs and office visits, and may therefore affect the effectiveness of drug advertising in sending patients to visit physicians for check-ups. For example, many private insurance plans subsidize a specific set of drugs listed on their publicly accessible formularies, whereas the uninsured pay the full price of prescription drugs. To explore whether insurance affects the responsiveness to advertising, we interact the log of direct-to-consumer drug advertising with an indicator variable corresponding to the insurance type of the individual. We construct five insurance indicators corresponding to an individual's primary form of insurance: indemnity, HMO, Medicare, Medicaid, and uninsured. We estimate models separately by sex and either educational status or race as in Table 3.

Results estimated separately by insurance type are presented in Table 4. The coefficient estimates in column 1 of Table 4 present the insurance type results separately by men and women. We do not find any statistical differences across insurance types in the responsiveness to advertising for men. Although the coefficient estimates suggest fairly large response differences between publicly and privately insured men, our estimates are imprecisely estimated. Therefore, we unfortunately cannot make definitive

[27] The coefficient estimate on the drug advertising variable for college educated men is .185 with a standard error of .070. The coefficient estimates for the high school graduates and those with less than a high school education are effectively zero (less than .004).

[28] The drug advertising coefficient estimates and standard errors (in parentheses) are: .252 (.132), .175 (.081), and .052 (.117) for college, high school and less than high school women, respectively.

statements about whether these differences are valid. We also have very imprecise estimates for women and cannot infer that the observed differences across insurance types for women are statistically valid. Again, however, the coefficient estimates suggest very large differences across insurance types for women. These differences are especially large between Medicaid patients and other female patients, where Medicaid patients appear to be much more responsive to advertising than patients with other insurance types.

The remaining columns of Table 4 correspond to different racial and educational subgroups. Here, again, the coefficient estimates are very imprecisely estimated. Generally within a sex group, there does not appear to be much differential effect by insurance type. For men the only pairing that generates a significant difference by insurance type is for Hispanic men. Hispanic men with Medicare insurance seem much more likely to schedule a check-up in response to drug advertising than those with any other form of insurance. While the check-up equation controls for age, income, and person-level fixed-effects, the group of Hispanic men who receive Medicare may be different than other Hispanics. For example, to be eligible for Medicare an individual must be a legal resident of the U.S. and have been employed in the formal labor market for a significant period of their working career. Hence, the observation that an individual is both Hispanic and a Medicare recipient may be a signal that the person is less likely to be a recent immigrant than Hispanics with other insurance types. With the exception of Hispanic men with Medicare insurance, we do not see any systematic relationship between insurance type and responsiveness to drug advertising. Instead, we see the same pattern shown in Table 3: relatively small effects for Hispanics and large effects for college graduates.

For women there does appear to be a larger effect for Medicaid insurance. We see relatively large effects for the Medicaid population across racial and educational groups. In contrast to Medicare policies during our sample, Medicaid insurance provides a large subsidy for both doctor visits (the check-up potentially induced by the drug advertising) and subsequent prescriptions (should a medical condition be diagnosed). However, for the other types of insurance we do not see a systematic relationship between insurance type and effect of drug advertising on check-ups. Instead, we see the same pattern seen in table 3: larger effects for Whites and Blacks relative to Hispanics, and larger effects for more educated women.

Test of Spurious Correlation

One might be concerned that check-ups and drug advertising have similar trends that lead to spurious correlation, despite the fact that our model includes fairly flexible controls for time (year effects and an indicator for whether an observation is the first half of the year). To address the concern that the estimated relationship between advertising and check-up visits is due to spurious correlation, we perform a falsification test by including a variable that should have a similar trend to our measure of advertising but that should not have any effect on an individual's decision to visit a physician for a check-up. Recall that we use age and gender characteristics of the individual to define whether particular types of drug advertising are potentially relevant to that person. For example, we assume that advertising for birth control medication should not affect check-up decisions for post-menopausal women, and advertising for prostate cancer drugs should only affect a man's decision to schedule a check-up. We conduct two falsification tests related to that assertion. First, we test to see if the inclusion of advertising for women's (men's) conditions affects a man's (woman's) decision to visit a physician for a check-up. We next conduct a more general test where we see if including advertising that "should not" affect an individual's choice to see a doctor in the check-up equation (because the advertising is for the wrong sex or age group) indeed affects decision making. We conduct this test by adding the additional advertising variable to the specifications of the check-up equation presented in Table 3. The results of these tests are shown in Table 5. In each case, our modeling approach "passes" the falsification test. The coefficient corresponding to our measure of DTC drug advertising is essentially unchanged when compared to Table 3, and is virtually always larger than the "incorrect" measure of drug advertising. In no case is the "incorrect" measure of advertising either economically or statistically important. The results of this test give us some confidence that we are measuring a causal relationship between DTC drug adverting and an individuals choice to visit a physician for a check-up.

Summary

We have estimated many variations of the check-up equations and have observed two important findings that appear to be robust to model specification. First, and most important, drug advertising generates more check-up visits among the population of individuals with no previously diagnosed medical condition. Advertising plays a role in informing individuals and encouraging them to schedule physician check-ups. Second, the effect of advertising appears to vary across demographic groups. While the estimated effects are imprecisely estimated, we find that women are more responsive to drug advertising than men; Blacks and Whites are more responsive than Hispanics; and the highly educated are more responsive than the less educated. Given the lack of precision in our estimates, it is not possible to draw strong conclusions regarding how insurance type affects the response to advertising. We see some evidence that women with Medicaid insurance are associated with a higher response to advertising. Although we estimate large differences across insurance types for men, we cannot determine whether these differences are statistically valid.

VI. Conclusion

The regulation of prescription drug advertising has been and remains a controversial policy issue. As recently as 1997, the FDA required extensive information disclosures for direct-to-consumer drug advertising that severely limited the effectiveness and use of costly media, such as television, for drug advertising. Since these changes were enacted both drug advertising and drug expenditures have increased dramatically. Coincidently, concerns have been raised that the FDA has not been effective in regulating the content of drug advertising and some have suggested limiting drug advertising, again. While limiting drug advertising may lower demand and lessen misleading advertisements, our study suggests that a restriction would have negative effects on some consumers. We measure how drug advertising encourages those with no previous medical diagnosis to see a physician for a check-up. Members of the “undiagnosed” population have much less frequent contact with the medical profession than the general population, and are a group likely to benefit from informative advertising. In our sample, individuals without a medical diagnosis visit the doctor *less* than five times as often as the general population. We find that drug advertising has a significant impact on an undiagnosed individual's decision to see a physician for a check-up: a 10% increase in drug advertising is predicted to increase the likelihood of a check-up in a six month time period by about 7.5%. We also find that the estimated effect of drug advertising on the likelihood of seeing a physician for a check-up varies across demographic groups. While our estimates are imprecisely estimated, our results suggest that women and the highly educated are more likely to visit a physician for a check-up in response to drug advertising. In contrast, Hispanics appear much less responsive to drug advertising than either Blacks or Whites. Our results suggest that current drug advertising is not very effective in encouraging less educated men or Hispanics to see a physician for a check-up.

Clearly, advertising has many effects beyond those measured in this study. Firms engage in advertising for private gain: to increase either the price of and/or the quantity sold of the prescription drugs they own. Our study does not examine the impact of advertising on the sale or pricing of drugs. Further, we do not examine how advertising affects the behavior of the general population. Most individuals, particularly older individuals, have preexisting medical conditions and are in regular contact with physicians. Drug advertising may play more of a persuasive role with these consumers; that is, encouraging them to change prescription drugs rather than informing them about a potential medical condition. However, if advertising were eliminated or severely curtailed our results suggest that fewer undiagnosed individuals would visit a physician for a check-up. As a result, at-risk patients would not learn about major medical conditions, advertised or not advertised, as quickly as they are today.

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Figure 1: Age Distribution of Several Heavily Advertised Medical Conditions

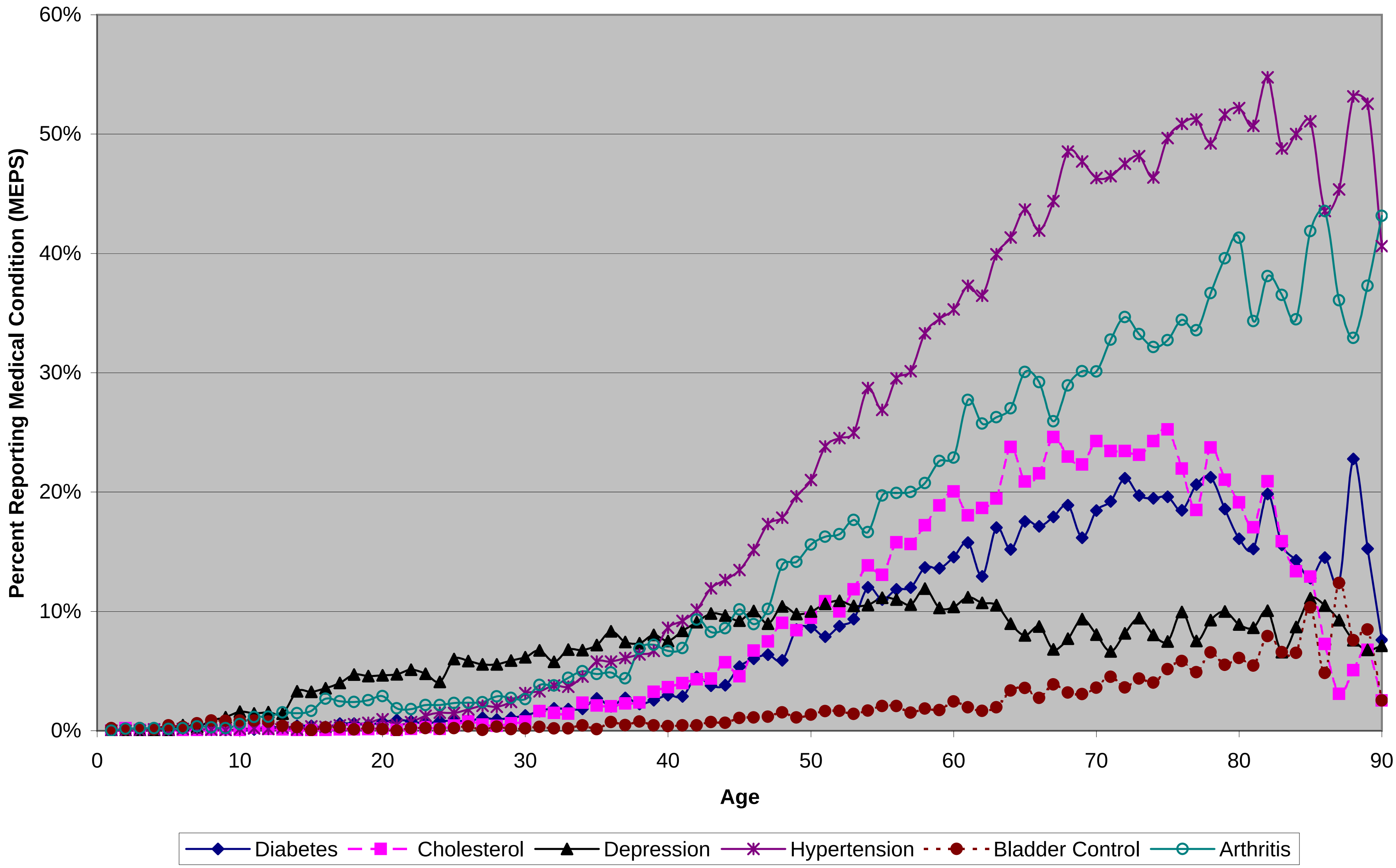

Figure 2: Age Distribution for Conditions Afflicting Women

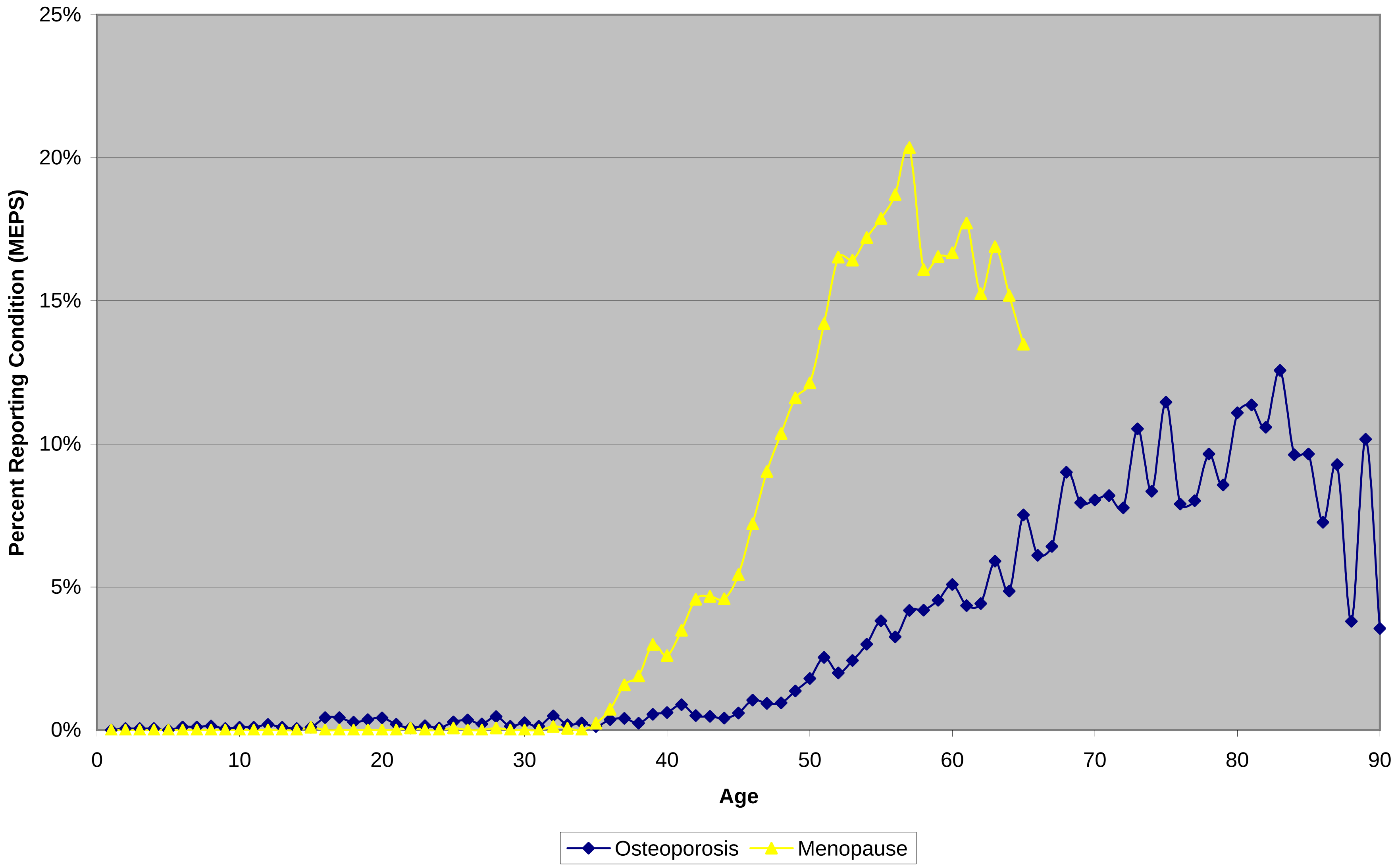

Figure 3: Percent of Individuals Without A Diagnosed Medical Condition

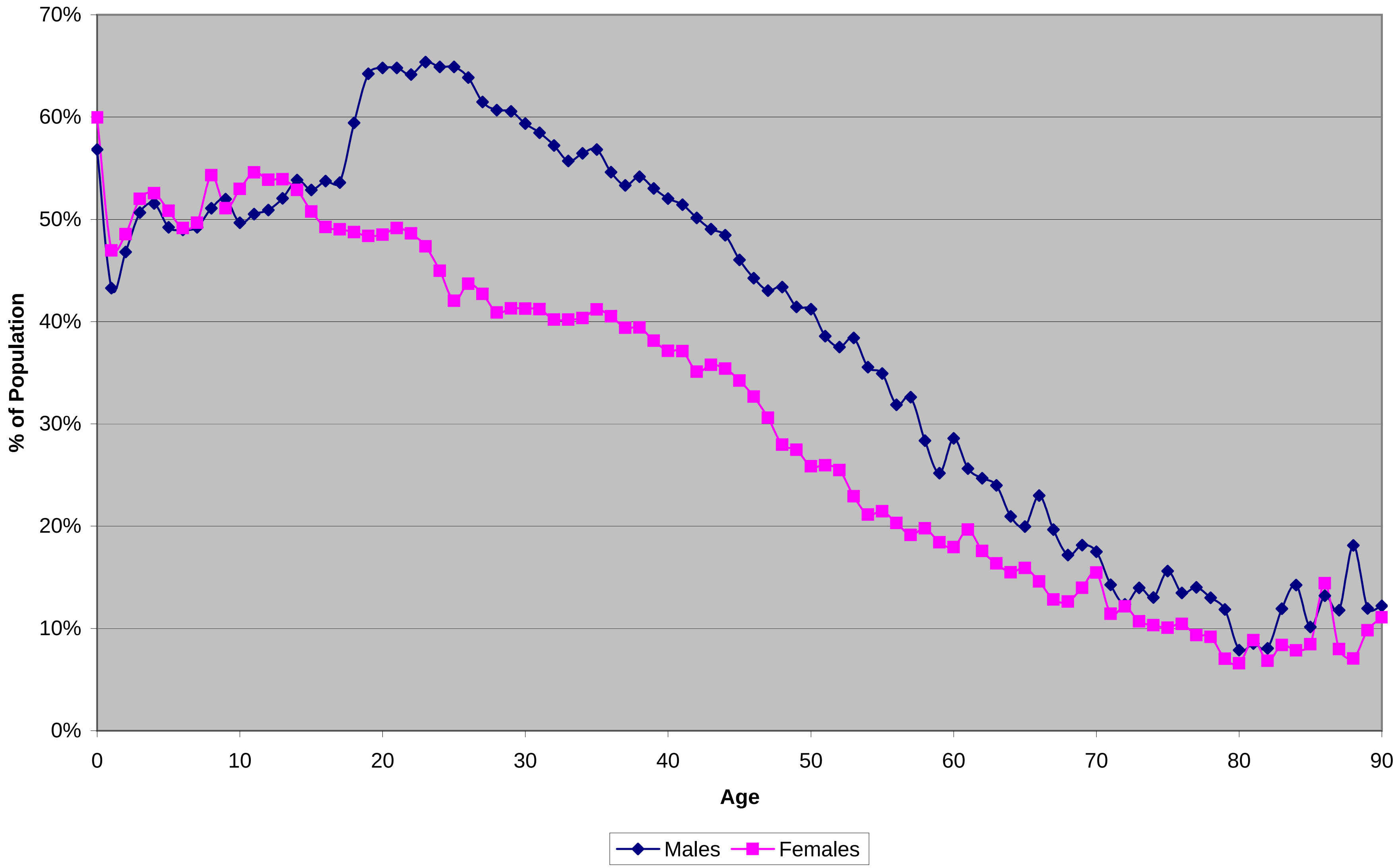

Figure 4: Unconditional Check-Up Propensity By Age

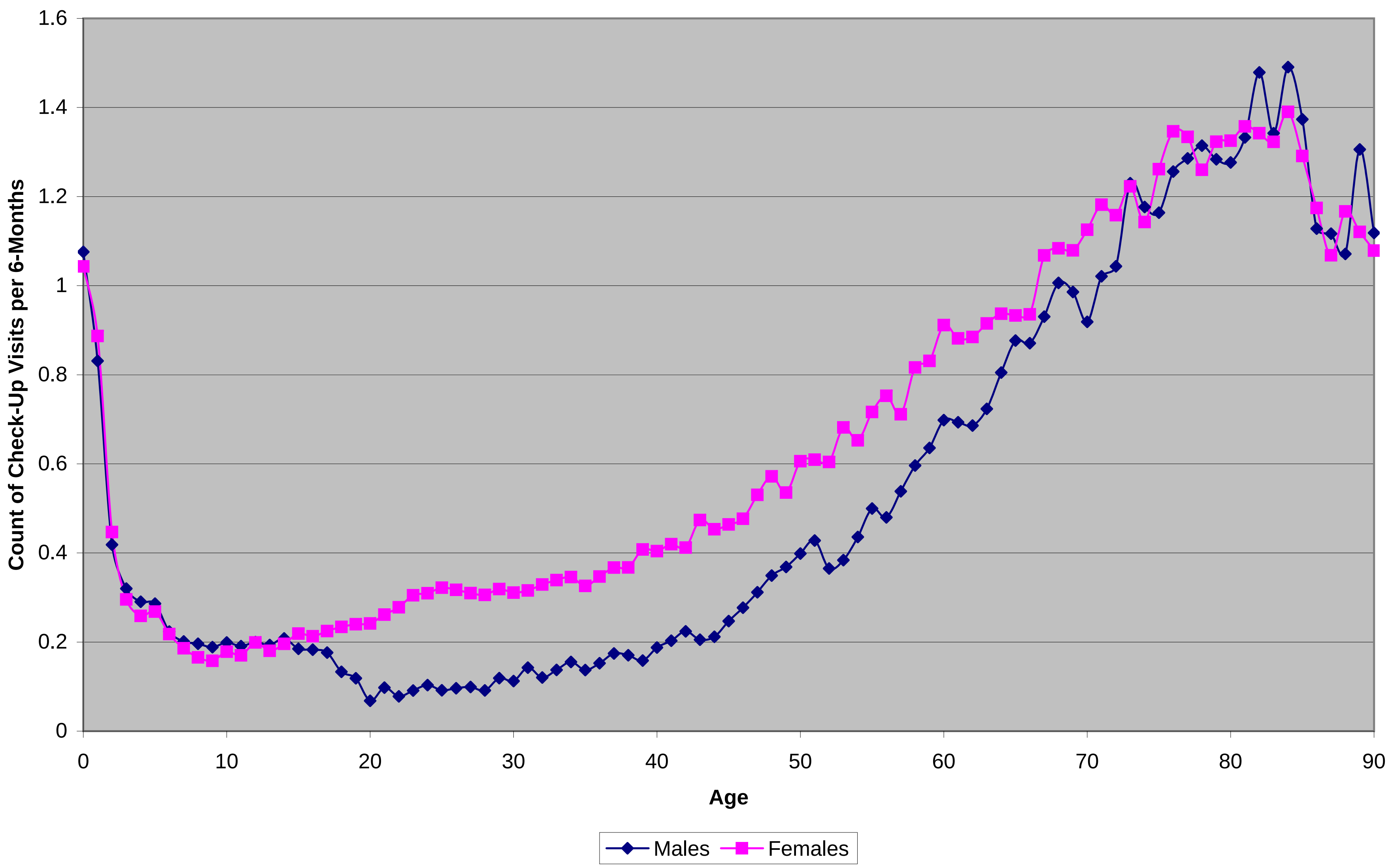

Table 1: Summary Statistics

Variable	Overall	Female	Male
Observations	67,658	30,619	37,039
Check-Up	0.111	0.150	0.079
Log(DTC)	13.62	13.62	13.62
DTC	918,155	914,817	920,914
Race/Ethnicity: White	0.551	0.521	0.576
Race/Ethnicity: Black	0.152	0.172	0.136
Race/Ethnicity: Hispanic	0.237	0.239	0.235
Race/Ethnicity: Other	0.060	0.068	0.054
Female	0.453	1.000	0.000
Married	0.689	0.634	0.735
Income < Poverty	0.111	0.133	0.093
Income 100-124% of Poverty	0.046	0.052	0.041
Income 125-199% of Poverty	0.150	0.159	0.142
Income 200-399% of Poverty	0.324	0.318	0.329
Income >=400% of Poverty	0.369	0.339	0.394
HMO Insurance	0.294	0.286	0.301
Indemnity Insurance	0.328	0.308	0.344
Medicare Insurance	0.121	0.127	0.115
Medicaid Insurance	0.044	0.061	0.030
Uninsured	0.214	0.218	0.210
Northeast	0.174	0.181	0.168
Midwest	0.186	0.179	0.192
Southeast	0.379	0.381	0.377
West	0.261	0.259	0.263
MSA	0.804	0.810	0.800
No Degree	0.241	0.246	0.236
GED	0.042	0.038	0.046
High School Diploma	0.445	0.457	0.434
Bachelor's Degree	0.135	0.127	0.142
Master's Degree	0.056	0.052	0.059
Ph.D.	0.018	0.009	0.026
Other Degree	0.063	0.070	0.057
Age	48.68	48.82	48.56
SRHS: Excellent	0.330	0.314	0.343
SRHS: Very Good	0.345	0.346	0.344
SRHS: Good	0.264	0.271	0.258
SRHS: Fair	0.054	0.062	0.048
SRHS: Poor	0.008	0.007	0.008
Activity Limitations	0.020	0.019	0.021
Social Limitations	0.009	0.009	0.009

Table 2: Estimates of Likelihood Of Checkup from Logit and Linear Probability Models
Full Set of Parameter Estimates

Variable	Linear Probability Model		Logit	
	Fixed-Effects	Random-Effects	Fixed-Effects	Random-Effects
Log(DTC)	0.084	0.056	1.152	0.588
	(.021)	(.015)	(.273)	(.189)
Indicators:				
1998	-0.018	-0.016	-0.367	-0.161
	(.029)	(.007)	(.236)	(.091)
1999	-0.040	-0.025	-0.792	-0.267
	(.057)	(.011)	(.450)	(.141)
2000	-0.074	-0.055	-1.365	-0.596
	(.085)	(.016)	(.662)	(.203)
2001	-0.050	-0.039	-1.161	-0.410
	(.111)	(.016)	(.842)	(.213)
2002	-0.045	-0.040	-1.204	-0.411
	(.136)	(.017)	(1.021)	(.222)
2003	-0.059	-0.056	-1.496	-0.591
	(.163)	(.020)	(1.218)	(.259)
2004	-0.070	-0.075	-1.746	-0.793
	(.190)	(.022)	(1.413)	(.291)
First Half of Year	-0.002	-0.003	-0.028	-0.037
	(.003)	(.003)	(.043)	(.033)
Married	0.004	0.013	0.075	0.130
	(.016)	(.003)	(.240)	(.038)
Female	n/a	0.113	n/a	3.205
		(.063)		(.608)
Income 100-124% of Poverty	0.002	-0.004	0.035	-0.072
	(.011)	(.006)	(.181)	(.096)
Income 125-199% of Poverty	-0.003	0.001	-0.067	0.016
	(.009)	(.005)	(.142)	(.070)
Income 200-399% of Poverty	-0.001	0.009	-0.013	0.135
	(.010)	(.005)	(.141)	(.065)
Income >=400% of Poverty	-0.004	0.022	-0.060	0.290
	(.011)	(.005)	(.157)	(.068)
HMO Insurance	-0.011	-0.012	-0.131	-0.143
	(.009)	(.004)	(.101)	(.039)
Medicare Insurance	-0.002	0.012	-0.044	0.091
	(.028)	(.008)	(.326)	(.072)
Medicaid Insurance	0.021	0.000	0.542	0.018
	(.021)	(.008)	(.369)	(.088)
Uninsured	-0.023	-0.056	-0.475	-0.984
	(.012)	(.004)	(.211)	(.060)
MSA Midwest	-0.026	-0.041	-0.155	-0.415
	(.102)	(.006)	(.941)	(.057)
MSA Southeast	-0.005	-0.035	-0.002	-0.351
	(.090)	(.005)	(.783)	(.048)
MSA West	-0.049	-0.040	-0.628	-0.417
	(.104)	(.006)	(1.117)	(.052)
Non-MSA Northeast	0.037	-0.023	0.268	-0.223
	(.111)	(.014)	(.939)	(.127)
Non-MSA Midwest	0.127	-0.046	1.587	-0.473
	(.112)	(.008)	(1.130)	(.080)
non-MSA Southeast	-0.028	-0.050	-0.277	-0.540
	(.094)	(.006)	(.895)	(.069)

Table 2: Estimates of Likelihood Of Checkup from Logit and Linear Probability Models
Full Set of Parameter Estimates

Variable	Linear Probability Model		Logit	
	Fixed-Effects	Random-Effects	Fixed-Effects	Random-Effects
Non-MSA West	-0.053	-0.041	-0.604	-0.412
	(.116)	(.009)	(1.308)	(.098)
GED	0.117	0.012	2.443	0.152
	(.037)	(.022)	(.848)	(.095)
High School Diploma	0.021	0.022	0.557	0.310
	(.026)	(.004)	(.421)	(.050)
Bachelor's Degree	0.041	0.053	0.725	0.628
	(.047)	(.006)	(.600)	(.063)
Master's Degree	0.129	0.069	1.421	0.751
	(.079)	(.009)	(.881)	(.078)
Ph.D.	0.145	0.043	1.897	0.523
	(.089)	(.013)	(1.195)	(.122)
Other Degree	0.018	0.033	0.485	0.433
	(.041)	(.007)	(.503)	(.076)
Black	n/a	0.004	n/a	0.062
		(.005)		(.049)
Hispanic	n/a	-0.015	n/a	-0.215
		(.004)		(.051)
Other Race	n/a	-0.011	n/a	-0.089
		(.007)		(.070)
Age	-0.046	-0.003	-0.705	0.029
	(.034)	(.002)	(.340)	(.019)
Age^2	0.000	0.000	0.005	0.000
	(.000)	(.000)	(.003)	(.000)
Female*Age	0.041	0.000	0.672	-0.061
	(.030)	(.002)	(.333)	(.022)
Female*Age^2	0.000	0.000	-0.006	0.000
	(.000)	(.000)	(.003)	(.000)
SRHS: Very Good	0.000	0.003	-0.010	0.048
	(.005)	(.003)	(.063)	(.037)
SRHS: Good	0.004	0.005	0.055	0.063
	(.006)	(.004)	(.078)	(.042)
SRHS: Fair	0.006	0.014	0.112	0.208
	(.010)	(.006)	(.154)	(.075)
SRHS: Poor	0.001	-0.009	-0.025	-0.065
	(.026)	(.014)	(.418)	(.192)
Activity Limitations	0.004	0.017	0.055	0.224
	(.020)	(.012)	(.272)	(.121)
Social Limitations	0.001	0.019	-0.008	0.188
	(.028)	(.018)	-(.008)	(.166)
Constant	n/a	-0.602	n/a	-12.286
		(.171)		(2.224)
Total Observations	65708		65708	
Hausman test p-value: Random Effects vs Fixed Effects	0.0141		0.0005	

Robust Standard Errors in parentheses.

Table 3: Effect of Drug Advertising on Likelihood Of Checkup
Estimated Separately by Subgroup

	Pooled	Black	Hispanic	White and Other	College	High School	Less than High School
Men:							
Log(DTC)	0.055	0.116	0.028	0.055	0.166	0.021	0.031
	(.023)	(.065)	(.035)	(.032)	(.062)	(.032)	(.036)
Observations	35918	4791	8441	22686	8209	17158	10551
Women:							
Log(DTC)	0.147	0.201	0.063	0.162	0.242	0.159	0.085
	(.043)	(.108)	(.071)	(.059)	(.116)	(.062)	(.067)
Observations	29790	5103	7178	17509	5596	14753	9441

Estimates from linear probability model. Robust Standard Errors in parentheses. All models include person-level fixed effects and controls for insurance type, marital status, age, age squared, measures of self-reported health status, income, year, and period. See Table 2 for full list of control variables.

Table 4: Effect of Drug Advertising on Likelihood Of Checkup
Estimated Separately by Subgroup with Insurance and Drug Advertising interactions

Interaction with Log(DTC):	Group						
	Pooled	Black	Hispanic	White and Other	College	High School	Less than High School
Men:							
HMO	0.065	0.074	0.051	0.074	0.175	0.027	0.073
	(.027)	(.076)	(.046)	(.036)	(.068)	(.037)	(.048)
Indemnity	0.042	0.147	0.017	0.035	0.141	-0.002	0.032
	(.026)	(.071)	(.045)	(.034)	(.066)	(.036)	(.042)
Medicare	0.092	0.085	0.164	0.082	0.249	0.095	-0.001
	(.043)	(.126)	(.081)	(.056)	(.121)	(.067)	(.064)
Medicaid	0.082	0.191	0.065	0.049	0.186	0.035	0.073
	(.040)	(.118)	(.056)	(.059)	(.086)	(.073)	(.053)
Uninsured	0.045	0.121	0.003	0.050	0.189	0.020	0.010
	(.024)	(.068)	(.035)	(.037)	(.086)	(.036)	(.036)
Obervations	35918	4791	8441	22686	8209	17158	10551
Women:							
HMO	0.136	0.154	0.007	0.176	0.290	0.134	0.050
	(.049)	(.119)	(.090)	(.067)	0.128	0.070	0.083
Indemnity	0.164	0.257	0.055	0.171	0.250	0.158	0.141
	(.047)	(.118)	(.085)	(.064)	0.124	0.067	0.079
Medicare	0.110	0.036	0.083	0.140	0.036	0.204	0.037
	(.063)	(.147)	(.138)	(.083)	0.188	0.099	0.093
Medicaid	0.224	0.252	0.120	0.313	0.668	0.201	0.147
	(.064)	(.145)	(.093)	(.113)	0.304	0.115	0.086
Uninsured	0.143	0.244	0.078	0.108	0.195	0.165	0.078
	(.045)	(.114)	(.072)	(.069)	0.175	0.066	0.068
Observations	35918	4791	8441	22686	8209	17158	10551

Estimates from linear probability model. Robust standard errors in parentheses. All models include person-level fixed effects and controls for insurance type, marital status, age, age squared, measures of self-reported health status, income, year, and period. See Table 2 for full list of control variables.

Table 5: Falsification Tests
Likelihood of Checkup Estimated Separately by Subgroup

	Pooled	Black	Hispanic	White and Other	College	High School	Less than High School
Men:							
Test 1: Include advertising for female drugs in men's estimating equation							
Log(DTC)	0.057	0.124	0.020	0.058	0.164	0.023	0.033
	(.024)	(.069)	(.036)	(.032)	(.063)	(.033)	(.037)
Log(Women's DTC)	0.004	0.017	-0.017	0.009	-0.003	0.005	0.005
	(.010)	(.026)	(.014)	(.014)	(.025)	(.014)	(.015)
Test 2: Include advertising for drugs not targeted at individual in men's estimating equation							
Log(DTC)	0.054	0.130	0.027	0.050	0.163	0.022	0.029
	(.023)	(.066)	(.036)	(.032)	(.063)	(.033)	(.037)
Log(Incorrect DTC)	-0.004	0.051	-0.002	-0.017	-0.009	0.004	-0.004
	(.010)	(.028)	(.016)	(.014)	(.027)	(.015)	(.016)
Women:							
Test 1: Include advertising for male drugs in women's estimating equation							
Log(DTC)	0.143	0.203	0.068	0.152	0.261	0.148	0.089
	(.043)	(.108)	(.071)	(.060)	(.118)	(.062)	(.066)
Log(Men's DTC)	0.002	-0.001	-0.002	0.004	-0.007	0.004	-0.002
	(.003)	(.007)	(.004)	(.004)	(.008)	(.004)	(.004)
Test 2: Include advertising for drugs not targeted at individual in momen's estimating equation							
Log(DTC)	0.148	0.202	0.063	0.162	0.239	0.160	0.086
	(.043)	(.108)	(.071)	(.059)	(.116)	(.062)	(.067)
Log(Incorrect DTC)	-0.007	-0.022	-0.006	-0.003	0.034	-0.020	-0.010
	(.015)	(.036)	(.024)	(.021)	(.045)	(.021)	(.023)

Estimates from linear probability model. Robust Standard Errors in parentheses. All models include person-level fixed effects and controls for insurance type, marital status, age, age squared, measures of self-reported health status, income, year, and period. See Table 2 for full list of control variables.

Appendix Table 1: Description of Demographic Categorization of Drugs for 30 Largest Advertised Drug Categories

Drug Type	Sex	Age Group	Direct-To-Consumer Advertising (thousands)	Share	Cumulative Share
Allergy Rx	Both	18 to 100	$3,183,599	17.41%	17.41%
Cholesterol Rx	Both	35 to 100	$1,601,855	8.76%	26.17%
Ulcer/heartburn Rx	Both	18 to 100	$1,509,912	8.26%	34.43%
Arthritis Rx	Both	45 to 100	$1,375,714	7.52%	41.95%
Depression Rx	Both	18 to 100	$1,175,087	6.43%	48.38%
Asthma Rx	Both	18 to 100	$1,057,995	5.79%	54.16%
Impotence Rx	Male	45 to 100	$937,500	5.13%	59.29%
Contraceptive Rx	Female	18 to 45	$687,332	3.76%	63.05%
Migraine Rx	Both	18 to 100	$539,242	2.95%	66.00%
Diabetes Rx	Both	50 to 100	$532,578	2.91%	68.91%
Herpes Rx	Both	18 to 100	$421,074	2.30%	71.21%
Skin Care Rx	Both	18 to 30	$406,309	2.22%	73.43%
Osteoporosis Rx	Female	45 to 100	$345,475	1.89%	75.32%
Bladder Control Rx	Both	40 to 100	$342,168	1.87%	77.19%
Fungus Rx	Both	18 to 100	$327,879	1.79%	78.99%
ADHD Rx	Both	18 to 100	$321,317	1.76%	80.74%
Anemia Rx	Both	18 to 100	$316,494	1.73%	82.47%
Crohns Disease Rx	Both	50 to 100	$291,615	1.59%	84.07%
Menopause Rx	Female	45 to 65	$261,238	1.43%	85.50%
Blood Thinner Rx	Both	45 to 100	$253,640	1.39%	86.88%
Stop Smoking Rx	Both	18 to 100	$238,690	1.31%	88.19%
Sleep Rx	Both	18 to 100	$234,800	1.28%	89.47%
Alzheimers Rx	Both	65 to 100	$223,359	1.22%	90.69%
Hair Loss Rx	Male	30 to 65	$218,119	1.19%	91.89%
Weight Loss Rx	Both	18 to 100	$166,153	0.91%	92.80%
Vaginal Yeast Rx	Both	18 to 100	$165,452	0.90%	93.70%
Flu Rx	Both	18 to 100	$142,258	0.78%	94.48%
Fat Blocker Rx	Both	18 to 100	$132,374	0.72%	95.20%
Antibiotic Rx	Both	18 to 100	$120,390	0.66%	95.86%
Acne Rx	Both	18 to 100	$111,857	0.61%	96.47%

DTC Advertising Expenditures correspond to the time period 1997-2004.