Published in final edited form as:

J Health Econ. 2017 September ; 55: 30–44. doi:10.1016/j.jhealeco.2017.06.003.

Vitamin Panacea: Is Advertising Fueling Demand for Products with Uncertain Scientific Benefit?¹

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Abstract

This study examines the effect of advertising on demand for vitamins—products with spiraling sales despite little evidence of efficacy. We merge seven years (2003–2009) of advertising data from Kantar Media with the Simmons National Consumer Survey to estimate individual-level vitamin print and television ad exposure effects. Identification relies on exploiting exogenous variation in year-to-year advertising exposure by controlling for each individual's unique media consumption. We find that increasing advertising exposure from zero to the mean number of ads increases the probability of consumption by 1.2 and 0.8 percentage points (or 2 and 1.4 percent) in print and television respectively. Stratifications by the presence of health conditions suggests that in print demand is being driven by both healthy and sick individuals.

JEL Codes

I12; I18; M37; M38

1. INTRODUCTION

Revenue of the vitamin and supplement manufacturing sector in the U.S. has grown steadily from approximately \$11 billion in 2008 to \$14 billion in 2013 (Statista 2014), and trend data indicate growth rates in sales of 5 to 7 percent annually over the past decade. According to the 2009–2010 National Health and Nutrition Examination Survey (NHANES) almost 50

¹A portion of the NCS data used in this study was supported with a grant from the NIH (Grant No. 5 R01-CA094020-5) and an unrestricted educational grant to Cornell University from the Merck Company Foundation, the philanthropic arm of Merck & Co. We thank Dhaval Dave, Kosali Simon, Neeraj Sood, participants at the 2015 Association for Policy Analysis and Management meetings, participants at the 2016 Southeastern Health Economics Study Group conference, and two anonymous reviewers for helpful comments and discussions. We thank Catherine Fernan and Nabeel Momin for superb research assistance. Any remaining errors are our own.

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percent of American adults report taking some form of dietary supplement, but only 10 percent of American adults have a nutritional deficiency (CDC 2012). Furthermore, strong growth in the vitamin sector is expected for the next decade as baby boomers age and health care costs continue to rise (Statista 2014).

The 2005 Food and Drug Administration (FDA) dietary guidelines advise nutrient needs be primarily met through consuming nutrient-rich foods (FDA 2015). The FDA guidelines also note that taking dietary supplements may address deficiencies in certain cases, and for certain populations, yet consumer surveys indicate that the top reasons consumers take vitamins and supplements are to boost general health (95 percent) and to ward off illness (86 percent) (Statista 2014). These reasons have uncertain support in clinical literature, as a recent meta-analysis of vitamin efficacy found that most vitamins have not been shown to be effective in either treating or preventing disease (Swartzberg 2016). Furthermore, consuming vitamins without physician direction or knowledge of the potential side effects might be risky and harmful to health (Tuomainen et al. 2012). Asymmetric information in this market could make consumers vulnerable to claims of efficacy and improved health, which might cause significant market inefficiencies if consumers are making purchasing decisions based on these claims. These market inefficiencies could be compounded by lax FDA and Federal Trade Commission (FTC) regulations surrounding vitamin labeling and advertising (Lellis 2015; Avery et al. 2013).

While there is a debate in terms of how much evidentiary burden should be imposed on these manufacturers, and how much to “crack down” on ad claims, evidence on the first-order question, i.e., the effect on consumption, is missing in the literature. In this study we determine the degree to which over-the-counter (OTC) vitamin/mineral product advertising impacts demand for these products, with a focus among those with ailments that some believe may be treated by specific vitamins/mineral supplements. Additionally, we examine these advertising effects in both television and print to test for differential effects across advertising media. These estimates are critical for understanding how effective regulatory policies might be, and for understanding any likely heterogeneity in the demand response should the FTC decide to increase the evidentiary burden for some kinds of vitamins relative to others.

This paper is, to the best of our knowledge, the first to estimate the causal impact of individual-level exposure to vitamin advertising on demand for vitamins and mineral supplements. We match consumer-level data from the Simmons National Consumer Survey (NCS) 2003–2009 to data on vitamin advertising obtained from Kantar Media for the same period. The NCS is a rich data source that includes detailed questions on vitamin/mineral supplement use and media consumption behavior (television and print). By combining questions on which television programs respondents watch (and which magazines they read) with data on when and where advertisements air/appear in these media, we are able to create an individual-level measure of potential exposure to print and television advertising. Furthermore, with data on the cost of each advertisement, we calculate exposure to advertising dollars, an analogous measure for exposure that reflects advertising reach and frequency.

The main empirical challenge in this paper is the endogeneity of advertising exposure. Consumers choose which programs to watch and which magazines to read, and these choices may be correlated with consumer-level unobservables that also are correlated with vitamin consumption. In addition, firms are likely to target their advertisements towards consumers who are likely to purchase vitamin products. This targeting would create an upward bias in our estimates. The richness of the NCS survey (used commercially by marketers for their media buying decisions) allows us to control for this targeting in a unique way. To mitigate the possible endogeneity bias, we saturate models with indicator variables for every television program and magazine asked about in the NCS survey. A similar approach was used in previous studies using these same data (Avery et al. 2007b; Avery et al. 2012). However, we further innovate on the targeting control approach used in those papers in two ways. First, we include indicator variables for watching (reading) a program (magazine) at a high frequency. Such controls allow us to better control for the targeting approach used by advertisers towards individuals who frequently read a magazine or watch a television program. Second, we include indicator measures for *how often* the respondent watches (reads) each program (magazine). Their inclusion refines our targeting control measures. The identifying variation in our models comes from two identical (on observables) respondents who watch (read) the same programs (magazines) at the same frequency, but at different times of the year leading to differences in the number of ads they are exposed to (i.e., program/magazine survey and wave ad variation).

The data also allow us to examine how the effect varies across the type of vitamin advertised. To accomplish this, we separately estimate demand for the seven most common supplements in our ads data (vitamins B, C and E; multivitamins; antioxidants; fish oil; and calcium).

Lastly, given the uncertainty surrounding the efficacy of vitamins and supplements in treating and/or preventing illness, we quantify demand for specific vitamins across the health distribution identified in the NCS. We explore links between advertising for specific vitamins/minerals and the ailments they target drawn from the medical literature (e.g., calcium and osteoporosis) and test if the vitamin-specific advertising increases demand for those individuals with or without the ailment.

Overall, we find statistically significant effects of increased advertising on vitamin demand. We find that increasing advertising exposure from zero to the mean number of ads increases the probability of consumption by 1.2 and 0.8 percentage points (or 2 and 1.4 percent) in print and television respectively. Our results are robust to a variety of specifications, different methods of controlling for targeting, and controlling for local unobserved demand shocks. When examining demand for specific vitamins, we find that a one hundred percent increase in print advertising exposure (about 3 additional total ads) increases the probability of consumption by anywhere from 2.5 (Antioxidants) to 4.16 (Vitamin B) percentage points. Lastly, we find heterogeneities across the effectiveness of advertising for vitamins associated with different types of ailments. We find evidence that advertising is creating demand for both therapeutic and preventative uses.

This paper proceeds as follows: Section 2 provides background on related literature on both Direct to Consumer Advertising (DTCA) and vitamin efficacy; Section 3 describes the data; Section 4 outlines the econometric model and identification strategy; Section 5 summarizes the results; and Section 6 provides a discussion of results and draws study conclusions.

2. BACKGROUND

2.1 Related Literature

A handbook chapter by Bagwell (2007) has reviewed the extensive literature on the effects of advertising on consumer purchasing behavior. More recent work has leveraged large-scale field experiments by exogenously manipulating internet advertising exposure. Lewis and Rao (2015) have been critical of these large-scale experiments and observational advertising studies due to a ‘signal-to-noise’ issue. Since some product purchasing is rare and the effect of advertising likely small, very large sample sizes may be needed in order to have sufficient power to detect effects. Johnson et al. (2016) studied one of these field experiments with 3 million Yahoo! users by randomly exposing a treatment group to retailer specific advertisements. In order to reduce leftover variance in purchasing behavior, they include over 200 individual covariates and by exposing the control group to control ads so that they may exclude purchases from control users who were not exposed to advertisements. Using this approach, they estimate advertising increases sales by 3.6 percent, when compared to a control group.

The effects of DTCA have been broadly studied, though not in any experimental setting. An econometric study undertaken by Rosenthal et al. (2003) looks at how DTCA (average monthly expenditure data) affects pharmaceutical sales, with a focus on whether advertising raises primary demand (market expansion) or selective demand (business-stealing and brand-specific demand). They conclude that DTCA is effective in raising sales for the entire therapeutic class. Other studies, also using aggregate expenditure and sales data, have noted the market-expansion effect, indicating that DTCA may be more effective in increasing aggregate demand per therapeutic class than in increasing the demand for a particular brand (Auton 2006; Iizuka & Jin 2005, 2007; Kalyanaram 2008, 2009; Kalyanara & Phelan 2013; Wosinska 2002; Sinkinson & Starc 2015). Exploiting the insurance expansion resulting from Medicare Part D implementation, Lakdawalla et al. (2013) find that prescription DTCA increases demand most in the least competitive drug classes, while Alpert et al. (2015) find that drug utilization increases mirror the increases in DTCA. Some studies also have found that, in addition to a market expansion effect, DTCA can increase drug adherence and encourage the continuation of an existing treatment (Bradford & Kleit 2011; Alpert et al. 2015).

While there is evidence that increased spending on DTCA results in increased market sales overall, all of these previous studies have used aggregate market-level advertising volume/expenditure data to draw conclusions regarding the impact of DTCA on individual consumption decisions. This approach assumes everyone within a market is exposed to the same amount of advertising. In this study we improve on aggregate market-level measures of exposure. Our measure combines vitamin advertising on television and in consumer magazines with reported individual-level media behavior (i.e., reported television viewing

and magazine reading) to estimate the impact of these ads on reported consumption of vitamins and mineral supplements, while accounting for biases from ad targeting behavior by marketers. This approach was used in recent studies focusing on other prescription drug product classes (Avery et al. 2007a,b; Avery et al. 2012; Byrne et al. 2013; Niederdeppe et al. 2013).

Prior studies almost exclusively have examined DTCA demand and sales effects using aggregated data on both broadcast and non-broadcast DTCA. Such aggregation may not be appropriate since broadcast and non-broadcast DTCA could have differential effects on price and sales, which may be masked by the estimation of a single parameter of effect for aggregated DTCA. One exception is a study by Dave and Saffer (2012), who investigate the separate effects of television and print DTCA on price and demand utilizing an extended monthly time series spanning 1994 through 2005 for all advertised and non-advertised drugs in four therapeutic classes. Their results indicate that television DTCA positively impacts own-sales and price, while print DTCA has a relatively smaller impact.

Bolton et al. (2008) examines consumer reactions (intentions to consume) to the marketing of drugs and supplements and the consequences for a healthy lifestyle. They find evidence that drug marketing undermines an individual's intention to engage in health-protective behaviors. There are two hypotheses for this effect: (1) drugs reduce risk perceptions and perceived importance of, and motivation to engage in, complementary health-protective behaviors, and (2) drugs are associated with poor health that reduces self-efficacy and perceived ability to engage in complementary health-protective behaviors. Similarly, Byrne et al. (2013) examined claims in statin advertisements and finds that ads offer a mixed message about the effectiveness of diet and exercise in reducing the risk of heart disease. Some ads made clear that diet and exercise worked with statins while others claimed that the statin was enough to achieve the desired cholesterol levels.

Given prior work in this area we believe this study contributes in two key ways. First, our study is the first to look at the individual level effects of vitamin and supplement advertising, a large and growing market. Second, we contribute to the growing literature that estimates the individual-level effects of advertising in an observational setting, improving on analyses that focus on market-level exposure.

2.2 Regulatory Oversight of the Vitamin Market

Unlike prescription drugs, which need to undergo randomized controlled clinical trials to prove efficacy and obtain FDA approval, vitamins, minerals, botanicals and other dietary supplements do not need FDA approval in order to be sold; the products do not have to undergo clinical testing in humans, which can take years and cost hundreds of millions of dollars. Under the *Dietary Supplement Health and Education Act* of 1994 (DSHEA), the dietary supplement/ingredient manufacturer is responsible for ensuring that a dietary supplement or ingredient is safe before it is marketed. Since 2007, vitamin manufacturers are required to follow certain guidelines in the manufacturing process to ensure their products are pure, have a consistent strength, and are manufactured appropriately (FDA Final Rule 21 CFR 111).

The FDA shares oversight of dietary supplement advertising with the FTC. The FDA regulates the safety, manufacturing, and labeling of supplements, while the FTC has primary responsibility for regulating advertising (FDA 2013). By law, supplement manufacturers may make two types of benefit claims for their products: *health claims* that describe an established scientific relationship between supplement ingredients and a reduction in the risk of a disease or health-related condition; and, *structure-function* claims which are regulated by 21 USC §343(a)(1) and by 21 USC §343(r)(6)(13)) and describe the intended benefit of the supplement on the structure or function of the body. The FDA has typically applied a substantiation standard for *health claims* of “competent and reliable scientific evidence,” and these claims must be evaluated and authorized by the FDA prior to marketing, as in the case of calcium with vitamin D products that have been approved to claim “reduce the risk for osteoporosis” (21 CFR §101.72) (Brody 2016). *Structure-Function* claims do not bear the same high evidentiary burden of scientific evidence and do not require FDA approval prior to marketing, are liberally used in advertising and labeling to suggest unproven product benefits. For products making structure-function claims the FDA requires that all product making these claims on their labeling or in their advertising carry a disclaimer stating, “This statement has not been evaluated by the FDA. This product is not intended to diagnose, treat, cure, or prevent any disease.”

The unregulated use of largely unsubstantiated structure-function claims has been cited as a concern among public health professionals (Zakaryan et al. 2012) due to the fact that it is nearly impossible to differentiate between substantiated health claims and these more suggestive structure-function claims (Sax 2015) (See example ads in the Appendix A1). Concerns focus on their potential to misleadingly imply that supplements treat diseases (Crawford et al. 2005; Zakaryan et al. 2012). In 2012, an investigation by the Inspector General of the Department of Health and Human Services highlighted these concerns and recommended that the FDA be given greater authority to crack down on such misleading claims (Levinson 2012).

2.3 Evidence for the Role of Vitamins and Mineral Supplements in Health

A 2016 report by Swartzberg (2016) assessed the efficacy and safety of vitamin and dietary supplements in a large meta-analysis. They conclude that existing scientific evidence for the efficacy of these products accumulated over the past decade is fairly ambiguous.

In Appendix Table 2, we report evidence for and against claims that the five most common vitamins in our sample prevent or treat any disease. To highlight some of the findings, while most studies have found no significant, causal relationship between vitamin B consumption and depression (e.g., Penninx et al. 2000; Tiemeier et al. 2002), many studies have found a positive relationship between vitamin D/calcium supplementation and bone health in women (e.g., Jackson et al., 2006; Chowdhury et al., 2014). Vitamin E has not been shown to have positive effects on heart health (e.g., Chae et al. 2012; Formann et al. 2013). Similarly, there is little evidence that fish oil can prevent or treat heart disease (e.g., Sydenham et al. 2012; Grey & Bolland 2014). Multivitamins, the most commonly consumed supplement in the U.S., have been shown to have little benefit for the majority of the U.S. population (Kamangar & Emadi 2012)

Measuring the efficacy of vitamins is challenging. The major limitation is a difficulty to tease out the effect of a vitamin from the effect of other factors, such as generally healthy living (Swartzberg 2016). Furthermore, many studies of vitamin efficacy fall short of the standard of causality by not employing randomized controlled trials (RCT). Studies that do attempt RCTs typically show no impact from vitamin use, or only a tiny effect in a small subset of people (see Appendix Table A2).

Most supplements contain higher amounts of nutrients than would be derived from food, and several compounds can be toxic in excessive amounts when consumed over a long period of time (Mursue et al. 2011). Some studies (Lappe et al. 2007; Hsia et al. 2007), but not all (Chlebowski et al. 2008), suggest that adult vitamin users have higher intakes of nutrients from their diets than do nonusers. For example, evidence suggests that individuals who use mineral-containing supplement have higher mineral intakes from food sources in their diets than do nonusers (Ervin et al. 1999; Schroeter et al. 2013).

Taken together, these clinical studies suggest that consuming dietary supplements without physician direction or knowledge of potential side effects has uncertain benefits and could possibly be harmful to health (Tuomainen et al. 2012). The evidence raises concerns regarding the long-term safety of dietary supplementation for asymptomatic individuals who are otherwise consuming a healthy diet. The cumulative effects of widespread supplement use, together with food fortification, raise public health concerns regarding overconsumption and, thus, long-term health safety.

3. METHODS

3.1 Data and Empirical Measures

3.1.1 Individual-level data—The source of our individual-level data is the Simmons National Consumer Survey (NCS), a proprietary nationally representative repeated cross-sectional survey conducted each six months (N=88,351 observations) (Simmons National Survey 2003–2009). For each wave, the survey is conducted using an independently drawn multi-stage stratified probability sample of individuals. The NCS data include an over-representation of higher-income households. This is an intentional over-sampling because of the marketing nature of the survey. Overall, the NCS weighted-sample statistics are comparable to U.S. Census data on socioeconomic characteristics such as age, gender, race, ethnicity, marital status, income, and health insurance coverage (U.S. Census 2010) (See Appendix Table A3.). Our analysis uses data from 13 NCS waves administered from 2003 to 2009. Furthermore, because our individual-level data come from a household survey with some households containing more than one adult, all of our regression models will have their standard errors clustered at the household level.

From the NCS data, we obtain information on each individual's demographic characteristics, such as age, race, ethnicity, gender, education, household income, location of residence (designated marketing area (DMA)¹), marital status, employment characteristics, number of members in the household, hours worked, and health insurance status. The NCS data enable us to determine the number of hours of television the respondent watches and the number of issues of various magazines they read in a typical week/month.

The NCS also provides information for our dependent variable, which is whether the respondent reports consuming an OTC vitamin supplement (vitamins A, B₁₂, B complex, C, D, E, amino acids, antioxidants, beta carotene, calcium, fish oil, garlic, herbal supplements, iron, multivitamins) in the past 12 months. Unfortunately, we do not observe brand-specific consumption and are thus unable to test directly for market stealing versus market expanding advertising effects. The NCS survey also collects information on 44 different ailments the respondent reports being at risk for, or suffering from, in the past 12 months/If the respondent reports suffering from the ailment, they are asked to report the severity of the condition (mild, moderate, severe).

3.1.2 Vitamin advertisements—Data on OTC vitamin television advertising was obtained from Kantar/TNS Media Intelligence (Kantar Global 2014). We matched the brand names found in the ads data to the vitamin categories in the Simmons data, which allows us to track all of the vitamin subgroups (vitamins A, B₁₂, B complex, C, D, E, amino acids, antioxidants, beta carotene, calcium, fish oil, garlic, herbal supplements, iron, multivitamins). The data provide information on the exact time and program during which a vitamin ad aired. We use data on advertisements that aired between 2002 (lagged year of advertising for the 2003 NCS survey) and 2009 on national networks, cable, and spot markets identified by Designated Marketing Areas (DMAs). The TNS data cover the largest 100 DMAs. The television advertising data set contains 3,237 “unique” OTC vitamin and mineral product ads that appeared 4,928,262 times during the observation period. TNS also provided the cost (media buy) of each television advertisement aired.

Data on OTC vitamin magazine advertising also was obtained from Kantar/TNS Media Intelligence (Kantar Global 2014). The magazine advertising data provide information on the exact magazine and issue that an ad appeared in, and the date of publication. All the magazines in our dataset are circulated nationally.² The print advertising data set contains 1,438 “unique” OTC vitamin and mineral product ads appearing 3,375 times during the observation period. TNS also provided the cost (media buy) of each print advertisement circulated.

All 1,438 unique print and 3,237 unique television advertisements were viewed and coded by two trained and independent research assistants to identify the primary and, if necessary, the secondary supplement being featured in the advertisement. Discrepancies were resolved by reexamination and discussion by the coders. The designation “primary” was assigned to an ad if the nutrient featured was the central one being advertised. Some advertisements featured additional supplement types (e.g., B Complex with C Stress Formula). In this case vitamin B was classified as the “primary” category and vitamin C was designated as the “secondary” product being advertised.

¹To assign a DMA to an individual, we use a unique combination of state and DMA Rank (provided to us in the NCS in a series of cut offs) to determine where a respondent lives. First, the NCS has a variable indicating if the respondent lives in one of 14 select DMAs (Atlanta, Boston, Chicago, Cleveland, Dallas, Detroit, Houston, Los Angeles, Miami, New York City, Philadelphia, San Antonio, San Francisco, and Washington DC). Next, for the remaining respondents, the NCS identifies DMA rank (1–5, 6–10, 11–25, 26–50, or 51–100). For these remaining individuals, we can assign a DMA based on the DMA rank variable and the State variable.

²TNS reports that that less than 10 percent of all magazine dietary supplement ads appeared in regional issues, with ~90%+ appearing in national issues.

3.1.3 Individual media behavior and vitamin advertising exposure—To measure potential exposure to OTC vitamin and mineral supplement advertisements, we link data on individuals' reported magazine reading and television viewing behavior in the past week/month to TNS data on vitamin ads appearing in television programs and magazines that respondents report watching/reading. A similar approach was used by two previous studies using the same NCS/TNS data (Avery et al. 2007b; Avery et al. 2012).

The NCS data includes detailed information on the intensity of the individual's consumption of TV and magazine media, including number of issues (and fractions of those issues) of specific magazines read; television programs they regularly watch on network and cable channels; and, times of the day they usually watch television on weekdays and weekend days. The NCS presents individuals with an expansive list of magazine and television programs to review, and asks them to indicate which they read/watch regularly, and for television, what time of day. The list of magazines and television programs included in the NCS survey does not cover the full spectrum of Spanish language magazines circulated and television channels/programs aired in the U.S. For this reason, we omit from our sample individuals who report Spanish as being their home language and having a preference for reading magazines and watching television mainly in Spanish.³ Our data does not include the exact date the respondent took the survey so we assign every individual the first day of the survey window and assume that the past month's viewing/reading behavior is similar to the past year's.

We measure a respondent's potential exposure to a vitamin advertisement appearing on *television* by matching ads that appeared over the past year during programs or time slots the respondent reports watching regularly. To identify which television programs (and thus the ads in those programs) were likely to have been viewed by an individual, we relied on several NCS questions. Each respondent in the survey is asked about whether they watch episodes from a list of approximately 1,075 broadcast and cable television programs on 765 different networks/channels⁴. They are then asked about whether they typically watch broadcast/cable television during specific, narrowly defined time slots of the week/weekend day. We consider an individual potentially exposed to a vitamin advertisement if the ad aired during specific programs they report watching regularly on television, aired during broadcast programs in time slots they report watching regularly, or aired in time slots and on specific cable networks they report watching regularly. Television advertising occurs at both the national and local (spot) level. To leverage this variation in our exposure measure, we match national ads that appeared in all DMAs to all respondents, and match only local ads that appeared in the respondent's DMA.

Our measure of potential advertising exposure will underestimate actual exposure since we rely on respondents to report episodes they watch from a certain list, which, while very

³The 2003–2009 NCS data contain N=156,775 observations; N=88,351 observations have both a DMA identified and include respondents whose primary language is English and who report preferring to read/watch television in English, which represents our analytic sample.

⁴Experian has done considerable research into assuring complete responses from respondents and ways to reduce burden and prevent fatigue. Questions are delivered in manageably sized booklets over the course of several weeks. Customer service representatives are available to answer questions about the survey or specific questions. Various experiments performed by Experian have shown ways to reduce non-response and have been implemented into the national methodology.

comprehensive, is not the universe of all possible programs. How much our measure understates a certain person's potential advertising exposure depends upon whether they happen to watch programs not recorded in the NCS survey. The television time slots not covered by our data are 1 a.m. to 5 a.m. for broadcast television and 1 a.m. to 6 a.m. for cable television.

To construct measures of potential *print* advertising exposure, we merge information on vitamin ads appearing in specific magazines/issues to each respondent in the sample, based on their reported magazine-reading behavior. Each respondent in the NCS sample reported how many issues of each magazine (presented on a comprehensive list of 151 nationally-circulated magazines) he/she reads on average out of the past four issues. We calculate the fraction of the last four issues the respondent reports reading and multiply this fraction by the number of ads appearing in that magazine over the past year.

We describe the measure of advertising exposure we use in this study as 'potential' exposure since we do not know if respondents in the NCS sample actually saw an advertisement airing on a television program they report watching regularly, as they could have been "surfing" channels when the advertisement aired or using a recording device (DVR)⁵. Similarly, they could have passed over the magazine page containing the advertisement without reading it, or read a different section of the magazine. Furthermore, since media consumption is only asked in the survey rather than gauged continuously, we assume that the reports of habitual ("typical") use are accurate over the year. For example, using our magazine advertising measure, we assume that an individual's reported reading habits over the past four issues of the magazine (one month for weekly magazines, four months for monthly magazines) reflects his/her reading habits over the past year. Although our measure is to be viewed as potential exposure to, it nevertheless has several advantages over aggregate national and market-level measures used in previous research, since those implicitly assume that all individuals in a particular market are exposed to the same level of advertising.

4. Econometric Model and Identification

4.1 Impact of Advertising Exposure on Demand

To estimate the effect of advertising exposure on demand for vitamins, we estimate models of the following form:

$$P(y_i=1)=f(\beta_0+\beta_1 Ads_{print,i}+\beta_2 Ads_{TV,i}+\beta_3 X_i+\beta_4 TV_i+\beta_5 Print_i+\beta_6 W_i+\varepsilon_i) \quad (1)$$

Where y is an indicator variable for vitamin consumption, Ads_{print} is the print DTCA exposure⁶, Ads_{TV} is the television DTCA exposure, X is a vector of demographic characteristics⁷, TV is a vector of television targeting controls (variables for each program)⁸

⁵While DVRs have become a common way of skipping through advertisements, Nielsen (2014) reports that the most common form of viewing during our study period was live viewing.

⁶Most studies in the advertising literature model advertising as a stock that depreciates over time. Unfortunately, since we do not observe the actual survey date nor follow respondents over time, we are unable to do this and instead model advertising as a static input.

and number of hours of TV watched), *Print* is a vector of print targeting controls (variables for each magazine and number of issues read), *W* is an indicator for the NCS wave, and ϵ is a Type 1 distributed error term. We calculate and present marginal effects from logit specifications. We estimate models with advertising exposure specified in a variety of function forms (linear, logs, quintiles) to examine the distribution of the effect (and if the result is robust to misspecification). When estimating logged models, we are unable to take the log of zero so we add one ad to every individual before taking logs.

While our measure of individual advertising exposure accurately captures the number of advertisements likely seen by the consumer, it does not capture how prominently the ad was placed or the length/size of the ad. Estimating the effect of exposure to ad dollars allows us to make more concrete comparisons between print and television media effects, where one ad will have differing reach and impact across media. We create measures of individual exposure to advertising spending and estimate the following model:

$$P(y_i=1)=f(\beta_0+\beta_1Spend_{Print,i}+\beta_2Spend_{TV,i}+\beta_3X_i+\beta_4TV_i+\beta_5Print_i+\beta_6W_i+\epsilon_i) \quad (2)$$

where *Spend_{print}* and *Spend_{TV}* are individual exposure to advertising dollars and the other variables are defined as in (1). We also estimate stratification models to test for gender and education differences, which have been found in previous literature (Avery et al., 2012; Ridley 2015).

4.2 Demand for Specific Vitamins

To test how the effect of advertising varies across vitamin types, we re-estimate equation (1) for the seven most commonly consumed vitamins (vitamins B, C and E, multivitamins, antioxidants, fish oil, and calcium). In these models, the dependent variable is consumption for the specific vitamin and the independent variable is advertising exposure for the specific vitamin (e.g., the effect of calcium advertising exposure on calcium consumption).

Next, we examine how the vitamin-specific advertising effects on specific vitamin consumption varies across the health distribution. We draw on the medical literature described in Section 2.3 and test the links between calcium advertising and osteoporosis, vitamin B and depression, fish oil and heart disease, and vitamin E and heart disease. These four case study vitamin-disease links were chosen for three reasons. First, osteoporosis, depression, and heart disease are all high prevalence diseases both in our data and across the U.S. Second, based on the medical literature described in Section 2.3, a substantial amount of research has been done to test if these vitamins can treat and or/prevent these ailments. Last, it allows us to look for differences across substantiated versus not substantiated claims. Specifically, calcium has been shown to have both treatment and preventive effects on osteoporosis (Moyer 2012; Chowdhury et al. 2014) while B vitamins, vitamin E, and fish oil

⁷Demographic controls include age, race, ethnicity, marital status, education, hours worked, household size, income, insurance status, and DMA.

⁸We provide more detail about the nature of the targeting controls in the identification section (Section 4.3).

have not been shown to prevent or treat depression and heart disease, respectively (Penninx et al. 2000; Chae et al. 2012; Grey et al. 2014).

This analysis allows us to test for preventative versus therapeutic demand creation. If we primarily observe effects in healthy and not sick individuals, then the results would suggest advertising creates preventative and not therapeutic demand, and vice versa. If consumers are responding to the clinical literature, we might observe calcium ads influencing both preventive and therapeutic demand. It's unknown, a priori, how consumers will respond to ads in the other three case study classes, as the clinical literature does not support disease prevention or treatment.

We estimate models of the following form:

$$P(y_i=1|H)=f(\beta_0+\beta_1 Ads_{print,i}+\beta_2 Ads_{TV,i}+\beta_3 X_i+\beta_4 W_i+\varepsilon_i) \quad (3)$$

where H is the health status of the consumer, y is the specific vitamin type (e.g., calcium), and Ads_{print} and Ads_{tv} are exposure to vitamin-specific advertising (e.g., calcium ads). In practice, we stratify the model on H and estimate the effect of advertising on demand for those who do/do not suffer from the ailment. For example, we estimate the effect of calcium advertising on calcium consumption for those who do not have osteoporosis and then again for those that do have osteoporosis.

4.3 Identification

Individual advertising exposure and exposure to ad expenditure are likely endogenous to vitamin consumption as marketers are targeting their ads to consumers who are more likely to purchase them. This would create an upward bias on our estimates of B_1 and B_2 . This targeting bias can lead researchers to incorrect conclusions and vastly overstate the effectiveness of advertising (Lewis et al. 2011; Hoban et al. 2015).

The richness of the NCS data allows us to mitigate this potential bias in two important ways. First, the data is available and used by marketers and we are able to control for the same demographic information that marketers use to determine their target market. Second, since ads appear on specific television programs and in particular magazines that marketers select for targeting, we include a set of dummy variables for every television program and magazine title that the NCS survey. In all, we include over 1,200 covariates to reduce variation in vitamin consumption not due to targeting.

We estimate and present three different ways of controlling for targeting. First, we include indicator variables equal to one if the respondent ever reported viewing (reading) each program (magazine). This identification strategy has been used in prior work (Avery et al., 2012). A second method estimates models with variables that measure how often the respondent watches (reads) the program (magazine). For example, for magazines, on a scale of 1=read every issue of the last four issues of the magazine, to .75= read three of the last four, .5= read two of the last four issues .25= read one of the last four issues, 0=none of the last four issues. A third method (our preferred specification) is to include indicator variables

for watching (reading) a program at a high frequency (greater than 75% of the time). We view this as the strictest specification as advertisers likely target viewers (readers) who regularly watch (read) a program (magazine). While our main tables use only the third specification of controlling for targeting, in an alternative model specification, we try each method and find our results do not change appreciably.

After controlling for these potential targeting confounders, the key identification assumption in this model is that the amount of advertising the consumer is exposed to is random after controlling for program viewership and magazine readership. The survey wave fixed effects we include in the models control for any national changes in price or availability. While firms choose advertising as a function of demand unobservables (Goeree 2008), we use and control for the same set of covariates available to firms by using a commercial marketing survey. Furthermore, by including the targeting controls, we exploit the plausibly random variation in advertising exposure across two individuals who are identical on observables and watch the same amount of the same television programs, but in different years. This year-to-year variation in advertising is the source of our identifying variation. It is important to note that this year-to-year variation of advertising expenditure (or pulsing) has been shown to be, under certain conditions, a rational firm policy from a theoretical (Mesak 1985) and empirical perspective (Danaher & Rust 1996).

One possibility is this year-to-year fluctuation, in it of itself, might be endogenous. Suppose that a new piece of information came from the medical literature that a certain vitamin is effective in treating a specific disease. This could drive an increase in advertising expenditure from firms producing that vitamin and simultaneously result in an increase in demand for that vitamin. If this increase was general or seasonal, the survey wave dummies should absorb this endogenous variation. However, it is possible that in our main model (demand for any vitamin) this is still a concern. While the wave dummies pick up all trends generally affecting all vitamins, information regarding different vitamin types may be flowing into the market at different points in time and this may be correlated with advertising volume. This source of bias is reduced in the vitamin-specific models, where survey wave dummies pick up any vitamin-specific flows of information or trends.

It is also possible that television advertising might be assigned in a more probabilistic nature or measured with greater error. This could be due to time shifting (DVR use) or less precision in consumer recall of specific time slots viewed. While live viewing was far more popular than DVR viewing during this time period (Nielsen 2014), we estimate additional robustness checks with less probabilistic exposure measures. Specifically, we estimate models where the exposure measure calculation only allocates print ads if the respondent reported viewing 3 or 4 of the past 4 issues and allocates television ads based on specific program viewings (instead of channels/time slots).

While the magazine advertising market is national, the television advertising market has a regional component and might be subject to unobservable regional shocks, which could introduce bias into our estimates. For example, if a local Vitamin B manufacturer that only sold in the Midwest lowered its price in combination with an ad campaign, the wave fixed effects would not adequately capture this variation and lead us to overstate the returns to

advertising. While our main specification controls for DMA, we estimate additional robustness checks with state fixed effects as well as DMA and state-specific time trends. These additional models estimate effects exclusive of any unobservable regional shocks.

It is also possible that firms are specifically targeting to certain areas that have a higher prevalence of sicker consumers or consumers with specific ailments. While DMA indicators and DMA-specific time trends should pick up overall trends, we estimate an additional robustness check to control for this. Specifically, we estimate two additional models. The first controls for overall sickness by including a variable counting the number of ailments (0 to 44) the respondent reports suffering from. Second, we estimate a model where we include indicator variables for each of the 44 ailments asked about in the NCS survey.

The readership of magazines and viewership of certain television shows might also change over time. If these readership/viewership changes are correlated with some differential information flows that are targeted at certain types of individuals (e.g., women), this might be driving both ad exposure as well as vitamin consumption. To address this concern, we first check to see if the fraction of different subgroups who are exposed to ads is changing over time. Second, we estimate a robustness check where we interact age and gender covariates with survey wave, to allow for different intercepts for each age and gender sub group.

As a final robustness check, we estimate a placebo effect where individuals are matched to ads that will appear after they take the survey. Ads that appear in future magazines and television programs should have no effect on current period consumption.

5. RESULTS

5.1 Sample Description

Our sample includes 88,351 individuals surveyed from 2003–2009. Table 1 reports descriptive characteristics of the sample. On the whole, the female sample is slightly older, has a higher percent non-white, and is slightly less educated. Approximately 85 percent of the sample has health insurance, which is slightly more than the U.S. as a whole during this time period⁹. We have an even regional balance (about a quarter in each of the four main census regions) and a similar household income distribution as the U.S. Women in the sample, on average, read more magazines (6.4 vs. 4.5 issues per year) and watch more television (39 versus 37 hours per week) than men.

Table 2 reports the frequency with which survey respondents consumed 19 different vitamins or supplements. Females are more likely than males to consume any vitamin (64.7 percent versus 51.4 percent). In addition, females are more likely to consume any individual category of vitamins. These differences are stark in categories that are specifically targeted toward women (e.g., calcium, prenatal supplements) and less apparent for gender-neutral supplements such as fish oil (11.1 percent for males and 13.7 percent for females).

⁹For a full comparison of the distribution of covariates in our sample versus the United States, see Appendix Table 2.

The trend in advertising exposure roughly tracts the total volume of ads over time (Figure 1). Print advertisements appear to have peaked in 2006, while television advertising continues to increase into 2009 (with a slight dip in the second half of 2009 coinciding with the recession). Multivitamins (Appendix Table A4) have the highest mean exposure rate (0.82 print ads and 183.58 television ads) and several products with low levels of consumption have zero advertising (e.g., beta carotene, garlic supplements). Females are, on average, exposed to more print and television ads across all subcategories. This gender difference is reflective of both firm-level targeting, as seen in the consumption patterns in Table 2, and of higher readership and viewership by females (Table 1). Appendix Table A5 reports exposure to advertising dollars and largely portrays the same patterns.

Appendix Figures A6 and A8 show the number of manufacturers advertising in the market for television and print, respectively. There is very little variation within category or over time, with the exception of an increase in manufacturers advertising in print media from 2004 to 2005. This is clear from new entrants in the calcium, multivitamin, fish oil, and herbal supplement markets. Appendix figures A7 and A9 show the number of products advertised per manufacturer over time. Here, there is almost no variation, with each manufacturer having only a few products, on average.

5.2 The Effect of Advertising on Vitamin Use

Table 3 presents results from our main estimating equations (1) and (2). Television and print advertising exposure are both significantly predictive of vitamin use. A 10 percent increase in television advertising increases the probability of vitamin use by 0.06 percentage points, while a 10 percent increase in print advertising is associated with a 0.44 percentage point increase in vitamin use. The sign and significance of this effect is consistent in both linear and log specifications (Columns 1 and 2). If we consider an individual moving from zero to the mean level of exposure (about 3 print ads and 300 television ads), we would expect an increase in the probability of consumption by 1.2 percentage points for print and 0.8 percentage points for television. Off of a base consumption rate of 58.9 percent, this corresponds to 2 and 1.4 percent increases for print and television, respectively.

Columns 3 and 4 present results on how increased exposure to advertising spending affects vitamin demand. As mentioned in Section 4, by specifying television and print advertising in the same unit (dollars), we can make cross-media comparisons. First, the spending models tell the same story as Columns 1 and 2; that advertising increases demand for the product. There is less evidence with regards to the difference between print and television effects. The coefficients on print and television are much closer in magnitude, particularly in the log specification.

Figure 2 presents a less parametric specification, with dummy variables for each quintile of advertising exposure.¹⁰ The effect of television advertising is fairly constant across the distribution. Compared with the bottom quintile of exposure, the effect of being exposed to 72 ads (2nd quintile) is 0.012. This effect decreases slightly in the third through fifth

¹⁰Quintile cutoffs are available in Appendix Table A10. Full model results associated with Figure 2 are available in Appendix Table A11.

quintiles and loses statistical significance. In contrast, the effect of print advertising is increasing in the number of ads, with the 3rd quintile of exposure (0.125 ads) being associated with a 3 percent increase in the probability of consumption, and the 5th quintile of exposure (3.125 ads) associated with a 10 percent increase in probability of consumption. This difference in the distributions of the print versus television effects is consistent with marketing theory (Braun et al. 2013; Lehnert et al. 2013), which predicts a “wearing out” of television advertising. Another possibility is that the demographic mix of viewers varies significantly by advertising quintile (Appendix Tables A12 and A13). Those that are exposed to more print ads are much more likely to be female while those that are exposed to more television ads are significantly older and more female. While these demographic variables enter our models as controls, it is possible that some of these differences in characteristics are driving some of the difference in the ad response.

In Table 4, we estimate the model stratifying by gender, education, and insurance status. We find slightly stronger effects for males than females. Though this difference is significant with television ($p=0.018$), the effects are not significantly different in print ($p=0.971$). Furthermore, for print, we find marginally significant ($p=0.097$) larger effects for individuals with lower levels of education. We find slightly larger effects for those with no insurance versus those who have health insurance which are marginally significant in television ($p=0.099$) and not significant in print ($p=0.188$). Smaller baseline consumption and less room to grow the market might explain part of these differences. Females consume more vitamins at baseline than males (64.7% and 51.4%, respectively) and likewise for high education and low education individuals (63.6% and 52.5%) and insured versus uninsured individuals (61.9% and 38.5%).

5.3 Robustness Checks

Table 5 presents results using the three different types of targeting controls. The first column uses simple targeting controls (an indicator for watching/reading the program/magazine), the second column includes controls that accurately control for high frequency viewers (readers), while the third column controls for how often the respondent watches (reads) each program (magazine). We test how much variation is left in the exposure variables after controlling for targeting. To do this, we estimate models with linear advertising exposure as the dependent variable and the targeting controls as the independent variables. The “high frequency” controls soak up more variation in exposure (0.216 to 0.183 for TV and 0.620 to 0.691 for print), while the continuous controls soak up even more variation (0.178 for TV and 0.583 for print). After estimating the model, the effect sizes do not change much, regardless of the type of targeting control used. Stricter controls lead to slightly larger estimates than the controls used in previous studies, suggesting that using weaker controls lead to a slight underestimation of effects.

In Table 6, we estimate additional models with the less probabilistic exposure measure defined in section 4.3. In column (1), we report our base model and, in column (2), we report results from this alternative exposure measure. We find no significant changes in the magnitude or significance of the coefficients.

In Table 7, we control for unobservable regional demand shocks that might be correlated with advertising and consumption. In column (1) we report our base model (DMA controls) from Table 3. In columns (2), and (3) we include DMA-specific time trends, and both fixed effects and time trends, respectively. In columns (5)-(7), we repeat using state instead of DMA measures. While the magnitude of the estimates and standard errors change slightly, the estimates remain statistically different from zero at the one percent level. Furthermore, if we compare the laxest specification (state fixed effects) to the strictest (DMA fixed effects and DMA-specific time trends), we find the coefficients change much more for television than print. This is consistent with the hypothesized direction we identified in section 4.3, specifically that the television advertising market has a regional component and is thus susceptible to regional shocks while the national magazine advertising market is not.

In Table A14, we estimate an additional robustness check controlling for the health status of the respondent. Column (1) has our base model. In columns (2) and (3), we control for the number of ailments and indicator variables for every ailment asked about in the NCS survey. While the results do move slightly in magnitude, the shifts are not significantly different.

We also check for different information flows across subgroups in Tables A15 and A16. In Table A15, we find that, stratifying by median ad exposure, the fraction of females and the average age of the respondents do not seem to be changing in any appreciable way. Additionally, in Table A16, we estimate models where we fully interact age and gender with survey wave to allow for differing trends in consumption by subgroup that may be driven by unobservable information flows. As seen in Column (2), our results do not significantly change when these controls are included.

In Table A17, we estimate a model using measures of future ad exposure as a placebo check. Given the high correlation between current and future exposure, we enter current exposure into the model in logs and future exposure in levels. When we include future exposure, we find that our main results slightly decrease in magnitude but not in significance. The effect on future television exposure is a precise zero. The effect on future print ads is significantly different from zero ($p < 0.05$) but is orders of magnitude smaller than the estimated effect for current print exposure, very close to zero, and not economically meaningful.

5.4 Demand for Specific Vitamins

Figure 3 presents results for the effect of vitamin-specific advertising on vitamin-specific use¹¹. We present results from the seven most commonly consumed vitamins and supplements (vitamins B, C and E; multivitamins; antioxidants; fish oil; and calcium). Vitamin-specific print advertising always increases the probability of consumption, while television advertising is only marginally significant at the 10 percent level for multivitamins. Given the null result for television advertising in all of the other categories, the television effects observed in Table 3 are being completely driven by multivitamin advertising and consumption (which makes up the largest share of all vitamin advertising). When we test the significance between the print coefficients, we fail to reject the hypothesis that print advertising has a differential effect across most vitamin categories. When we estimate these

¹¹Full model results are available in Appendix Table A18.

models with advertising expenditure instead of ads (Appendix A19), we find largely similar results, except that fish oil and multivitamin television ad spend are larger in magnitude and significantly different from zero.

In Table 8 we report how exposure to specific vitamin advertising affects demand for specific vitamins across the health distribution. By stratifying by health status we are able to see if these effects vary by the ailment that the product claims to treat or prevent. We find effects for increased calcium exposure for those women without osteoporosis (Panel A), though the difference between those with and without osteoporosis is not significant. Panel B finds that there is an effect of increased vitamin B print advertising in females, both for those with and without depression. A 10 percent increase in ads featuring vitamin B suggests a 0.47 percentage point increase in the probability of consuming vitamin B for those females without depression (Column (1)) with is significantly greater ($p < 0.001$) than the 0.26 percentage point increase in the probability of consuming for those with depression.

In Panels C and D we examine the effects of advertising for those with and without heart disease¹². Based on our review of the medical literature in section 3.3 and the variables available in the NCS, we link heart disease to two supplements, fish oil and vitamin E. For fish oil (Panel C), we find there is an effect of print advertising for both those with (0.0272) and without heart disease (0.0543). We find similar effects for Vitamin E.

In summary, we find various vitamin-specific effects for print advertising and slight evidence for television advertising (in multivitamins). We find effects for increased calcium exposure for females without osteoporosis. The effect for vitamin B advertising occurs for those without depression (in females). Fish oil and Vitamin E-specific effects occur for those with and without heart disease. Given the small sample sizes among those with individual ailments, we are unable to make any conclusive statements across health status. We can only rule out that vitamins are used strictly for prevention or strictly for therapy, particularly among those with and without heart ailments.

6. DISCUSSION AND CONCLUSIONS

To the best of our knowledge, this study is the first to examine how individual-level exposure to vitamin advertising affects the probability of vitamin consumption. We estimate these effects for a variety of different vitamins using measures of ad volume and advertising expenditure. Furthermore, we innovate on past identification strategies by controlling for not only which programs (magazines) are watched (read), but also how *often* they are watched (read). We find evidence that advertising is driving demand for these products, with large and robust effects in the medium of print. This is in contrast to what prior literature has found in prescription drug markets (Avery et al. 2012; Dave & Saffer 2012) suggesting differing advertising effectiveness in OTC markets. Effects are slightly larger for males than females, significantly larger in the less educated, and significantly larger among those without health insurance. These results may provide evidence of possible information

¹²We define a respondent as having heart disease if they report having suffered a heart attack, suffer from heart disease, suffer from high cholesterol, or suffer from hypertension, in the past 12 months.

asymmetries in the market, or they may indicate that low-education individuals respond more to the information claims made in vitamin advertisements. In our stratifications to test for preventive versus therapeutic demand creation, we find possibly larger preventive effects for ailment-vitamin links that have a stronger clinical evidence base (calcium and osteoporosis). However, due to small sample sizes, we are unable to reject the null that the effect of advertising is the same across health and sick individuals. Overall, our results contribute to the literature on how consumers respond to advertising and information in healthcare markets in general, and whether such ads can raise overall demand, as opposed to just having brand switching effects.

The effect sizes we estimate are small, but still economically meaningful. If a consumer moved from seeing zero to the mean level of print advertising (just 3 additional ads), we would expect a 1.2 percentage point increase in the probability of consumption, or a 2 percent increase off a base consumption rate of 58.9 percent. The results are in line with what has been found in studies examining other DTCA markets (antidepressants 3 percentage points found by Avery et al., 2012; smokeless tobacco 2.5 percentage points found by Dave and Saffer 2013) and advertising experiments (Johnson et al. 2016). Given the monetary cost of the good and the possible health consequences (Swartzberg 2016), these small effects might still have a large impact on public health.

Our analysis has several important limitations. First, given the nature of our exposure measure, we are unable to observe if the consumer actually read/watched the advertisement they were exposed to. While this should only bias our estimates downward, we agree that future work could examine vitamin advertising in a controlled experimental setting. However, experimental settings come with their own limitations (e.g. difficult to observe consumption effects). Second, we can only observe the effect of advertising on the probability of *any* consumption. We are unable to see if advertising increases the quantity of vitamins consumed or if it increases the likelihood of brand switching. Third, while our sample is comparable to the ACS across most observables, it appears to have a higher rate of television viewing than comparable time use studies. We observe consumers reporting 38 hours per week of television while the 2005 Bureau of Labor Statistics estimated roughly 20 hours per week (BLS 2009). This might limit our external validity, though our strongest effects are observed only in print. Fourth, recent large field experiments have suggested that measuring the accurate returns to advertising can be very difficult in an observational setting (Lewis and Rao 2015). Lewis and Rao report that when estimating the effect of advertising on the extensive margin using observational data, it is difficult to precisely estimate small effects when the outcome variable has a high variance. Though experimental research comes with their own limitations and we employ extremely rigorous targeting controls to isolate plausibly causal effects, future work should attempt to isolate the impact of vitamin advertising in a more controlled experimental setting to eliminate all sources of targeting bias. Lastly, though we find similar marginal effects of similar magnitudes when using expenditures instead of ads, there is not a statistically significant different response to print versus television ad expenditures. This is in contrast to the stronger print response we find when using ad exposure, though, it is consistent with firms allocating ad budgets across media in a profit maximizing way, where the last dollar spend in each media is achieving the same marginal benefit.

Given the possible lack of efficacy for treatment/prevention of disease of some of these products, it is concerning that advertising is fueling demand, especially among the less educated and uninsured. However, as we noted above, research on vitamins has been mostly focused on observational studies and large scale randomized controlled trials of vitamin effectiveness have been lacking. Additionally, some sub-populations have been shown to benefit from vitamin consumption (e.g., calcium and osteoporosis, folic acid as a prenatal supplement). Furthermore, other literature on DTCA of prescription drugs has shown some positive spillover effects, such as increasing the likelihood of high-cholesterol diagnosis or diet and exercise (Niederdeppe et al., 2013; Niederdeppe et al., 2016). Given this uncertain evidence and our focus on utilization (not health outcomes or spillovers effects), we are unable to say for certain if the demand creation we observe is welfare increasing or welfare reducing. Despite lack of evidence of the overall welfare gains or losses associated with vitamin DTCA State Attorneys Generals are investigating the industry they claim is “plagued by misleading labels” (O’Connor, 2015). Furthermore, DTCA practices in general are coming under harsher criticism, with the American Medical Association recently calling to ban all prescription drug advertising in the United States (AMA, 2015).

The uncertain scientific evidence for the efficacy of these products leads us to believe that this market is characterized by information asymmetries leading to significant market inefficiencies. We find strong evidence that advertising by manufacturers of these products (and potentially exaggerated claims made in these ads) is fueling demand and capitalizing on this possible informational asymmetry. We are unable to determine exactly what claims are being made in these supplement ads (we leave that for future researchers to identify) but a general examination of these ads used in this study suggests, like Hensley (2012), that “one could be forgiven for thinking they are good for just about anything that could ever ail you.” Once the claims made in these advertisements have been analyzed, the FTC might consider taking a similar approach as they used in their “Red Flag” initiative in the weight loss product market (Avery et al. 2013), although there is mixed evidence as to whether the FTC was successful in reducing the most egregious claims being made in these weight-loss ads (Lellis, 2015).

In addition, future work should examine exactly who is being targeted by these ads, and where the advertising dollars are being directed. Targeting vulnerable populations (e.g., low income or the elderly) might exacerbate health disparities in these populations, and thus should be carefully examined by policymakers.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1. Total Advertising and Advertising Exposure Over time

Notes: Graphs show the total number of ads that appear nationally in the Kantar/TNS data (right axis) and the average advertising exposure in our sample (left axis) by Simmons Survey wave.

Figure 2. Model Coefficients with Quintiles of Print and TV Exposure

Notes: Marginal effects from logit models reported. Full model results available in Appendix Table A10. Lines indicate 95% confidence intervals based on clustered standard errors. Due to the large number of zeros, there is no second quintile for print exposure. Demographic controls include race, age, education, household income, health insurance status, marital status, number of hours worked per week, DMA, household size and survey wave dummies. Targeting controls include dummies for watching each television program and reading each magazine (where =1 if watched/read greater than 75% of the time). Targeting controls also include number of magazine issues read and average hours of television watched per week.

Figure 3. The Effect of Vitamin-Specific Advertising on Specific Vitamin Use

Notes: Marginal effects from logit models reported for Vitamin B, Vitamin C, Vitamin E, Fish Oil, Multiple Formula and Vitamin D or Calcium. Linear probability model coefficients on log exposure reported for Antioxidants. Full model results available in Appendix Table A2. Clustered standard errors at the household level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Demographic controls include race, age, education, household income, health insurance status, marital status, number of hours worked per week, DMA, household size and survey wave dummies. Targeting controls include dummies for watching each television program and reading each magazine (where =1 if watched/read greater than 75% of the time). Targeting controls also include number of magazine issues read and average hours of television watched per week

Table 1

Sample Statistics by Gender: Simmons National Consumer Survey 2003–2009

	Male N = 38,795		Female N = 49,556		Entire Sample N = 88,351	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Age						
18 – 30	0.131	0.337	0.127	0.333	0.129	0.335
30 – 39	0.133	0.340	0.142	0.349	0.138	0.345
40 – 49	0.206	0.405	0.205	0.403	0.205	0.404
50 – 59	0.215	0.411	0.215	0.411	0.215	0.411
60 – 69	0.165	0.371	0.160	0.367	0.162	0.369
Above 70	0.150	0.357	0.152	0.359	0.151	0.358
Race						
White	0.844	0.363	0.837	0.369	0.840	0.367
Black	0.0690	0.253	0.0822	0.275	0.0764	0.266
Other	0.0872	0.282	0.0808	0.273	0.0836	0.277
Ethnicity						
Hispanic	0.125	0.331	0.122	0.327	0.123	0.329
Not Hispanic	0.875	0.331	0.878	0.327	0.877	0.329
Marital Status						
Married	0.695	0.461	0.597	0.491	0.640	0.480
Never Married/Separated/Divorced/Widowed	0.305	0.461	0.403	0.491	0.360	0.480
Highest Level of Formal Education						
Did Not Graduate High School	0.0942	0.292	0.0788	0.269	0.0855	0.280
Graduated High School/<1 Year College	0.321	0.467	0.358	0.480	0.342	0.474
Attended College 1 – 3 Years	0.206	0.404	0.225	0.417	0.216	0.412
Graduated College or More	0.379	0.485	0.338	0.473	0.356	0.479
Hours Worked						
0 Hours	0.362	0.481	0.461	0.498	0.417	0.493
1 – 14 Hours	0.0252	0.157	0.0482	0.214	0.0381	0.191
15 – 29 Hours	0.0518	0.222	0.0946	0.293	0.0758	0.265

		Male N = 38,795		Female N = 49,556		Entire Sample N = 88,351	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
Number of People in Household	30 – 39 Hours	0.0613	0.240	0.102	0.303	0.0843	0.278
	40 Hours	0.176	0.381	0.151	0.358	0.162	0.368
	41 – 50 Hours	0.221	0.415	0.113	0.317	0.160	0.367
	50+ Hours	0.103	0.304	0.0300	0.170	0.0621	0.241
People in Household		3.017	1.442	2.919	1.491	2.962	1.471
Overall Household Income							
	< \$30,000	0.108	0.310	0.154	0.361	0.134	0.340
	\$30,000 – \$60,000	0.226	0.418	0.243	0.429	0.236	0.424
	\$60,000 – \$100,000	0.266	0.442	0.251	0.434	0.257	0.437
	\$100,000 – \$150,000	0.200	0.400	0.180	0.384	0.189	0.391
	\$150,000 – \$200,000	0.137	0.344	0.119	0.324	0.127	0.333
	> \$250,000	0.0633	0.244	0.0534	0.225	0.0578	0.233
Health Insurance Status							
	Insurance	0.856	0.351	0.881	0.324	0.870	0.336
	No Insurance	0.144	0.351	0.119	0.324	0.130	0.336
Media Use							
	Number of Magazine Issues read per year	4.479	12.76	6.413	14.45	5.564	13.76
	Number of TV Hours watched per week	37.75	31.57	39.55	31.18	38.76	31.37
Census Region							
	Northeast	0.240	0.427	0.242	0.428	0.241	0.428
	Midwest	0.226	0.418	0.224	0.417	0.225	0.417
	South	0.316	0.465	0.318	0.466	0.317	0.465
	West	0.217	0.412	0.216	0.411	0.217	0.412

Note: Respondents in the NCS sample used for this analysis were restricted to those who are English speakers, and bilingual respondents who indicated on the survey that they prefer to watch television/read magazines in English. Similar descriptive statistics on the full NCS sample for these years, including bilingual respondents who do not prefer to watch television/read magazines in English, are available from the authors upon request.

Table 2

Percent of Sample Reporting Consuming a Vitamin/Mineral by Type of Vitamin/Mineral and Gender

		Male N = 38,795 Mean	Female N = 49,556 Mean	Entire Sample N = 88,351 Mean
Vitamin Consumption				
	Any Vitamins	0.514	0.647	0.589
	Vitamin A	0.0160	0.0189	0.0176
	Vitamin B	0.102	0.146	0.127
	Vitamin C	0.125	0.145	0.136
	Vitamin D	0.0331	0.0640	0.0504
	Vitamin E	0.0918	0.111	0.103
	Amino Acids	0.0168	0.0156	0.0161
	Antioxidants	0.0406	0.0476	0.0445
	Beta Carotene	0.0164	0.0169	0.0167
	Calcium Supplement	0.0745	0.289	0.195
	Dietary Supplement	0.0311	0.0403	0.0362
	Fish Oil Supplement	0.111	0.137	0.125
	Garlic Supplement	0.0302	0.0288	0.0294
	Herbal Supplement	0.0347	0.0523	0.0446
	High Potency Supplement	0.0157	0.0125	0.0139
	Iron Supplement	0.0194	0.0524	0.0379
	Multiple Formula	0.369	0.436	0.406
	Other Minerals	0.0336	0.0440	0.0394
	Prenatal Supplement	0.00134	0.0243	0.0142
	Other Vitamins	0.0697	0.0876	0.0798

Note: The NCS question asks the respondent "Do you use them?" in reference to Vitamin/Mineral Tablets, Capsules, or Liquids (Non-Prescription). If the respondent marks yes, he/she is then asked the "Types you use", marking "Most Often", "Also Use", or Missing. The consumption of these vitamins/minerals was based off of the respondent marking either "Most Often" or "Also Use." Vitamin B is a combination of Vitamin B12, Vitamin B Complex and Vitamin B Complex with C. If a respondent marked yes to consuming any of those Vitamin B categories, the respondent was coded as consuming Vitamin B. Stress Formula was combined into Multiple Formula. If a respondent marked yes for consuming Stress Formula or Multiple Formula, the respondent was coded as consuming Multiple Formula

Table 3**The Impact of Vitamin Ads and Spending on Vitamin Use**

	(1) Vitamin Use	(2) Vitamin Use	(3) Vitamin Use	(4) Vitamin Use
Ad Exposure				
TV Ads (100)	0.00274** (0.00119)			
Print Ads	0.00402*** (0.000302)			
Ln(TV Ads)		0.00607*** (0.00147)		
Ln(Print Ads)		0.0438*** (0.00232)		
Ad Spending				
TV (10,000 \$)			0.000174** (7.74e-05)	
Print (10,000 \$)			0.000385*** (2.89e-05)	
Ln(TV \$)				0.00317*** (0.000734)
Ln(Print \$)				0.00522*** (0.000316)
Demographic Controls	Yes	Yes	Yes	Yes
Targeting Controls	Yes	Yes	Yes	Yes
Observations	88,329	88,329	88,329	88,329
R-squared	0.112	0.113	0.112	0.112
Dependent Var Mean	0.589	0.589	0.589	0.589

Notes: Marginal effects from logit models reported. Clustered standard errors at the household level are in parentheses.

p<0.01,

**

p<0.05,

*

p<0.1. Demographic controls include race, age, education, household income, health insurance status, marital status, number of hours worked per week, DMA, household size and survey wave dummies. Targeting controls include dummies for watching each television program and reading each magazine (where = 1 if watched/read greater than 75% of the time). Targeting controls also include number of magazine issues read and average hours of television watched per week. Due to the large number of program fixed effects, we had to drop 22 observations that had programs that perfectly predicted the outcome variable

Table 4

Gender and Education Stratifications

	(1) Total Sample Vitamin Use	(2) Males Vitamin Use	(3) Females Vitamin Use	(4) > High School Vitamin Use	(5) <= High School Vitamin Use	(6) Insurance	(7) No Insurance
Ad Exposure							
Ln(TV Ads)	0.00607*** (0.00147)	0.00989*** (0.00216)	0.00301 (0.00193)	0.00613*** (0.00193)	0.00716*** (0.00224)	0.00478*** (0.00162)	0.0111*** (0.00344)
Ln(Print Ads)	0.0438*** (0.00232)	0.0431*** (0.00475)	0.0429*** (0.00259)	0.0404*** (0.00302)	0.0481*** (0.00356)	0.0431*** (0.00247)	0.0534*** (0.00741)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strong Targeting	Yes		Yes			Yes	Yes
Controls		Yes		Yes	Yes		
Observations	88,329	38,670	49,511	50,515	37,727	76,839	11,459
R-squared	0.113	0.108	0.115	0.0970	0.138	0.0947	0.2235
Dependent Var Mean	0.589	0.514	0.647	0.636	0.525	0.619	0.385

Notes: Marginal effects from logit models reported. Clustered standard errors at the household level are in parentheses.

p<0.01,

**
p<0.05,

*

p<0.1. Demographic controls include race, age, education, household income, health insurance status, marital status, number of hours worked per week, DMA, household size and survey wave dummies. Targeting controls include dummies for watching each television program and reading each magazine (where =1 if watched/read greater than 75% of the time). Targeting controls also include number of magazine issues read and average hours of television watched per week. Due to the large number of program fixed effects, we had to drop observations that had programs that perfectly predicted the outcome variable (less than 100 in each model).

Table 5**Different Targeting Controls**

	(1) Vitamin Use	(2) Vitamin Use	(3) Vitamin Use
Ad Exposure			
Ln(TV Ads)	0.00279* (0.00157)	0.00607*** (0.00147)	0.00381** (0.00157)
Ln(Print Ads)	0.0364*** (0.00249)	0.0438*** (0.00232)	0.0398*** (0.00246)
Demographic Controls	Yes	Yes	Yes
Targeting Controls	Dummies	>75% Dummies	Continuous
Observations	88,329	88,329	88,351
R-squared	0.149	0.143	0.147
Dependent Var Mean	0.589	0.589	0.589
Remaining variation in TV exposure	0.216	0.183	0.132
Remaining variation in print exposure	0.620	0.583	0.557

Notes: Marginal effects from logit models reported. Dummy targeting controls include an indicator variable for each television program and each magazine. >75% targeting controls include dummies for watching each television program and each magazine (where =1 if watched greater than 75% of the time). Continuous targeting controls include variables for how often each respondent watches each program/magazine (0, 0.25, 0.5, 0.75, 1). All targeting controls also include number of magazine issues watched and average hours of television watched per week. Clustered standard errors are in parentheses.

p<0.01,

**
p<0.05,

*
p<0.1. Demographic controls include race, age, education, household income, health insurance status, marital status, number of hours worked per week, DMA, household size and survey wave dummies. Remaining variation in exposure measures is the R squared from an OLS model with exposure on the left hand side and the vector of targeting controls on the right hand side.

Table 6

The Impact of Vitamin Ads and Spending on Vitamin Use with Restricted Viewership/Readership

	(1) Vitamin Use	(2) Vitamin Use
Ad Exposure		
Ln(TV Ad s)	0.00607 *** (0.00147)	
Ln(Print Ads)	0.0438 *** (0.00232)	
Ln(Different TV Ads)		0.00618 *** (0.00129)
Ln(Different Print Ads)		0.0240 *** (0.00291)
Demographic Controls	Yes	Yes
Targeting Controls	Yes	Yes
Only Network/>.75 Readership	No	Yes
Observations	88,329	88,329
R-squared	0.113	0.111
Dependent Var Mean	0.589	0.589

Notes: Marginal effects from logit models reported. Clustered standard errors at the household level are in parentheses.

p<0.01,**
p<0.05,

*
p<0.1. Demographic controls include race, age, education, household income, health insurance status, marital status, number of hours worked per week, DMA, household size and survey wave dummies. Targeting controls include dummies for watching each television program and reading each magazine (where =1 if watched/read greater than 75% of the time). Targeting controls also include number of magazine issues read and average hours of television watched per week. Due to the large number of program fixed effects, we had to drop 22 observations that had programs that perfectly predicted the outcome variable

Table 7

Location Controls

	(1) Vitamin Use	(3) Vitamin Use	(4) Vitamin Use	(5) Vitamin Use	(6) Vitamin Use	(7) Vitamin Use
Ad Exposure						
Ln(TV Ads)	0.00607 *** (0.00147)	0.00591 *** (0.00146)	0.00591 *** (0.00146)	0.00631 *** (0.00147)	0.00607 *** (0.00146)	0.00607 *** (0.00146)
Ln(Print Ads)	0.0438 *** (0.00232)	0.0436 *** (0.00232)	0.0436 *** (0.00232)	0.0439 *** (0.00232)	0.0437 *** (0.00232)	0.0437 *** (0.00232)
DMA Controls						
DMA Indicators	Yes	No	Yes	No	No	No
DMA Specific Time Trends	No	Yes	Yes	No	No	No
State Controls						
State Indicators	No	No	No	Yes	No	Yes
State Specific Time Trends	No	No	No	No	Yes	Yes
Observations	88,329	88,329	88,329	88,329	88,329	88,329
R-Squared	0.113	0.113	0.113	0.113	0.113	0.113
Dependent Var Mean	0.589	0.589	0.589	0.589	0.589	0.589

Notes: Marginal effects from logit models reported. Clustered standard errors at the household level are in parentheses.

p<0.01,

**

p<0.05,

*

p<0.1. Demographic controls include race, age, education, household income, health insurance status, marital status, number of hours worked per week, household size and survey wave dummies.

Targeting controls include dummies for watching each television program and reading each magazine (where =1 if watched/read greater than 75% of the time). Targeting controls also include number of magazine issues read and average hours of television watched per week. Due to the large number of program fixed effects, we had to drop 22 observations that had programs that perfectly predicted the outcome variable

Table 8**Effect of Specific Vitamin Exposure on Consumption**

	(1) No Ailment	(2) With Ailment
Panel A: Calcium/Osteoporosis Females		
Log(# of Calcium or Vit. D TV Ads)	0.00237 (0.00202)	0.00627 (0.0129)
Log(# of Calcium or Vit. D Print ads)	0.0506 *** (0.00531)	0.0505 (0.0315)
Observations	47,028	1,852
R-squared	0.133	0.341
Dependent Variable Mean	0.291	0.663
Panel B: Vitamin B/Depression Females		
Log(# of Vitamin B TV Ads)	0.000731 (0.00555)	-0.00422 (0.0235)
Log(# of Vitamin B Print ads)	0.0464 *** (0.00496)	0.0255 (0.0198)
Observations	44,967	3,606
R-squared	0.0740	0.256
Dependent Variable Mean	0.142	0.191
Panel C: Fish Oil/Heart Disease Entire Sample		
Log(# of Fish Oil TV Ads)	0.00883 (0.00673)	0.00848 (0.0146)
Log(# of Fish Oil Print Ads)	0.0272 *** (0.00664)	0.0543 *** (0.0145)
Observations	67,466	19,671
R-squared	0.108	0.114
Dependent Variable Mean	0.107	0.189
Panel D: Vitamin E/Heart Disease Entire Sample		
Log(# of Vitamin E TV Ads)	-0.00340 (0.00219)	0.00249 (0.00480)
Log(# of Vitamin E Print Ads)	0.0262 *** (0.00370)	0.0302 *** (0.00859)
Observations	67,560	19,604
R-squared	0.112	0.112
Dependent Variable Mean	0.0894	0.148

Notes: Marginal effects from logit models reported. Clustered standard errors at the household level are in parentheses.

p<0.01,

**
p<0.05,

*
p<0.1. Demographic controls include race, age, education, household income, health insurance status, marital status, number of hours worked per week, DMA, household size and survey wave dummies. Targeting controls include dummies for watching each television program and reading each magazine (where =1 if watched/read greater than 75% of the time). Targeting controls also include number of magazine issues read and average hours of television watched per week. Due to the large number of program fixed effects, we had to drop observations that had programs that perfectly predicted the outcome variable (less than 100 in each model)