NBER WORKING PAPER SERIES

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Working Paper 24277
http://www.nber.org/papers/w24277

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2018

This paper was presented at a session sponsored by the Health Economics Research Organization (HERO) at the 2018 Meetings Conference of the Allied Social Science Associations in Philadelphia, PA, January 5-7, 2018; the 87th Annual Meetings of the Southern Economic Association in Tampa, FL, November 17-19, 2017; the Eleventh World Congress of the International Health Economics Association in Boston, MA, July 8-11, 2017; and the 43rd Annual Conference of the Eastern Economic Association in New York, NY, February 23-26, 2017. The paper also was presented at seminars at IZA in Bonn, Germany, November 7, 2017 and at Auburn University in Auburn, Alabama, December 1, 2017. We are grateful to participants in those forums, especially Kitt Carpenter, Hope Corman, Thomas Dohmen, David Jaeger, Robert Kaestner, Ji Yan, and Aaron Yellowitz, for helpful comments and suggestions. Research for this paper was supported by grant 1R01DA039968A1 from the National Institute on Drug Abuse to the NBER. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 24277
February 2018
JEL No. I18

ABSTRACT

Only recently introduced into the U.S. market, e-cigarettes have been aggressively promoted, and use is increasing rapidly among both adults and youths. At the heart of the regulatory debate are fundamental questions regarding whether e-cigarettes will draw cigarette smokers away from a dangerous habit or lure new initiates into tobacco use. We provide some of the first causal evidence on whether e-cigarette advertising on television and in magazines (which comprise about 90% of total media spending on e-cigarettes) encourage adult smokers to quit. We find that the answer to this question is a yes for TV advertising but no for magazine advertising. Our results indicate that a policy to ban TV advertising of e-cigarettes would have reduced the number of smokers who quit in the recent past by approximately 3%, resulting in roughly 105,000 fewer quitters in that period. On the other hand, if the FDA were not considering regulations and mandates that would likely eliminate many e-cigarette producers during our sample period, e-cigarette ads might have reached the number of nicotine replacement therapy TV ads during that period. That would have increased the number of smokers who quit by around 10%, resulting in an additional 350,000 quitters.

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I. Introduction

Electronic Nicotine Delivery Systems (ENDS), of which electronic cigarettes (e-cigarettes) constitute the most common sub-product, are a non-combustible alternative to smoking. As opposed to smoking cigarettes, the use of ENDS, termed vaping, delivers nicotine to the user without exposing that person to tar—the substance in cigarette smoke responsible for most of its harm. In all ENDS products (referred to as e-cigarettes or e-cigs from now on), a liquid containing nicotine is vaporized by a battery powered heating device. The use of e-cigarettes has increased dramatically since they were first introduced in the US in 2007. According to the upper portion of Figure 1, participation among adults grew from 0.3 percent in 2010 to 6.9 percent in 2014. Participation by 18-24 year olds approximately doubled that of adults of all ages, over the years in which data for the former group are available. The upper portion of Figure 2 depicts similar trends for youth. Past-month participation in e-cigarettes by youths in grades 6 through 12 increased from 1.0 percent in 2011 to 11.3 percent in 2015.

Concurrent with the surge in e-cigarette use, there has been a substantial increase in advertising from \$3.6 million in 2010 to \$112 million in 2014, with the vast majority of spending devoted to magazines (59 percent) and television (27 percent) with national reach (Kim, Arnold, and Makarenko 2014; U.S. Surgeon General 2016). Figure 3 depicts these trends in more detail. There was virtually no advertising before 2012, followed by a sharp increase through 2014. Advertising decreased in 2015 but increased again in 2016.[1] Almost 48 percent of adults have been exposed to e-cigarette marketing (Kim, Arnold, and Makarenko 2014) and youth exposure to TV ads increased over 250 percent between 2011 and 2013 (Duke et al. 2014).

[1] Mickle (2015) attributes the reduction in advertising in 2015 to inventory backlogs, new state laws, and uncertainty concerning final rules regarding the regulation of e-cigarettes by the Food and Drug Administration. These regulations were announced in May 2016 (see below).

E-cigarette use and advertising have surged during an extremely contentious policy debate. At the heart of this regulatory debate are fundamental questions regarding whether e-cigarettes will draw cigarette smokers away from a dangerous habit or lure new initiates into tobacco use and lead to a new generation of nicotine addicts. On one side of the debate is the argument that e-cigarettes constitute a tobacco harm reduction strategy. E-cigs are less dangerous than cigarettes because the vapor does not contain the toxins contained in the smoke of conventional cigarettes (Goniewicz; et al. 2013; Czogala et al. 2014 U.S. Food and Drug Administration 2016b; U.S. National Institute on Drug Abuse 2016). While e-cigarettes are not a completely safe alternative to cigarettes, in April 2016 the Royal College of Physicians in Great Britain issued a report urging smokers to switch to e-cigarettes (Royal College of Physicians 2016). That echoed advice some physicians had started giving to their patients who smoked (Kandra et al. 2014).

The recent trends in U.S. smoking rates provide hints that the growth of e-cigarette use might be helping reduce smoking. The lower portion of Figure 1 highlights the well-known downward trend in adult smoking. The rate fell from 20.9 percent in 2005 to 15.1 percent in 2015. During the 2011-2015 period in which data on e-cigarette use are also available, adult smoking participation fell by almost four percentage points. The almost two percentage point decline in smoking between 2014 and 2015 was the largest in more than twenty years (Jamal et al. 2016). In other national data, Zhu et al. (2017) find that the quit attempt rate and annual cessation rate were higher in 2014-15 compared to surveys earlier in the 2000s prior to the surge in e-cigarettes use.

Figure 2 shows that the growth in e-cigarette use among youth was also accompanied by a downward trend in youth smoking. Past month smoking participation fell from 10.5 percent in 2011 to 6.1 percent in 2015, continuing a longer-term downward trend in youth smoking.

On the other side of the policy debate are several arguments that suggest caution about e-cigarettes. There is no research on the long-term health effects of e-cig use. Nicotine exposure during the prenatal period is harmful. Adolescent nicotine exposure via e-cigarettes may have lasting adverse consequences for cognitive development (U.S. Surgeon General 2014).[2] Accidental poisoning can result from the damaging of e-cigarette products as reflected by the large increase in the number of calls to poison centers involving e-liquids (Richtel 2014). The greatest danger may be that these products may induce adolescents to begin nicotine addiction first by using e-cigs and then transitioning into smoking (Marcus 2014).

The general debate over e-cigarettes has carried over to the regulation of e-cigarette advertising. In the U.S. until 2016, e-cigarettes were regulated as an ordinary consumer product and allowed to advertise as long as they did not make health or cessation claims. In 2016, the Food and Drug Administration (FDA) extended its authority over tobacco products (created by the 2009 Family Protection and Tobacco Control Act) to include e-cigarettes. The FDA announced regulations that would ban the sale of e-cigarettes and related products to minors and would require all products that were not commercially marketed prior to February 15, 2007 to submit marketing applications (U.S. Food and Drug Administration 2016a). Because the marketing application approval process can be quite lengthy and costly, it has the potential to eliminate many current producers and result in significant price increases. In July 2017, FDA Commissioner Scott Gottlieb indicated these regulations will not be required until August 2022

[2] Controlled trials on cognitive development are based on animal studies, as it is difficult to study this question experimentally for humans.

and that he would consider endorsing e-cigs as a method to quit smoking (Kaplan 2017). The status quo remains that e-cigarette manufacturers are allowed to advertise in magazines, television and other media in the U.S. In 2016, however, the European Court of Justice, Europe's highest court, found that the European Union had the right to regulate e-cigarettes including banning advertising (Jolly 2016).

The purpose of this paper is to shed light on one side of the contentious debate just outlined by investigating whether e-cigarette advertising on television and in magazines encourage adult smokers to quit. To preview our results, the answer to this question is a tentative yes for TV advertising but no for magazine advertising. We use extremely detailed information on TV viewing patterns and magazine issues read in the Simmons National Consumer Survey and match this information to all e-cigarette ads aired on national and local broadcast and cable stations and all ads published in magazines from Kantar Media. The match yields estimates of the number of ads seen and read by each survey respondent in the past six months. Quasi-random variation in advertising exposure provides a credible strategy to identify the causal effects of advertising. We find that an additional ad seen on TV increases the number of adults who quit smoking by almost 1 percent relative to a mean quit rate of 9 percent in the past year.

II. Prior Studies

There are no prior studies that have estimated the effects of e-cigarette advertising on quit behavior of current smokers. Three streams of literature do, however, bear on our study. One addresses the effectiveness of e-cigarettes when used to aid smoking cessation in comparison with nicotine replacement therapy (NRT) and with unaided quitting ("cold turkey" quitting). Brown et al. (2014) and Zhuang et al. (2016) found that quit rates were higher among e-cigarette users than among the other two groups. On the other hand, Kalkhoran and Glantz (2016) review a number of studies that reach the opposite conclusion, although the studies find that the use of e-cigarettes is associated with some quitting. Some of this research is based on small samples of smokers and does not control for unobserved factors that may be correlated with the decision to use a particular method to attempt to quit.

The second group of studies contains estimates of the effects of advertising on sales or consumption of e-cigarettes and combustible cigarettes. Two related papers that use time series data from 30 U.S. cities for 2009 through 2013 but with slightly different estimation methods (Zheng et al. 2016, 2017) find that TV advertising was associated with increased per capita e-cigarette sales by convenience stores. Results for magazine advertising were inconclusive as were those for the effects of both types of ads on cigarette sales. Clearly, these results do not pertain specifically to the behavior of consumers, and there is no way of assessing whether individuals who made the purchases actually were exposed to the ads. Furthermore, estimates may be confounded by reverse causality due to targeting wherein manufacturers are advertising in response to strong demand.

In a modification of the sales-advertising design, Tuchman (2017) uses weekly sales and TV advertising data for the top 100 designated market areas (DMAs, which are media market areas similar to Standard Metropolitan Statistical Areas) for the period from 2010 through 2014. Firms set advertising levels for a given DMA based on its urban center, where most of the population lives. Since borders between DMAs tend to fall in more rural areas, residents of these areas should have similar observed and unobserved characteristics but may be exposed to different levels of advertising because of differences in the urban centers of their respective DMAs. After limiting her sample to residents of border areas, she finds that an increase in e-cigarette advertising is associated with an increase in e-cigarette sales and a reduction in conventional cigarette sales. While her design is an improvement of the ones employed by Zheng et al. (2016, 2017), she cannot determine whether individuals were actually exposed to the ads and cannot treat quitting smoking as an outcome. Moreover, her advertising measures are limited to local or spot TV ads. As we indicate below, over 90 percent of e-cigarette ads viewed in our data appear at the national level.

O'Connor et al. (2017) report that subjects who participated in an experimental auction in which they bid for e-cigarettes were willing to pay more if they saw print ads for the product prior to the auction compared to those who saw no ads. This result did not carry over to those who saw TV ads. In a study with a similar research design, Rousu, O'Connor, and Corrigan (2017) report cases in which participants who were exposed to an ad for a specific brand of e-cigarettes were willing to pay more for that brand and less for a competing product. They also report cases in which exposure to an ad for one product appears to increase demand for that product as well as for cigarettes based on willingness to pay bids. If these results carry over to a real-world setting as opposed to an experimental setting, they suggest reasons why advertising may not encourage quit behavior. But they are based on small samples of individuals who reside in one or two cities. Hence, they may not generalize to the population of smokers at large.

Current FDA regulations do not allow e-cigarette ads to mention that the product can be used for smoking cessation and are less harmful than combustible cigarettes. Yet Kim et al. (2015) find that 75 percent of a sample of Florida adult smokers reported that seeing a TV ad for e-cigarettes "made me think about quitting smoking." The main message of the ad was that one can use e-cigarettes anywhere. At the end, it mentions that the product is available in flavors, different nicotine levels, and costs less than cigarettes. This study contradicts findings in the one by Rousu, O'Connor, and Corrigan (2017). It suggests that even though quitting is not explicitly mentioned, it induced viewers to think about quitting.

From a methodological perspective, our study is most closely related to a set of studies that use the same data and similar approach to assess the causal effects of advertising on the demand for cigarettes (Avery et al. 2007; Kenkel, Mathios, and Wang forthcoming); smokeless tobacco (Dave and Saffer 2013); alcohol (Molloy 2016); pharmaceutical products to treat allergies, arthritis, asthma, high cholesterol (Avery et al. 2008); antidepressants (Avery, Eisenberg, and Simon 2012); weight-loss products (Avery et al. 2013); and vitamins (Eisenberg, Avery, and Cantor 2017). Each of these studies uses detailed information on consumer TV viewing and/or magazine reading patterns in the Simmons National Consumer Survey (NCS, http://www.simmonssurvey.com) combined with comprehensive measures of advertising in these two media primarily from Kantar Media (https://www.kantarmedia.com/us). Most of these studies find positive effects of advertising on the outcomes being considered. The one by Avery et al. (2007) is especially relevant because they find that an increase in exposure to magazine advertisements of nicotine replacement therapy (NRT) products is associated with higher quit rates among cigarette smokers.

The NCS is a nationally representative proprietary marketing survey whose media usage and consumer demographic information are utilized by virtually all major marketing and advertising firms in the U.S. (Avery et al. 2013). Hence, the use of the NCS allows one to observe the same consumer information and characteristics as the advertiser, minimizing the "targeting bias" that would result from ads potentially being targeted based on factors not observed by the researcher (Avery et al. 2007). Furthermore, the in-depth information on media usage allows one to construct detailed and salient measures of advertising exposure that vary at the individual level to identify plausibly causal effects of this exposure. For instance, even readers of the same magazine may be exposed to different levels of e-cigarette ads due to the staggering of ads across different months and issues. Along the same lines, viewers of the same number of a given TV program in, for example, the last half of 2015, may view a different number of ads because they do not watch exactly the same episodes of that show. By exploiting these sources of variation and others described in the next section, we develop a credible identification strategy to estimate the causal effects of e-cigarette advertising on smoking cessation.

III. Empirical Implementation

A. Sample and Measurement of Outcomes

The NCS is a repeat cross section conducted on a quarterly basis and contains approximately 25,000 individuals ages 18 and over each year. All individuals in a given household in that age category have the opportunity to participate in the survey and are compensated if they do. Because no information on e-cigarettes was obtained prior to the fourth quarter of 2013, we use data from that quarter through the fourth quarter of 2015.[3] That yields an approximate sample size of 58,000 individuals. Respondents report their current smoking status, any smoking cessation attempt over the past year, and methods used to attempt smoking cessation over this period. Based on information on respondents' current smoking status for those who attempted to quit smoking over the past year, we can define whether the respondent successfully quit or whether the cessation attempt was unsuccessful.

One limitation of the NCS is that information on e-cigarette use is available only in the context of quitting. That is, individuals respond whether they attempted to quit smoking in the

[3] We cannot include more recent Simmons surveys because they are extremely expensive.

past year and, if so, whether they used e-cigarettes as a method. A second limitation is that there is no information on the number of e-cigarettes currently smoked or smoked in the past year. Note, however, that a key question at the center of the harm reduction/policy debates concerns whether e-cigarette advertising impacts smoking cessation. To that end, the structure of the questions in the NCS are helpful towards assessing whether that advertising has impacted smoking cessation in general, and smoking cessation with the aid of e-cigarettes in particular. Furthermore, the NCS also asks respondents whether their quit attempt involved FDA-approved nicotine replacement therapy (NRT). One concern among public health officials and policymakers is that the use of e-cigarettes as an unapproved cessation aid may crowd-out other FDA-approved (and possibly more effective) modes of smoking cessation. Thus, with the NCS, we directly test whether e-cigarette advertising has affected smoking cessation through approved methods such as NRT.

Given the structure of the survey, we limit our sample to individuals who are either past-year quitters or current smokers (N = 8,291). There are three groups in the sample: successful quitters or simply quitters (Q = 747), unsuccessful quitters or simply failures (F = 2,324), and non-attempters (D = 5,220). The last two groups form the larger group of current smokers.[4]

Panel A of Table 1 contains the basic outcomes that we consider in our empirical analysis and the mean of each outcome. The quit rate in the sample (q = Q/N) expressed as a percentage is 9.0 percent, and the failure rate (f = F/N) is 28.0 percent. Hence, the attempt rate

[4] We note here that the term "failure" as used in the paper specifically refers to those who attempted to quit smoking but were unsuccessful, and is separate from those who did not make any attempt towards smoking cessation. Because it may often take several attempts to quit smoking, unsuccessful attempts are often a necessary first step towards successful smoking cessation. With 77 percent of smokers reporting that they would like to quit smoking (Gallup Poll 2017), an unsuccessful quit attempt is therefore closer to these smokers' realized goal than non-attempts.

(A/N = a = q + f, where A = Q + F) is 37.0 percent, or almost 40 percent of the sample attempted to quit in the past year. In addition to considering the attempt, quit, and failure rates as outcomes, we examine the determinants of the success rate conditional on an attempt or the conditional probability of success (π = Q/A = q/a). The mean of that outcome is 24.3 percent.[5]

Panel B of Table 1 contains outcomes related to those in Panel A that we also examine. They are the percentage of attempts accounted for by each of four specific methods of quitting and the success rate of each method. The methods are the use of e-cigarettes only, the use of nicotine replacement therapy (NRT) only, cold turkey (attempts without the use of any products and without any assistance), and other methods (gradual reduction, hypnosis, acupuncture, quit smoking programs, and mixed methods). Attempts using e-cigarettes account for the second highest percentage of all attempts (24.1 percent compared not surprisingly to 40.0 percent for mixed methods). Attempts using e-cigarettes have the second highest success rate (28.9 percent compared to 31.2 percent for cold turkey attempts). It is notable that the NRT quit rate is somewhat lower than the e-cigarette rate. Again not surprisingly, attempts to quit by other methods are the least successful.[6]

Note that the sample includes starters, individuals who began to smoke for the first time sometime during the past year, and re-starters, that is individuals who smoked in the past, quit at

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[5] When divided by 100, the rates just defined can be interpreted as probabilities at the individual level.

[6] The relative success of NRT and e-cigarettes is generally consistent with evidence from randomized control trials (RCTs). There is no consistent evidence that other methods such as hypnotherapy or acupuncture (and related techniques) have a sustained benefit on smoking cessation of six months or longer (Barnes et al. 2010; White et al. 2014), which may explain why attempts to quit by other methods in the NCS are the least successful. On the other hand, based on data from 150 RCTs, there is consistent evidence that NRTs significantly raise the rate of successful quits by about 50-60 percent or more (relative risk ratio of 1.6) (Stead et al. 2012). In comparison, RCTs for e-cigarettes are quite sparse, though some limited evidence indicates that e-cigarettes significantly raise the likelihood of six-month smoking abstinence by about 129 percent (compared to a placebo e-cigarette; relative risk ratio of 2.29), and that there may be no statistically significant difference between electronic cigarettes and NRTs with respect to the six-month smoking abstinence rate (Hartmann-Boyce et al. 2016). The slightly higher success rate for "cold turkey" attempts in our observational data may potentially reflect that smokers who use e-cigarettes and NRTs might have failed previous cold turkey attempts. Thus, their lower success rate (for e-cigarettes and NRTs relative to cold turkey attempts) might reflect that they may be relatively more hard-core addicted smokers.

some point, and then took up smoking again.[7] While we cannot identify these specific groups in the sample,[8] both are salient to our analyses as they may have quit in the past year. Starters are likely to comprise a very small percentage of the sample, however, since almost all smokers initiate that behavior by their early twenties.[9]

B. Measurement of Advertising

The in-depth information on media usage in the NCS allows us to construct detailed and salient measures of advertising exposure that vary at the individual level. Specifically, to measure the NCS respondent's potential exposure to e-cigarette advertising, we combine questions that ask respondents about their TV watching and magazine reading habits with ad placements in TV and magazine. There are two sets of broad questions in the NCS about TV viewing behavior. One set of questions tells us the times they have watched specific channels in the past week. To give some examples, a respondent may report that they have watched NBC from 8:00 PM-8:30 PM, sometime from Monday-Friday, or that they watched Bravo from Noon-3 PM on the weekend. Note that the time slot can be narrow or broad depending on if it is a time slot that is frequently watched such as a weekday network primetime time slot or uncommonly watched such as the afternoon cable weekend time slot.

A second set of questions asks respondents to recall whether they usually watch specific programs on each channel. For network TV, the survey asks the frequency that the respondent usually watches a program; one to four times a month for weekly programs or one to five times a week for daily programs. For example, a respondent can report that she has watched The Big

[7] Put differently, the sample is not limited to individuals who smoked exactly one year prior to their interview date as smoking status exactly one year prior is not available in the NCS.
[8] This is because smoking status exactly one year prior to the interview date is not available in the NCS.
[9] Over 80 percent of ever-smokers have initiated smoking prior to age 18 (Substance Use and Mental Health Services Administration 2014).

Bang Theory on CBS one out of four times a month or that she has watched Good Morning America on ABC three times out of five a week. For cable TV, the survey asks only whether she has watched a program at all in the past seven days or in the past four weeks. For example, she could have viewed American Dad on TBS in the past seven days, or Bones on TNT in the past four weeks.

Kantar Media provides us a list of advertising placements for e-cigarettes, that includes the date and time the ad aired, on what channel, during what program, and what brand of e-cigarette is advertised. The data we connect to the NCS extends from the 2nd quarter of 2013 through the 4th quarter of 2015. We consider a respondent to have been potentially exposed to an ad if she reports watching a program and channel where an electronic cigarette ad aired in the past six months, and having watched a time slot on the same channel where that same electronic cigarette ad aired in the past six months.

We use this strict criterion for several reasons. First, a program can air on a channel many times throughout the day. E-cigarette ads tend to air on network television outside of the primetime schedule where most respondents report watching television. If we simply counted all ads that aired on this network without regard to what time the respondent watches television on this channel, we would over-count e-cigarette ad exposure. Second, as mentioned, the time slots are specified for any time between Monday through Friday, or separately on the weekend. Therefore, if an ad simply aired during a time slot the respondent reports watching but on a day that airs a program they do not actually watch, this would again be over-counting e-cigarette ad exposure. Third, the time slots are broad and off-hours can be as large as six-hour time frames. A report of watching a time slot does not necessarily imply the respondent watched every program in that time slot. The application of this strict matching criterion therefore minimizes positive measurement error (assigning ad exposure to a respondent when he or she may not have been) given the available information, assuming regularity in viewing behavior over a six-month period.

For spot ads that appear only in certain designated market areas (DMAs, which are media market areas similar to Standard Metropolitan Statistical Areas), there is the additional restriction that we only assign persons as exposed if they live in the DMA in which the ad appeared. In this sample of the NCS, 46 DMAs can be identified, which include 72 percent of the total NCS sample. Nevertheless, we still include the sample of adults that reside in areas outside the 46 identified DMAs. For these adults, we are unable to measure their spot advertising exposure but this leads to only a minor amount of measurement error: when we are able to measure spot ad exposure, they only account for approximately 3 percent of the estimated exposure to all ads.

Total TV ad exposure is thus a weighted sum of all ads to which a respondent is exposed based on the programs, channels, and time slots that the respondent views and the ads that aired on these programs, channels, and time slots. We apply summation weights to ad exposure depending on the frequency of viewing a program. The weight for a respondent watching a daily show where an e-cigarette ad airs on network TV and watches it once a week, twice a week, three times a week, four times a week, or five times a week, is 0.2, 0.4, 0.6, 0.8, or 1, respectively. Similarly, the weight for a respondent watching a weekly show where an e-cigarette ad airs on network TV and watches it once a month, twice a month, three times a month, or four times a month is 0.25, 0.5, 0.75 or 1 respectively. Finally, the weight for a respondent watching a cable TV show, and has watched it in the past four weeks or the past seven days, is 0.5 or 1 respectively.

Although the TV advertising exposure data pertains to exposure in the past six months, the actual information on viewing patterns pertains to the past week or the past month. This information as well as all other information is obtained from respondents by means of a questionnaire that they receive in the mail, complete, and return. While their answers are subject to recall error, this is minimized by limiting the recall period to the past month as opposed to the past six months. Clearly, we assume that viewing patterns in the past week or past month are representative of those in the past six months.

Our advertising exposure measure assumes that exposure does not depreciate over time until six months after exposure when it depreciates completely. This is the same assumption that has been employed in other studies with the NCS data cited in Section II. It is supported in reviews of the literature by Leone (1995) and Dave and Kelly (2014).

Time-shifting, distractions, and changing channels are long-standing issues in all TV advertising studies that use data from actual experience rather than from limited laboratory settings. While time-shifting and non-traditional TV viewing are on the rise, most viewing still occurs live and on the TV screen. Bronnenberg et al. (2010) find that 95 percent of television was watched live rather than recorded, and even when viewers were given the opportunity to skip commercials (through the use of a DVR), many users did not do so. Nielsen (2014) confirms that about 94 percent of the time spent watching original TV series by adults and teens is on traditional TV, with the remainder viewed through the internet on alternative devices. Moreover, among the time spent watching traditional TV (on the TV screen), 91 percent (for both adults and teens) is watched live and the remaining is time-shifted. Thus, the average effect of time-shifting is minimal; this is consistent with a recent international study that found advertising awareness to be generally similar across live and delayed viewers (TVNZ/Colmar

Brunton 2013). Furthermore, as long as the level of distraction while watching TV or time-shifting are not systematically correlated with e-cigarette advertising per se (relative to other advertising), estimated effects will be biased towards zero because of random measurement error and any general trends in time-shifting or differences across areas/demographic groups will be captured, by demographic controls and area and time fixed effects.

Kantar Media also provides the issue and date that e-cigarette ads appear in magazines. NCS respondents provide detailed information on their magazine reading behavior. For each magazine, they report whether they read or looked into it in the past six months, and further report on the number of issues that they read out of every four issues, on average. Magazine ad exposure is measured as the weighted sum of the number of ads that appeared in all magazines in the past six months that the respondent has read, weighted by the frequency (number of issues consumed) with which the respondent reads each magazine. Specifically, the weights for reading a magazine less than one out of four, one out of four, two out of four, three out of four, or four out of four issues, are 0.1, 0.25, 0.5, 0.75, and 1 respectively. While the recall period for magazine exposure is longer than the one employed for TV exposure, the amount of information requested from respondents is much more limited. Hence, there is no reason to believe that random measurement error for the two types of exposure differs.

In addition to estimating the effects of e-cigarette advertising on quit behavior, we also estimate the effects of NRT advertising with measures obtained from Kantar. There are virtually no NRT ads in magazines, and hence we do not control for magazine ad exposure.[10] TV ad exposure for NRT is constructed the same way as described above for e-cigarettes, combining

[10] In the past, most NRT products had to be obtained with a prescription from a physician. If they were advertised on television, a printed source of information on them was required. This no longer is the case because almost all of these products can be acquired over-the-counter.

information on actual NRT ads airing on TV with the TV consumption habits of the NRT respondents.

We note that there are no prior studies that have estimated how e-cigarette advertising affects smoking cessation behaviors. Furthermore, our individual-level measures of ad exposure are superior to other market-level measures such as market-level ad spending or average ratings points, which have been typically used in prior work to study the effects of advertising in health-related markets, including tobacco and alcohol (Dave and Kelly 2014). Market-level variation in ad spending mostly reflects spot or local ads, which misses most advertising in these markets. Furthermore, aggregated market-level measures provide a measure of the average exposure in a market, while we capture individual-level variation in TV viewing and magazine reading habits. Outside of a controlled laboratory experiment, these measures from the NCS provide the most precise and salient matching of ad exposure to date in any national tobacco study of individuals in a real-world setting (Dave and Kelly 2014; Dave and Saffer 2013; Avery et al. 2007).

C. Definitions of Other Variables and Sample Characteristics

All models estimated in Section IV contain age, gender, race, education, household income, employment status, insurance status, and marital status, as independent variables. All of these variables are defined in Table 2, and their means in each of the three groups in the sample (quitters, failures, and non-attempters) are shown. Means of exposure to TV and magazine e-cigarette ads and to NRT TV ads in each group are also reported in Table 2.

Males, whites, those with high levels of education, and those residing in households with high levels of income are over-represented in the sample of quitters. The relationship between age and the probability of quitting is nonlinear, with the two youngest and the oldest age groups accounting for larger percentages of the quit group than of the other two groups. It also is notable that quitters are exposed to more TV ads for e-cigarettes (4.5 ads on average over the past 6 months) than failures (3.7) or non-attempters (2.9). The latter pattern, does not, however hold in the case of magazine ads. Quitters have more exposure to these ads than non-attempters but less exposure than failures. The average respondent is exposed to 4-5 times more NRT ads relative to e-cigarette ads, but quitters are less likely to be exposed to these ads than those whose quit attempts are not successful. All of the differences just mentioned are statistically significant at the one percent level.

D. Identification Strategy

At several points in this paper, we have mentioned that firms are likely to target ads for their products to individuals who have certain characteristics. Hence, efforts to identify the causal effects to ads for the product in question must control as much as possible for the characteristics of the targeted groups. If this is not done, estimates are biased due to omitted characteristics that make it more likely that given consumers are exposed to more ads and have unobserved propensities to quit, the key outcome in our case.

The advertising exposure that varies at the individual level can be exploited to identify plausibly causal effects of this exposure. For instance, even readers of the same magazine may be exposed to different levels of e-cigarettes ads due to variation in their reading frequency (issues read) and the staggering of ads across different months and issues. A similar comment applies to individuals who viewed the same number of episodes of a given TV show but in different quarters or different years. Our identification strategy isolates these sources of variation and others specified below by means of fixed effects to control for unobservable characteristics that may be correlated with both outcomes such as quitting and the key independent variable of interest--advertising exposure.

In addition to the variables in Table 2, the most complete specifications in Section IV are saturated with year-quarter, magazine, program, time slot, and channel fixed effects. Year-quarter fixed effects, one for each year and quarter combination, are necessary because there is variation in advertising spending over time, which may be correlated with any other variables that would influence quitting rates in the U.S. over time. DMA fixed effects, which include a fixed effect for 46 identified DMA's and one for all the unidentified DMA's, are necessary because people in different areas may be exposed to spot ads at different rates, or more importantly have different viewing patterns based on the local preferences of an area.

Magazine fixed effects (one for each of the 32 magazines that carried e-cigarette ads at some point over the sample period) are included for each magazine that the respondent has read or looked into, regardless of their frequency of reading that magazine. Program fixed effects (one for each of a set of 326 programs that aired e-cigarette ads at some point over the sample period) are included for each program that the respondent watched regardless of the channel on which it was watched or the time slot during which it was watched.

A set of 62 time slot indicators are included to identify different time slots during which a respondent may have watched TV regardless of the program watched and the channel on which it was aired. Time slot fixed effects are different by weekend and weekday viewing, as well as by cable or network viewing. Finally, a set of 131 channel indicators are included for channels that aired ads and were watched by the respondent regardless of the time slot during which the program was watched or the program that was watched.

The magazine, channel, time slot, and program fixed effects are necessary because advertisers may target e-cigarette ads to viewers that are prone to be more likely to quit and try e-cigarettes if induced. They help us identify variation in individual ad exposure that is orthogonal to any targeting bias resulting from advertisers allocating ads across magazines, TV programs, time-slots, and network and cable channels, based on unobserved characteristics of viewers and readers. Note that the time slot fixed effects are extremely highly correlated with the amount of time spent watching television. Therefore, our results are unaffected when the latter variable is added as a regressor.

Even after controlling for all of the fixed effects, there are still sources of variation in advertising exposure. For example, someone could watch the same programs, watch the same channels, watch TV in the same general timeframes, in the same quarter, in the same DMA, and have the same demographics but still have different TV ad exposure. For example, person A could be watching The Big Bang Theory on TBS at 8:30 PM and an e-cigarette ad could air, while person B is watching Law and Order: SVU on USA Network at 8:30 PM and no e-cigarette ads air. Person B could also watch The Big Bang Theory on TBS but at 4:00 PM while person A watches Law and Order: SVU on USA Network at 4:00 PM and no e-cigarette ads air on either show. Therefore, person A and person B would have the same year-quarter, DMA, program, channel, and time slot fixed effects but different ad exposure.

Other sources of variation net of fixed effects were mentioned above and are consistent with the way in which advertising typically is scheduled: high levels of ads for a limited time followed by no ads for a period of time (Bogart 1984; Dubé et al. 2005). By using such "pulses" or "flights" of advertising, diminishing marginal product at higher levels of ads is moderated while lingering effects of advertising may keep the consumer aware of the brand. Such pulsing may also explain shifts in advertising within a given magazine or program at different points in time or at different frequencies. Thus, two individuals consuming the same TV program or magazine would be exposed to different levels of ads based on their frequency and time-slot of consumption.

To highlight the significant amount of variation in TV and magazine e-cigarette exposure on which our estimates are based, we regressed each exposure measure on the sociodemographic variables in Table 2 (age, gender, race/ethnicity, education, household income, employment status, insurance status, and marital status) and on year-quarter, channel, program, time slot, and magazine fixed effects. In the TV ad exposure regression, the R^2 is 0.5126. The corresponding statistic in the magazine ad exposure regression is 0.6808. Both R^2s indicate a substantial amount of residual variation in the exposure measures.[11]

Not only does our procedure control for unobservables, but it also balances the sociodemographic characteristic of groups defined by different amounts of advertising exposure. Table 3 contains the means for all sociodemographic characteristics across three groups exposed to different levels of ads: no exposure, less than the median ad exposure, and greater than the median ad exposure. Panel A reports these means across levels of TV ad exposure, and Panel B reports them across levels of magazine ad exposure. In general, respondents are unbalanced on their observable characteristics across advertising exposure.

To highlight the unbalance in the case of TV ad exposure, we run three regressions in which this measure is the dependent variable. In the first, the independent variables are limited to the set of sociodemographic characteristics. In the second, year-quarter and DMA fixed effects are included. In the third, channel, time slot, and program fixed effects are added. In each regression, we test the hypothesis that the sociodemographic variables as a set are not

[11] Each of the two regressions also includes NRT TV advertising exposure and additional program fixed effects that are unique to this variable. We treat NRT exposure as a control variable rather than one of interest because its coefficient never is significant in the regressions in Table 4 and 5. In Tables A1 and A2 in the appendix, we show that our results in Tables 4 and 5 are not affected when the NRT measure is excluded.

related to advertising exposure. The p-value associated with this test is 0.000 in the first regression and second regression and 0.603 in the third regression. Clearly, the sociodemographic variables are significant predictors of TV ad exposure when the program, channel, and time slot indicators are not held constant but are not significant predictors when these indicators are held constant.

The same results emerge in the case of magazine ad exposure. The sociodemographic characteristics have significant effects on exposure with or without controls for year-quarter and DMA fixed effects (p-value equals 0.000 in each case). But there is no relationship between these characteristics and exposure once magazine fixed effects are included in the regression (p-value equals 0.648). We conclude that the three groups in Table 3 are balanced on observables once we control for fixed effects that pertain specifically to TV viewing and magazine reading patterns. Indicators for year-quarter and DMA residence is not sufficient to achieve this balance. This finding strengthens our identification strategy because there may be additional individual characteristics that we do not observe and that are correlated with the ones that we do observe. That suggests that the saturation of the regressions estimated in the next section with the large set of fixed effects just discussed eliminates biases that could be generated by these missing individual characteristics.[12]

E. Empirical Specifications

Recall that the sample consists of individuals who are either past-year quitters or current smokers (N = 8,291) and that there are three groups in it. These are successful quitters or simply quitters (Q = 747), unsuccessful quitters or simply failures (F = 2,324), and non-attempters (D =

[12] These results are not affected when indicators for magazines read are included in the TV ad exposure regression, when indicators for programs, time slots, and channels are included in the magazine ad exposure regression, and when NRT exposure is included in both regressions.

5,220). We begin by estimating a multinomial logit function with three outcomes: successfully quitting smoking or simply quitting, attempting to quit and failing or simply failing, and not attempting to quit. The mean probability of quitting (q, expressed as a percentage) is 9.0 percent. The comparable probabilities of failing (f) and not attempting (d) are 28.0 percent and 63.0 percent, respectively. We take non-attempters (D) as the omitted category in the logit so that the logit coefficients pertain to changes in the log odds of q or f relative to d.

Since the attempt rate (*a*) is the sum of the quit rate and the failure rate and since

$$d = 1 - a = 1 - q - f, \tag{1}$$

the marginal effect of any variable, x, on a is the negative of the marginal effect of that variable on d or the sum of the marginal effect of that variable on q and its marginal effect on f. This estimate is more flexible than one obtained from a binomial logit in which the two outcomes are attempts and non-attempts because it allows the marginal effects on q and f to differ. Similar considerations underscore the advantage of obtaining quit effects from the multinomial logit model rather than from a binomial logit model in which the two outcomes are quits and the other two are combined (f + d), the non-quitters. In particular, the latter model is appropriate only if x has no impact on the log odds of f relative to d. From, however, an empirical perspective, effects that emerge from the two binomial logit models just described are similar to those that emerge from the multinomial logit model.[13]

In addition to treating q, f, and a as outcomes, we also treat the conditional probability of success ($\pi = q/a$) as a fourth outcome. This is the success rate conditional on a quit attempt. Conceptually, this can be done in two ways. The first involves deleting all the individuals who

[13] We also estimated these two binomial logit models for attempts vs. non-attempts and for quits vs. non-quitters via OLS. Our estimates and results are not sensitive to using linear probability models, and yield highly similar marginal effects to those reported in Table 4.

do not attempt to quit and then estimating a binomial logit model with two outcomes: quits or failures. That is, the logit is limited to observations for individuals who attempt to quit. The second method is to obtain the relevant logit coefficient of *x* on the log odds of q relative to f as the difference between the logit coefficient of x on the log odds of q relative to d and the logit coefficient of *x* on the log of f relative to d. We prefer the first method because it is more convenient to compute the marginal effect from it, but we want to emphasize that the two methods are identical save for rounding due to the algorithm used to achieve convergence.[14]

Finally, we estimate logit models in which the outcomes are the method-specific attempt or success rates defined in Panel B of Table 1. The former logits are limited to individuals who attempt to quit and allow us to determine whether exposure to advertising induces crowd-out from other methods of quitting, especially nicotine replacement therapy, to the use of e-cigarettes. The latter logits contain an important specification or falsification test. If e-cigarette advertising encourages successful quitting, that effect should be largest for those who use e-cigarettes to quit relative to those who attempt to quit using other methods. We extend these models to perform additional specification and validation checks.

IV. Results

Marginal effects of e-cigarette TV and magazine advertising exposure from multinomial logit models that examine the probabilities of quitting, failing to quit, and attempting to quit are reported in Table 4.[15] Five specifications are shown. In the first, the only fixed effects included

[14] This result illustrates the property of independence of irrelevant alternatives (IIA) that characterizes multinomial and conditional logit models. The former refer to models in which the regressors that vary among individuals but not among choices (our case), while the latter refer to models in which the regressors vary among choices as well as among individuals. IIA can be tested in a conditional logit model by deleting one of the choices and then comparing the remaining coefficients to those in the full model. That test cannot be performed with a multinomial model because that model allows for a full set of interactions between the regressors and the choices. On the other hand, in a conditional logit model, choice-specific regressors are forced to have the same coefficient for each choice.

[15] These are marginal effects averaged over individuals. Since more than one individual in a given household can be included in the survey, standard errors are clustered at the household level in Table 4 and in all tables that follow it.

pertain to year and quarter. In the second, DMA indicators are added followed by time slot indicators in the third. In the fourth model, channel and magazine fixed effects are included. In the last and most comprehensive specification, program indicators join the set of fixed effects.

Focusing on the marginal effect of TV advertising on the probability of quitting, one sees that this effect is positive and significant at the 5 percent level in the first two models and at the 1 percent level in the last three models. The size of the effect is fairly stable across alternative specifications and actually gets larger as more fixed effects are added.[16] In the most comprehensive model, an increase in exposure to one additional ad raises the quit probability by 0.0009 *100 = 0.09 percentage points (approximately 1 percent relative to the mean quit probability). The magnitude of this effect is identical to the impact of an increase in exposure to one additional magazine ad for an NRT product in a study by Avery et al. (2007). They use Simmons NCS data for fall and spring quarters from the fall of 1995 through the fall of 1999. The quit rate in their sample of 10 percent is approximately the same as the 9 percent rate in our sample.

TV advertising has no statistically or economically significant impact on the failure rate across all specifications. Exposure to an additional ad does raise the attempt probability by between 0.06 and 0.08 percentage points; the marginal effect is 0.07 percentage points in the most saturated model, though these effects are imprecisely estimated and not statistically significant. Together, these estimates indicate that most of the quit effect is due to an increase in the success rate conditional on attempting. That issue is explored in more detail in the next table.

Since 51 percent of the observations have only one individual per household and 33 percent have two observations per household, standard errors that ignore clustering are extremely similar to those that take it into account.

[16] This indicates a form of negative selection such that ads may be targeted to individuals with unobservable characteristics that may make them less likely to use e-cigarettes to quit smoking. Such targeting is consistent with e-cigarette manufacturers attempting to attract new populations of users.

Exposure to an additional magazine ad never has a significant effect on the quit probability. The effect is small in magnitude and becomes negative in the last two models. The failure effect is positive, significant, and quite large in the first three models but is greatly reduced and insignificant once magazine fixed effects are included.

The estimated TV effects are not sensitive to the exclusion of magazine advertising since the two advertising variables are weakly correlated. The estimated TV effects also are not sensitive to the order in which the different types of fixed effects are included. In summary, the results in Table 4 indicate that exposure to TV ads raises the quit probability but exposure to magazine ads does not.

When we stratify by age (comparing adults ages 18-34 vs. those ages 35+; see Table A4 in the appendix), we find that the marginal effect of TV ad exposure on the quit probability is significantly larger among younger adults. Specifically, one additional TV ad raises the quit probability by 0.16 percentage point among 18-34 year olds and by 0.07 percentage point among older adults; both estimates are statistically significant. However, the effect of TV ads on the probability of making an attempt is suggestively larger among older adults (0.13 percentage point vs. 0.10 percentage point; though the effects are imprecise and we cannot reject the null of no difference) in the most comprehensive specification. Thus, while e-cigarette ads on TV lead both groups to attempt to quit smoking, the stronger successful quit effect among younger adults may reflect their lower addictive nicotine stock, as well as relatively their weaker habit formation related to the actual experience of smoking conventional cigarettes.

In multinomial logits not shown, we have examined the effects of advertising on method-specific attempt rates and find no significant effects of each type of advertising on these rates. Hence, there is no evidence of crowd-out. Instead, TV advertising for e-cigarettes appears to encourage smokers to attempt to quit by each of the four methods that we consider. This result is similar to one reported by Avery et al. (2007). They find that exposure to NRT ads in magazines raises the attempt rate but does not increase attempts using NRT relative to cold turkey attempts.

In Table 5 we specifically assess how ad exposure impacts the conditional probability of success. The table reports the results of linear probability models in which the conditional probability of success (quits conditional on attempts denoted by π) is the outcome.[17] These models are estimated separately for all attempts to quit and for each of four method-specific attempts to quit. Only the marginal effects and standard errors of the TV advertising exposure measure are shown because the magazine exposure effects are not meaningful and insignificant. Magazine ad exposure is, however, included in all specifications.

Focusing on the results for all attempts, one sees that an increase in exposure to e-cigarette advertising on TV has a positive effect on the success rate. The effect is significant in all specifications and is fairly stable across alternative specifications. It ranges in magnitude from a 0.14 percentage point increase in the probability of success to a 0.19 percentage point increase in that probability.

The results just reported can be combined with those in Table 4 to decompose the quit effect into a component due to an increase in the attempt rate (a) and one due to an increase in the success rate (π). This decomposition also puts the magnitude of these effects in perspective. Since $q = a\pi$,

$$(q_x/q) = (a_x/a) + (\pi_x/\pi), \qquad (2)$$

[17] We report estimates from linear probability models (LPM), rather than the binary logit, due to the smaller sample sizes as we condition the sample on attempters and method-specific attempters. As we saturate the models with fixed effects in specifications (4) and (5) some logit models fail to converge. We confirm that for models (1) through (3) where we are able to estimate both LPM and logit specifications, the marginal effects are highly similar.

where x is the advertising variable and a subscript denotes a partial derivative. The means of q, a, and π are 9.0 percent, 37.0 percent, and 24.3 percent, respectively. Based on the fifth and most comprehensive specification in Tables 4 and 5, our results imply that an additional exposure to an e-cigarette advertisement on TV raises the quit rate by about 1 percent, the attempt rate by 0.2 percent, and the success rate by 0.8 percent. Clearly, most of the one percent increase in the number of smokers who quit is due to the increase in the success rate. While these effects are somewhat modest, they pertain to a small change in exposure. Computations suggest that the logits are fairly linear in the range in which we estimate them. Hence, an exposure to five additional ads would increase the number of quitters by 5 percent.

The remainder of the estimates in Table 5 pertain to marginal effects of exposure to TV ads on attempt-specific success rates. As in the case with the models for success with all attempts, magazine effects are not shown because they never are significant. The fifth model could not be estimated because the sample size was too small to include all the fixed effects.

The only case in which success effects are positive, generally significant, and generally stable pertains to e-cigarette only attempters. These range from a marginal effect of 0.25 percentage points to 0.62 percentage point. The pattern of larger and more significant effects as additional fixed effects are included mirrors that observed for all attempters.

How reasonable are the effects just observed? As an identity,

$$\pi = k^e\pi^e + k^n\pi^n + k^c\pi^c + k^o\pi^o, \qquad (3)$$

where the superscript denotes the method (*e* for electronic cigarettes only, n for NRT only, c for cold turkey, and o for other methods) and k^e, for example is the fraction of all attempts accounted for by e-cigarette attempts. We find that exposure to additional ads has no effect on the attempt-specific fractions just defined. Hence,

$$(\partial\pi/\partial x) = k^e*(\partial\pi^e/\partial x). \qquad (4)$$

The fraction of attempts accounted for by e-cigarette attempts (k^e) equals 0.241 (Table 1), and in the third specification in Table 5, $\partial\pi^e/\partial x = 0.0044$. Therefore, the estimated value of the right-hand side of equation (4) is 0.0011. That is very similar to the actual value of $\partial\pi/\partial x$ of 0.0015 in the third specification of the success rate logit for all attempters in Table 5. In the fourth specification, $\partial\pi^e/\partial x$ equals 0.0062. So the right-hand side of equation (4) becomes 0.0015. That is also close to that actual value of $\partial\pi/\partial x$ of 0.0019 in the fourth specification of the success rate logit for all attempters.

In summary, the lack of effects for attempt methods other than with e-cigarettes amounts to an important falsification test. In addition, the agreement between the two methods of estimating the success rate for all attempts provides further validation of our specifications.

Our estimate that exposure to an additional TV e-cigarette message increases the quit rate by one percent obviously is a small effect. It pertains, however to a small change in exposure. A better way to evaluate the magnitude of the effect is to apply our estimate to potential policies to reduce or expand advertising. A complete ban on advertising is an obvious example of the former. It would have reduced the average number of ads seen in our sample period from three to zero and lowered the quit rate from 9.0 percent to 8.7 percent. Based on the smoking participation rates that underlie the lower portion of Figure 1, this reduction in the quit rate translates into approximately 105,000 fewer quitters in 2015.

A policy that has the potential to encourage advertising would be to eliminate the FDA mandate requiring that all e-cigarette products not commercially marketed prior to February 15, 2007 to submit costly and lengthy marketing applications originally by August 2018. While this deadline was extended to August 2022 in July 2017 and post-dates our sample period, the mandate was under discussion during our sample period. If that had not been the case, it is likely that e-cigarette producers would have devoted more expenditures to advertising. Suppose that this increased exposure to 14 ads—the mean number of NRT ads seen during our sample period. Then the quit rate would have risen to 10.1 percent, which would have resulted in an additional 350,000 quitters in 2015.[18]

In evaluating the magnitudes of these effects, keep in mind that the estimate of a ban is based on a small number of ads actually being aired. Moreover, the policy that expands advertising does not allow producers to advertise the health benefits of e-cigarettes or their use as a method to stop smoking.

V. Discussion

The title of this paper poses the question whether e-cigarette advertising encourages smokers to quit. The results in the paper suggest that the answer is yes for TV advertising but no for magazine advertising. We find that exposure to an additional ad seen on TV increases the number of adults who quit by about 0.09 percentage point, about 1 percent relative to a mean quit rate of 9 percent in the past year. Most of this effect is due to an increase in the success rate conditional on attempts rather than to an increase in attempts. We predict that a ban on TV advertising would lower the quit rate by around 3 percent, while a policy that would not discourage it would raise the quit rate by slightly more than 10 percent. We find no effects of exposure to magazine ads on quit behavior. We label the TV findings as tentative because they pertain to a short period of time (the fourth quarter of 2013 through the fourth quarter of 2015). Studies that span a longer period of time deserve a high priority on an agenda for future research.

[18] Both policy simulations fix all independent variables other than the TV ads at their values for each individual. In the first simulation, the value of the ads is set equal to zero for each individual. In the second simulation, the value of the ads is increased by 11 for each person so that the new mean is equal to 14. Then the new quit rates that result from these changes are computed and averaged.

Given the short period of time that e-cigarettes have been on the market, the lack of information on the use of the product in the NCS until the fourth quarter of 2013, and the absence of comparable sources, this research will require the use of very current data. One advantage of such research is that it can address the issue of whether e-cigarettes may continue to promote the continued reduction in adults' smoking participation possibly because of lagged responses to the introduction of the product.

How much of the sharp reduction in adult smoking depicted in Figure 1 can be "explained" by the increase in e-cigarette advertising? Consider the period from 2010 through 2015. In the former year, the smoking participation rate of adults 18 years of age and older was 19.34 percent. In the latter year, it fell to 15.11 percent or by 4.23 percentage points. If there were no TV ads during this period, our estimates suggest that smoking participation in 2015 would have been 15.22 percent, which amounts to a difference of 0.11 percentage points between the predicted and the actual rate in that year. Hence, we account for (0.11/4.23) *100 or 2.6 percent of the observed decline. While the ads explain only a small portion of the trend, they probably also account for only a small portion of the introduction and rapid diffusion of a new product.[19]

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[19] Consider a time series of annual smoking participation rates indexed by t where t = 0 is the base year (2010 in our case) and t =n in the last year (2015 in our case). Assume that the population is fixed over the six-year time period and that no one starts or restarts smoking in that period. Then

$$S_n = S_0 \prod_{t=1}^{n} (1 - q_t),$$

where $\prod$ is the symbol for multiplication and q_t is the annual quit rate $q_t = (S_{t-1} - S_t)/S_{t-1}$. In computing S_n, we assume that the quit rates in periods 1 and 2 (2011 and 2012) are the ones implied by the data that underlie the lower portion of Figure 1. That is because there was almost no advertising in those two years. In 2013, 2014, and 2015, we reduce the quit rates from the actual rates implied by the data to ones that we predict would have been in effect in each of those three years. That is, we use our estimates only to <u>reduce</u> the quit rate in each year in the NHIS series. The quit rates in the NCS are higher than those in the NHIS, possibly because the rates in the former are more short term than those in the latter. Taken by itself, that might cause us to overstate the contribution of the ads because they may have smaller effects on longer term quit rates. A factor that goes in the opposite direction is that the ads might have had bigger effects if they mentioned benefits and the use of e-cigarettes as a method to quit smoking.

Our results and those by Majeed et al. (2017) should give pause to those who advocate a complete ban on e-cigarette advertising. Majeed and colleagues examine whether the perceived harm of e-cigarettes among U.S. adults changed between 2012 and 2015. They find that it did. In 2015 approximately 36 percent of adults perceived that e-cigarettes had the same level of harm as cigarettes compared to only 12 percent in 2012. Even more striking, there was a four-fold increase in the number of adults who perceived e-cigarettes to be more harmful than cigarettes from roughly 1 percent in 2012 to 4 percent in 2015. In light of contradictory evidence in the medical literature, these trends point to a lack of information about a product that potentially is harm-reducing.

Of course, it is far too early for us or other investigators to advocate unrestricted advertising of e-cigarettes. Medical researchers need to investigate the long-term health consequences of the use of the product. Economists need to investigate the role of e-cigarettes in initiation in the use of nicotine by youths. Do youths who otherwise would start to smoke cigarettes substitute e-cigarettes instead? Or does the availability of a new source of nicotine attract youths who otherwise would not use the product? And does initiation into the use of nicotine by both types of youths eventually lead them to start to smoke conventional cigarettes by means of a "gateway" effect?

Some of these questions revolve around whether e-cigarettes and combustible cigarettes are substitutes or complements. Friedman (2015) and Pesko, Hughes, and Faisal (2016) find that state bans on e-cigarette sales to minors raise smoking rates among youths ages 12-17 in two different data sets. These studies suggest that the two products are substitutes, but do not use recent data and do not verify that the use of e-cigarettes was affected in states with higher minimum purchase age laws. Using a third different data set, Abouk and Adams (2017) report that state bans on e-cigarette sales to minors actually lower youth smoking participation rates. They also present suggestive evidence that the bans lower youth e-cigarette participation rates. These results suggest that the two sources of nicotine are complements, although the findings for e-cigarettes are based on within-state monthly changes in the laws banning sales in a single year. These conflicting findings and our remarks above concerning research on quit behavior by adults and advertising underscore the rich nature of future research by economists on e-cigarettes.

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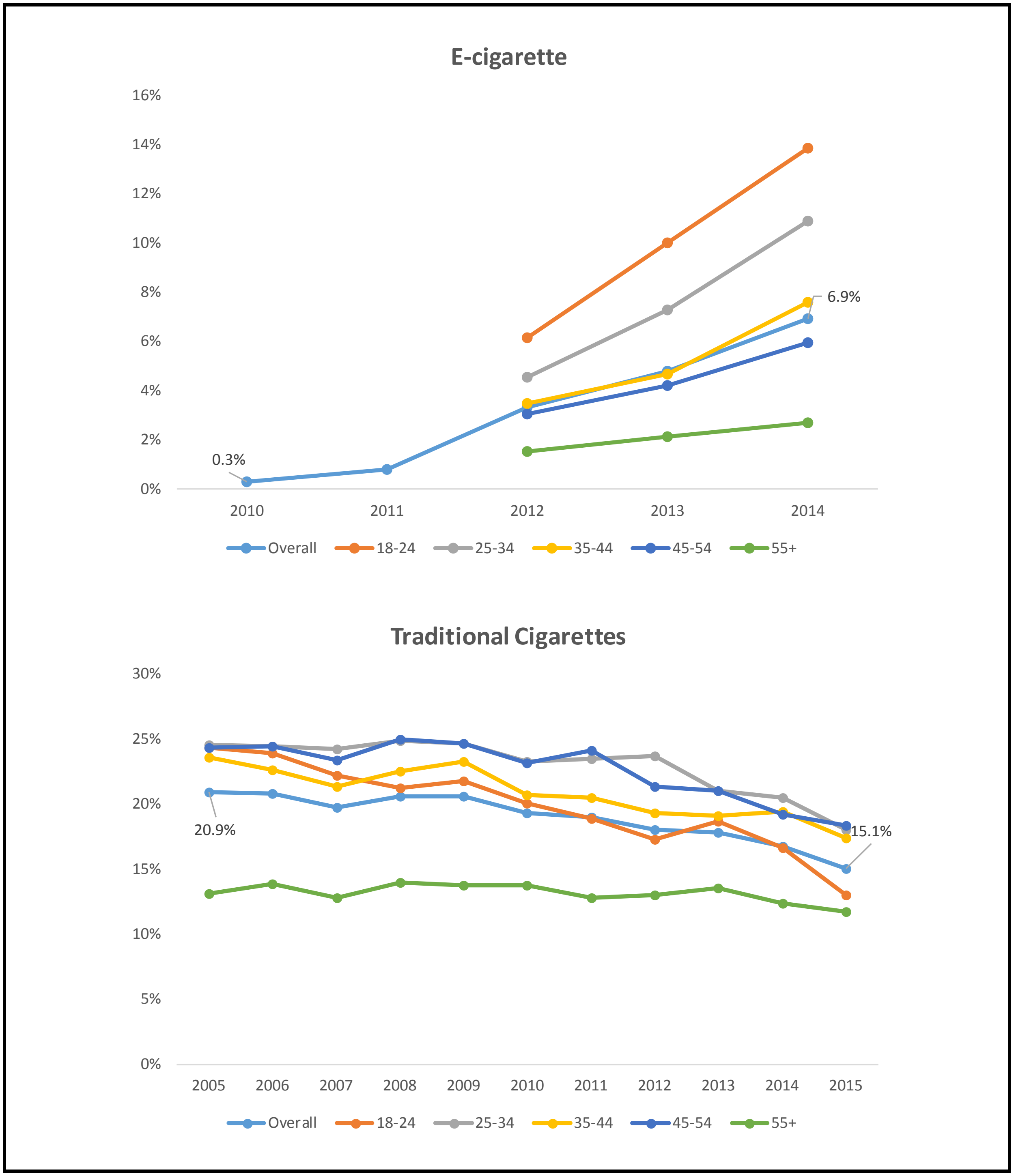
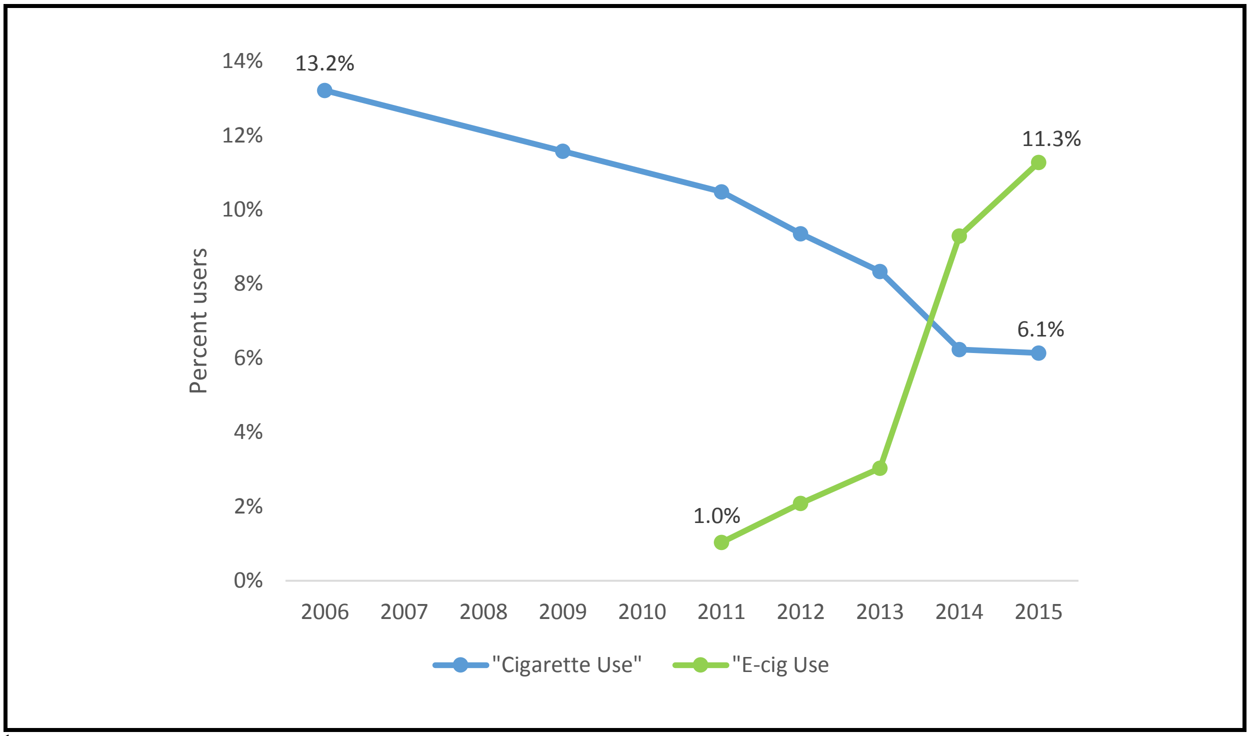
Figure 1
E-Cigarette[1] and Traditional Cigarette Use[2] Trends, Adults



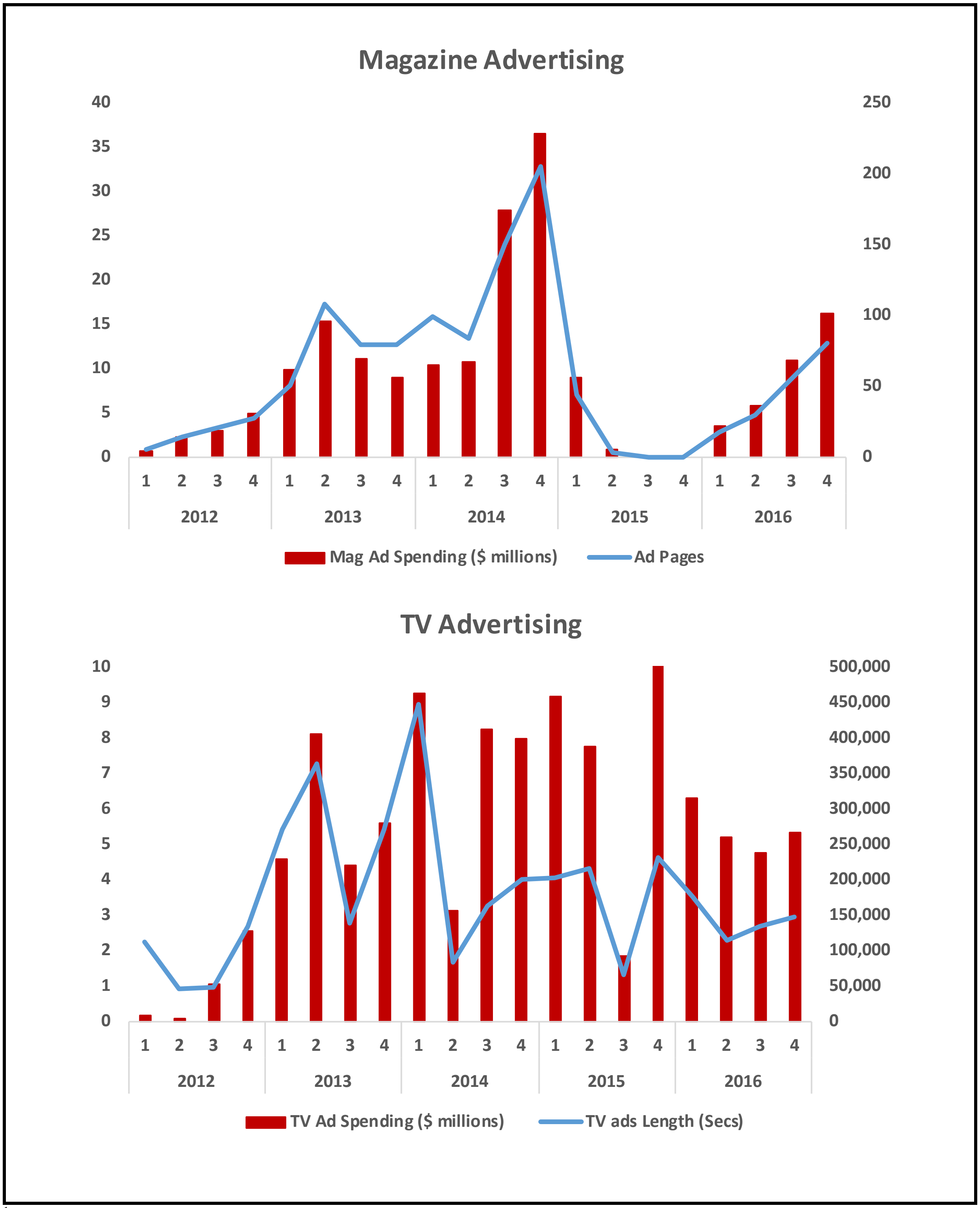
[1]Source: National Adult Tobacco Survey (2012-2014); McMillen et al. (2015) for 2010 and 2011. Figures for overall population comparable from both sources for 2012-2013
[2]Source: National Health Interview Survey (2005-2015)

Figure 2
E-Cigarette and Traditional Cigarette Use Trends, Youths [1]



[1]Source: National Youth Tobacco Survey (2006-2015)

Figure 3
E-Cigarette Magazine and Television Advertising Trends[1]



[1]Source: Kantar Media, purchased from the source

Table 1: Definitions and Means of Key Outcomes[1]

Panel A: Basic Outcomes

Variable	Definition	Mean
Attempt Rate:	$a = A/N$	37.0%
Quit Rate	$q = Q/N$	9.0%
Failure Rate:	$f = F/N$	28.0%
Success Rate	$\pi = Q/A = q/a$	24.3%

Panel B, Percentage Distribution of Attempts by Method and Success Rates by Method

Method	Percentage of Attempts	Success Rate
E-cigs only	24.1%	28.9%
NRT only	18.2%	27.4%
Cold Turkey	17.8%	31.2%
Other[2]	40.0%	17.1%

[1]Sample (N = 8,291) consists of quitters in past year (Q), failures in past year (F), and non-attempters in past year (D). $N = Q + F + D$, $A = Q + F$, $a = q + f$, current smokers = F + D.

[2]Includes gradual reduction only and mixed methods.

Table 2: Means of Independent variables by quitting, failing to quit, and not trying

Variable/Outcome	Quitters (Q)	Failures (F)	Non-Attempters (D)
Gender			
Male	55.2%	41.8%	51.0%
Female	44.8%	58.2%	49.0%
Education			
Less than HS	12.2%	17.9%	22.2%
HS	30.4%	34.4%	36.6%
Some College	34.9%	33.4%	28.2%
College or more	22.5%	14.3%	13.0%
Insurance Status			
Private or Medicare	69.3	58.8	50.9
Medicaid	8.6	15.1	11.6
No Insurance	22.1	26.1	37.5
Age			
18-24	9.2%	7.9%	8.7%
25-34	18.9%	15.5%	17.0%
35-44	18.5%	17.2%	18.3%
45-54	20.2%	22.4%	23.8%
55-64	17.0%	23.0%	20.2%
65+	16.2%	13.9%	12.1%
Income			
<$15k	7.6%	15.0%	13.7%
15k-34.99k	13.7%	18.5%	19.5%
35k-49.99k	13.3%	14.8%	15.8%
50k-99k	34.7%	30.6%	31.4%
100k+	30.8%	21.1%	19.6%
Race			
White or other races	73.8%	65.0%	60.8%
Black	6.5%	11.4%	10.3%
Hispanic	19.7%	23.6%	28.9%
Marital Status			
Married	51.9	44.7	44.0
Divorced or separated	18.5	21.0	21.1
Widow	3.5	6.9	5.0
Single	26.1	27.5	30.0
Employment Status			
Employed Full-time	51.0	42.9	45.3
Employed part-time	10.8	10.5	12.0
Retired	15.5	14.7	13.1
Unemployed	6.8	9.6	11.2
Disabled	7.9	14.3	10.9

Student	1.7	1.5	1.2
Homemaker	6.2	6.5	6.3
E-cig TV Ad Exposure	4.5	3.7	2.9
NRT TV Ad Exposure	16.5	17.9	14.1
Magazine Ad Exposure	3.8	4.8	3.3
N	747	2,324	5,220

Table 3: Means of Demographics by Advertising Exposure

Panel A: Means by E-cigarette TV Advertising Exposure

Variable	**No Advertising Exposure**	**Less than Median[1] Advertising Exposure**	**Greater than Median[1] Advertising Exposure**
Gender			
Male	48.7%	49.3%	48.6%
Female	51.3%	50.7%	51.4%
Education			
Less than HS	21.1%	16.3%	17.4%
HS	35.1%	36.4%	36.6%
Some College	29.6%	31.7%	33.5%
College or more	14.2%	15.6%	12.6%
Insurance Status			
Private or Medicare	53.9%	56.4%	59.3%
Medicaid	11.9%	13.0%	14.3%
No Insurance	34.2%	30.7%	26.4%
Age			
18-24	8.7%	6.3%	9.6%
25-34	16.5%	16.4%	18.3%
35-44	17.7%	17.6%	20.3%
45-54	22.9%	24.8%	22.6%
55-64	20.8%	20.7%	20.0%
65+	13.3%	14.2%	9.2%
Income			
<$15k	13.7%	12.8%	13.0%
15k-34.99k	19.3%	16.8%	16.4%
35k-49.99k	15.2%	16.9%	13.9%
50k-99k	31.0%	31.6%	34.0%
100k+	20.7%	21.8%	22.7%
Race			
White or other races	62.6%	64.6%	65.5%
Black	9.6%	12.6%	12.2%
Hispanic	27.8%	22.7%	22.3%
Marital Status			
Married	45.3%	46.1%	41.2%
Divorced or Separated	21.1%	19.7%	19.9%
Widow	5.4%	5.5%	5.1%
Single	28.2%	28.8%	33.9%
Employment Status			
Employed Full-time	45.3%	42.4%	46.4%
Employed Part-time	11.6%	10.9%	11.0%
Retired	14.2%	14.8%	10.3%
Unemployed	10.0%	12.1%	10.6%
Disabled	11.1%	12.3%	14.2%

Student	1.3%	1.1%	1.6%
Homemaker	6.4%	6.3%	5.9%

[1]The median is defined for those that have been exposed to at least 1 ad.

Table 3: Means of Demographics by Advertising Exposure

Panel B: Means by E-cigarette Magazine Advertising Exposure

Variable	**No Advertising Exposure**	**Less than Median[1] Advertising Exposure**	**Greater than Median[1] Advertising Exposure**
Gender			
Male	51.4%	47.8%	43.0%
Female	48.6%	52.2%	57.0%
Education			
Less than HS	22.6%	17.3%	16.4%
HS	37.3%	33.2%	32.7%
Some College	27.4%	31.9%	36.1%
College or more	12.7%	17.6%	14.8%
Insurance Status			
Private or Medicare	53.3%	59.5%	54.5%
Medicaid	12.4%	11.3%	13.1%
No Insurance	34.4%	29.3%	32.4%
Age			
18-24	8.2%	7.9%	9.8%
25-34	16.4%	15.0%	19.1%
35-44	17.8%	16.4%	19.9%
45-54	23.4%	22.6%	22.8%
55-64	20.7%	22.5%	19.1%
65+	13.5%	15.7%	9.3%
Income			
<$15k	13.9%	11.9%	14.0%
15k-34.99k	19.4%	17.5%	18.1%
35k-49.99k	15.3%	15.6%	15.1%
50k-99k	31.3%	33.0%	30.4%
100k+	20.1%	22.0%	22.5%
Race			
White or other races	63.2%	65.2%	61.3%
Black	9.8%	10.2%	11.6%
Hispanic	27.0%	24.6%	27.2%
Marital Status			
Married	47.0%	45.5%	39.1%
Divorced or Separated	20.2%	21.1%	22.1%
Widow	5.4%	5.2%	5.5%
Single	27.5%	28.2%	33.2%
Employment Status			
Employed Full-time	45.4%	44.7%	44.9%
Employed Part-time	11.4%	10.4%	12.4%
Retired	14.3%	17.0%	9.7%
Unemployed	10.1%	9.6%	11.6%

Disabled	11.6%	11.3%	11.9%
Student	1.1%	1.5%	1.8%
Homemaker	6.1%	5.4%	7.7%

[1]The median is defined for those that have been exposed to at least 1 ad.

Table 4: Multinomial Logit Model, Marginal Effects [S.E.][1]

Independent Variable **Outcome**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
E-cig TV Ads					
Q	0.0005 [0.0003]**	0.0006 [0.0003]**	0.0007 [0.0003]***	0.0008 [0.0003]***	0.0009 [0.0003]***
F	0.0000 [0.0005]	0.0000 [0.0005]	0.0000 [0.0005]	0.0000 [0.0005]	-0.0002 [0.0006]
A	0.0006 [0.0005]	0.0006 [0.0005]	0.0006 [0.0005]	0.0008 [0.0005]	0.0007 [0.0006]
Magazine Ads					
Q	0.0002 [0.0003]	0.0002 [0.0003]	0.0003 [0.0003]	-0.0005 [0.0005]	-0.0009 [0.0006]
F	0.0023 [0.0005]***	0.0024 [0.0005]***	0.0020 [0.0005]***	0.0001 [0.0008]	0.0010 [0.0008]
A	0.0025 [0.0005]***	0.0026 [0.0006]***	0.0023 [0.0005]***	-0.0004 [0.0008]	0.0001 [0.0009]
Year-qtr. fixed effects, and demographic controls	Yes	Yes	Yes	Yes	Yes
DMA fixed effects	No	Yes	Yes	Yes	Yes
Time slot fixed effects	No	No	Yes	Yes	Yes
Channel and Magazine fixed effects	No	No	No	Yes	Yes
Program fixed effects	No	No	No	No	Yes

[1] Each column represents a separate multinomial logit model with the three outcomes being successful quits (Q), failures (F), and non-attempters (D), the latter being the reference category. Marginal effects are reported, with standard errors clustered at the household level in brackets. Instead of reporting the marginal effect on D (non-attempters), we report the marginal effect of the regressor on A (attempts) since this is just the negative of the marginal effect of the regressor on D, and thus the sum of marginal effects of the regressor on Q and F. *p<0.10, **p<0.05, ***p<0.01.

Table 5: LPM of Successful Quitting Given Attempting, Marginal Effects of TV Ads [S.E.][1]

Independent Variable **Sub-population**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
E-cig TV Ads					
All Attempters	0.0015 [0.0008]*	0.0014 [0.0008]*	0.0015 [0.0008]**	0.0019 [0.0008]**	0.0018 [0.0009]*
E-cig Only Attempters	0.0025 [0.0017]	0.0034 [0.0019]*	0.0044 [0.0019]**	0.0062 [0.0025]**	2
NRT Only Attempters	0.0021 [0.015]	0.0022 [0.0017]	0.0028 [0.0014]*	0.0031 [0.0021]	2
Cold Turkey Attempters	-0.0017 [0.0015]	-0.0015 [0.0016]	-0.0020 [0.0018]	-0.0000 [0.0033]	2
Other Method Attempters	0.0010 [0.0012]	0.0007 [0.0013]	0.0005 [0.0014]	0.0003 [0.0013]	2
Year-qtr fixed effects, and demographic controls	Yes	Yes	Yes	Yes	Yes
DMA fixed effects	No	Yes	Yes	Yes	Yes
Time slot fixed effects	No	No	Yes	Yes	Yes
Channel and Magazine fixed effects	No	No	No	Yes	Yes
Program fixed effects	No	No	No	No	Yes

[1] Each cell represent a separate linear probability model on successfully quitting smoking. Samples are restricted to those who attempted smoking cessation (when considering overall quit probability) and to those who attempted smoking cessation with a specific method (when considering method-specific success). Standard errors clustered at the household level are reported in brackets. *p<0.10, **p<0.05, ***p<0.01.

[2] Models did not converge because of insufficient sample size

[3] N=3,076 for All attempters, N=740 for E-cig Only, N=561 for NRT Only, N=546 for Cold Turkey Only, N=1,229 for Other Method.

Appendix

Table A1: Multinomial Logit Model, Marginal Effects (w/o NRT) [S.E.][1]

Independent Variable **Outcome**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
E-cig TV Ads					
Q	0.0005 [0.0002]**	0.0005 [0.0002]**	0.0006 [0.0002]***	0.0007 [0.0003]***	0.0008 [0.0003]**
F	0.0005 [0.0004]	0.0005 [0.0004]	0.0001 [0.0004]	-0.0001 [0.0004]	-0.0001 [0.0005]
A	0.0010 [0.0004]**	0.0010 [0.0004]**	0.0007 [0.0004]	0.0006 [0.0005]	0.0006 [0.0005]
Magazine Ads					
Q	0.0002 [0.0003]	0.0002 [0.0003]	0.0002 [0.0003]	-0.0005 [0.0005]	-0.0010 [0.0006]*
F	0.0024 [0.0005]***	0.0025 [0.0005]***	0.0020 [0.0005]***	0.0001 [0.0008]	0.0007 [0.0009]
A	0.0026 [0.0005]***	0.0026 [0.0005]***	0.0023 [0.0005]***	-0.0004 [0.0009]	-0.0003 [0.0009]
Year-qtr. fixed effects, and demographic controls	Yes	Yes	Yes	Yes	Yes
DMA fixed effects	No	Yes	Yes	Yes	Yes
Time slot fixed effects	No	No	Yes	Yes	Yes
Channel and Magazine fixed effects	No	No	No	Yes	Yes
Program fixed effects	No	No	No	No	Yes

[1] Each column represents a separate multinomial logit model with the three outcomes being successful quits (Q), failures (F), and non-attempters (D), the latter being the reference category. Marginal effects are reported, with standard errors clustered at the household level in brackets. Instead of reporting the marginal effect on D (non-attempters), we report the marginal effect of the regressor on A (attempts) since this is just the negative of the marginal effect of the regressor on D, and thus the sum of marginal effects of the regressor on Q and F. *p<0.10, **p<0.05, ***p<0.01.

Table A2: LPM of Successful Quitting Given Attempting, Marginal Effects of TV Ads (w/o NRT) [S.E.][1]

Independent Variable **Sub-population**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
E-cig TV Ads					
All Attempters	0.0008 [0.0006]	0.0008 [0.0007]	0.0013 [0.0007]**	0.0017 [0.0007]**	0.0019 [0.0008]***
E-cig Only Attempters	0.0024 [0.0016]	0.0033 [0.0017]*	0.0045 [0.0018]**	0.0065 [0.0025]**	[2]
NRT Only Attempters	0.0013 [0.010]	0.0016 [0.0011]	0.0022 [0.0010]**	0.0025 [0.0018]	[2]
Cold Turkey Attempters	-0.0017 [0.0014]	-0.0018 [0.0015]	-0.0026 [0.0018]	-0.0000 [0.0031]	[2]
Other Method Attempters	0.0002 [0.0010]	0.0001 [0.0011]	0.0006 [0.0012]	0.0008 [0.0012]	[2]
Year-qtr fixed effects, and demographic controls	Yes	Yes	Yes	Yes	Yes
DMA fixed effects	No	Yes	Yes	Yes	Yes
Time slot fixed effects	No	No	Yes	Yes	Yes
Channel and Magazine fixed effects	No	No	No	Yes	Yes
Program fixed effects	No	No	No	No	Yes

[1] Each cell represent a separate linear probability model on successfully quitting smoking. Samples are restricted to those who attempted smoking cessation (when considering overall quit probability) and to those who attempted smoking cessation with a specific method (when considering method-specific success). Standard errors clustered at the household level are reported in brackets. *p<0.10, **p<0.05, ***p<0.01.

[2] Models did not converge because of insufficient sample size

[3] N=3,076 for All attempters, N=740 for E-cig Only, N=561 for NRT Only, N=546 for Cold Turkey Only, N=1,229 for Other Method.

Table A3: Multinomial Logit Model by Age Group, Marginal Effects (w/ NRT) [S.E.][1]

Independent Variable **Outcome**	**(1)**	**(2)**	**(3)**	**(4)**
		Panel A 18-34		
E-cig TV Ads				
Q	0.0008 [0.0004]**	0.0009 [0.0005]**	0.0012 [0.0004]***	0.0016 [0.0005]***
F	0.0000 [0.0008]	0.0000 [0.0006]	-0.0003 [0.0008]	-0.0004 [0.0009]
A	0.0008 [0.0009]	0.0009 [0.0007]	0.0009 [0.0009]	0.0010 [0.0010]
		Panel B Ages 35+		
E-cig TV Ads				
Q	0.0003 [0.0004]	0.0003 [0.0004]	0.0005 [0.0003]	0.0007 [0.0003]**
F	0.0000 [0.0006]	0.0001 [0.0007]	0.0001 [0.0007]	0.0006 [0.0007]
A	0.0004 [0.0006]	0.0003 [0.0007]	0.0005 [0.0008]	0.0013 [0.0008]
Year-qtr. fixed effects, and demographic controls	Yes	Yes	Yes	Yes
DMA fixed effects	No	Yes	Yes	Yes
Time slot fixed effects	No	No	Yes	Yes
Channel and Magazine fixed effects	No	No	No	Yes
Program fixed effects	No	No	No	No

[1] Each column represents a separate multinomial logit model with the three outcomes being successful quits (Q), failures (F), and non-attempters (D), the latter being the reference category. Marginal effects are reported, with standard errors in brackets. Instead of reporting the marginal effect on D (non-attempters), we report the marginal effect of the regressor on A (attempts) since this is just the negative of the marginal effect of the regressor on D, and thus the sum of marginal effects of the regressor on Q and F. *p<0.10, **p<0.05, ***p<0.01.
[2]Sample size of 18-34 sample is 3,587 and for 35+ is 4,704.