DOES E-CIGARETTE ADVERTISING ENCOURAGE ADULT SMOKERS TO QUIT?

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We provide the first causal evidence on whether e-cigarette advertising on television and in magazines encourages adult smokers to quit. We find the answer to be yes for TV advertising but no for magazine advertising. Our results indicate that a policy banning TV advertising of e-cigs would have reduced the number of smokers who quit in the recent past by approximately 3%. If the FDA were not considering regulations and mandates, e-cig 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%. (JEL I10, I12, I18)

I. Introduction

Electronic Nicotine Delivery Systems (ENDS), of which electronic cigarettes (e-cigs) constitute the most common sub-product, are a non-combustible alternative to smoking. As

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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-cigs from now on), a liquid containing nicotine is vaporized by a battery powered heating device.

Participation in the use of e-cigs has increased dramatically since they were first introduced in the U.S. in 2007. According to the upper portion of Figure I, participation among adults grew from 0.3 percent in 2010 to 6.9 percent in 2014. Participation by 18-34 year olds was 1.75 times higher than that of adults of all ages, over the years in which data for the former group are available. The figure depicts similar trends for youth. Participation 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-cig 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 II 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] In 2014 Q3, spending per ad increased. E-cig advertisers moved from showing ads on infrequently watched programs to showing e-cig ads on frequently watched programs.[2] Almost 48 percent of adults had been exposed to e-cig marketing in a 2013 sample of Florida residents (Kim, Arnold, and Makarenko 2014). Youth and young adult exposure was at least equal to 10 percent at the national level in the same year (Duke et al. 2014).

E-cig use and advertising have surged during an extremely contentious policy debate. At the heart of this regulatory debate are fundamental questions regarding whether e-cigs will draw cigarette smokers away from a dangerous habit or lure new initiates to tobacco use and lead to a new generation of nicotine addicts. On one side of the debate is the argument that e-cigs 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

[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-cigs by the Food and Drug Administration. These regulations were announced in May 2016 (see below).
[2] We confirm this by dividing the average number of ads per person seen in each quarter by the total number aired using Simmons data, which is described later.

(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-cigs 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-cigs (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-cig participation might be helping reduce smoking. The lower portion of Figure I 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-cig participation are also available, adult smoking participation fell by almost four percentage points. 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-cig participation. The figure further shows that the growth in e-cig participation among youth was also accompanied by a downward trend in youth smoking.

On the other side of the policy debate are several arguments that suggest caution about e-cigs. 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-cigs may have lasting adverse consequences for cognitive development (U.S. Surgeon General 2014).[3] Accidental poisoning can result from the damaging of e-cig 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-cigs has carried over to the regulation of e-cig advertising. In the U.S. until 2016, e-cigs 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 to include e-cigs. The FDA announced regulations that would ban the sale of e-cigs and related products to minors effective immediately and would require advertisements to carry warnings that the product contains nicotine, which is addictive, effective in August 2018. In addition and also effective in August

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

2018, all products that were not commercially marketed prior to February 15, 2007 would have to submit marketing applications (U.S. Food and Drug Administration 2016a). Because the marketing application approval process can be quite lengthy and the cost of preparing it has been estimated at between $200,000 and $2 million by the FDA, it has the potential to eliminate many current producers and result in significant price increases. In July 2017, FDA Commissioner Scott Gottlieb indicated marketing applications will not be required until August 2022 and that he would consider endorsing e-cigs as a method to quit smoking (Kaplan 2017).

The status quo remains that e-cig manufacturers are allowed to advertise in magazines, television, and other media in the U.S, although the advertisements had to carry warning labels starting in August 2018. In 2016, however, the European Court of Justice, Europe's highest court, found that the European Union had the right to regulate e-cigs including banning advertising (Jolly 2016). Moreover, in March 2018 seven health and medical groups sued the FDA over the four-year delay in the marketing applications requirement (McGinley 2018).

The purpose of this paper is to shed light on one side of the contentious debate just outlined by investigating whether e-cig advertising on television and in magazines encourages adult smokers to quit. To preview our results, the answer to this question is yes for TV advertising but no for magazine advertising. We use detailed information on TV viewing patterns and magazine issues read in the Simmons National Consumer Survey and match this information to all e-cig 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 by all smokers increases the number of adults who quit smoking by almost 1 percent relative to a mean quit rate of 9 percent.

II. Prior Studies

There are no prior studies that have estimated the effects of e-cig advertising on quit behavior of current smokers. Three streams of literature do, however, bear on our study. One addresses the effectiveness of e-cigs 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-cig 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-cigs 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-cigs 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-cig 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, Tuchman finds that an increase in e-cig advertising is associated with an increase in e-cig 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-cig 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-cigs 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-cigs 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-cig 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-cigs "made me think about quitting smoking." The main message of the ad was that one can use e-cigs anywhere.[4] 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 2018); 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

[4] Since the research for the study by Kim et al. (2015) was completed, a number of states and localities have banned e-cigs in public places, bars, restaurants, and in the workplace.

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-cig 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-cig 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-cigs was obtained prior to the fourth quarter of 2013, we use data from that quarter through the fourth quarter of 2015.[5] That yields an approximate sample size of 58,000 individuals. Respondents report their current smoking status,[6] any smoking cessation attempt over the past year, and methods used to attempt smoking cessation over that period.[7] Based on information on respondents' current smoking status for

[5] We cannot include more recent Simmons surveys because they are extremely expensive.
[6] After adjusting for differences between the US population and the NCS by weighting, smoking participation trends and levels in the NCS are consistent with smoking participation trends and levels in the NHIS.
[7] Because respondents are not asked whether they smoked a year prior to the survey, all of them are asked whether they attempted to stop smoking in the past year and whether they smoke currently.

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-cig use is available only in the context of quitting. That is, individuals respond whether they attempted to quit smoking in the past year and, if so, whether they used e-cigs as a method. A second limitation is that there is no information on the number of e-cigs 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-cig advertising impacts smoking cessation. To that end, the structure of the questions in the NCS are helpful towards assessing whether advertising has impacted smoking cessation in general, and smoking cessation with the aid of e-cigs 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-cigs 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-cig 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.[8]

Panel A of Table I 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 ($A/N = a = q + f$, 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 ($\pi = Q/A = q/a$). The mean of that outcome is 24.3 percent.[9]

[8] 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.

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

Panel B of Table I 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-cigs 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-cigs 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-cigs 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-cig rate. Again not surprisingly, attempts to quit by other methods are the least successful.[10]

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 some point, and then took up smoking again.[11] While we cannot identify these specific groups in the sample,[12] 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.[13]

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-cig advertising, we combine questions that ask respondents about their TV watching and magazine reading habits with ad placements in TV and magazines. 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

[10] The relative success of NRT and e-cigs is generally consistent with evidence from randomized control trials (RCTs). The slightly higher success rate for "cold turkey" attempts in our observational data may potentially reflect that smokers who use e-cigs and NRTs might have failed previous cold turkey attempts. See Dave et al. (2018) for a more detailed discussion.

[11] 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.

[12] This is because smoking status exactly one year prior to the interview date is not available in the NCS.

[13] Over 80 percent of ever-smokers have initiated smoking prior to age 18 (Substance Use and Mental Health Services Administration 2014).

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 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-cigs, that includes the date and time the ad aired, on what channel, during what program, and what brand of e-cig 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-cig 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-cig 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-cig 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 10 percent of the estimated exposure to all ads. In addition, the results in this paper are not substantially affected by inclusion or exclusion of spot ads into the exposure measure, although we include them where available in our results. [14]

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-cig 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-cig 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 pertain 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

[14] For national ads in all areas, including unidentified areas, we adjust for time zone differences as the timing of ads are reported based on EST airing.

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. Other studies with the NCS data cited in Section II have either made that assumption or have assumed that viewing patterns can be extrapolated to the past year. In addition, our measure follows the ones in those studies because it assumes that exposure does not depreciate over time until six months after exposure when it depreciates completely. The latter assumption is supported in reviews of the literature by Leone (1995) and Dave and Kelly (2014).

To be sure, issues can be raised with respect to the assumptions that TV viewing patterns in the past week/month are representative of the past six months and that advertising effects last for six months and then depreciate fully. Therefore, we examine how the results differ when we modify these assumptions. In one modification, we assume that reported viewing patterns are representative of the past four months. This reduces the number of ads to which an individual can be exposed since those aired in the last and next to last months of the six-month period are eliminated.

In a second modification, we use the six-month period but created a depreciated advertising stock. Since we know the exact date on which a respondent completed her Simmons survey and the exact date on which a program aired, we define the stock of advertising associated with a given ad (AD) according to the following function:

$$\mathrm{AD_{it}} = \sum_{\mathrm{j}=0}^{183}\left(\mathrm{AD_{t-j}}\right)(1-\mathrm{r})^{\mathrm{j}}. \qquad (1)$$

In this equation, j is the number of days before the day (denoted by t) on which person i completed the survey (t =j = 0 if an ad aired one day prior to completion) and r is the daily compounded rate of depreciation of exposure to the ad. We set r such that

$$(1 - \mathrm{r})^{30} = (1 - \delta) = 0.8. \qquad (2)$$

That is, we set δ equal to 0.20, so that 20 percent of the exposure to a message seen on the first day of the month preceding completion of the survey has depreciated by the end of that month. This implies that r equals 0.0074. Since 1 - 0.0074 = 0.9926 and since $(0.9926)^{183} = 0.26$, it also implies that 74 percent of the exposure to a message seen on the first day of the beginning of a six-month period has depreciated by the end of the period.[15]

In a third modification of the assumptions of no depreciation and a six-month viewing period, we set the period equal to twelve months and continue to assume a daily compounded rate of depreciation (r) of 0.0074. Since $(0.9926)^{365} = 0.07$, this implies that 93 percent of a message seen on the first day of the twelve-month period has depreciated by the end of the period.

Each of the three alternative ways to compute the number of TV ads seen has advantages and disadvantages. The four-month viewing period reduces measurement error due to changes in viewing patterns but increases the likelihood that some ads that were actually seen are missed. The six- and twelve-month periods with depreciation increase potential exposure while giving less weight to ads seen in the more distant past. The assumed rate of depreciation is, however, somewhat arbitrary. Moreover, we do not know when in the past year an individual quit smoking. The depreciated measure may seriously understate the value of exposure around the time that a quit attempt was made or a successful quit was achieved.

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-

[15] Results are not sensitive to alternative values of δ of 0.1, 0.3, and 0.4. The rate of 0.2 is consistent with studies reviewed by Bagwell (2007) that show that if exposure depreciates gradually rather than all at once, most of it has dissipated by the end of six months.

shifting are not systematically correlated with e-cig 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-cig 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. Since respondents are asked a limited number of questions about their reading habits in the past six months, we do not experiment with measures generated from alternative assumptions about reading habits during alternative periods of time and the rate of depreciation.[16]

In addition to estimating the effects of e-cig 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.[17] TV ad exposure for NRT is constructed with each of the same four algorithms as described above for e-cigs (past six months based on past month, past four months based on past month, past six months with depreciation, and past twelve months with depreciation), combining 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-cig advertising affects smoking cessation behaviors. Furthermore, our individual-level measures of ad exposure are

[16] We also do not show results with alternative estimates of the number of magazine ads read because the measure described above never has significant effects on our outcomes. In preliminary results that are available on request, we found no differences when alternative estimates of exposure to magazine ads were employed.
[17] 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.

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/ethnicity, education, household income, employment status, insurance status, and marital status, as independent variables. All of these variables are defined in Table II, and their means in each of the three groups in the sample (quitters, failures, non-attempters; and overall) are shown. Means of exposure to TV and magazine e-cig ads and to NRT TV ads in each group are also reported in Table II.

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-cigs (4.5 ads on average over the past six months) than failures (3.7) or non-attempters (2.9).[18] 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 five times more NRT ads relative to e-cig 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 1 percent level.

D. Identification Strategy

[18] All measures of TV advertising messages seen in this subsection and the next one pertain to the six-month viewing patterns with no depreciation.

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 of 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 plausible causal effects of this exposure. For instance, even readers of the same magazine may be exposed to different levels of e-cigs 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 II, 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 DMAs and one for all the unidentified DMAs, 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-cig 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-cig 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-cig ads to viewers that are prone to be more likely to quit and try e-cigs 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-cig ad could air, while person B is watching Law and Order: SVU on USA Network at 8:30 PM and no e-cig 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-cig 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.

We show one major source of variation that identifies the effects of e-cig TV advertising exposure in Figure III. Shown is the average six-month exposure to electronic cigarette advertising on 5 frequently watched, nationally aired programs. For example, advertising on "Breaking Bad" is highest of the 5 programs in 2013 q4, but begins declining after 2014 q1, while advertising for "The Big Bang Theory" is increasing. Another example, is that advertising on "Bones" is increasing beginning in 2015 q1 while advertising on other programs is declining. Also shown is the average 6-month exposure to e-cig advertising by magazine. "Sports Illustrated" and "GQ" advertising is increasing beginning in 2014 q2 while advertising on "TV Guide" and "Star" are declining. The key is that quarter-to-quarter advertising changes across TV and magazines are not constant and the changes take different magnitudes and directions. This leaves plausibly exogenous variation that is unexplained by year-quarter and program fixed effects from which we can obtain estimated effects.

To highlight the significant amount of variation in TV and magazine e-cig exposure on which our estimates are based, we regressed each exposure measure on the sociodemographic variables in Table II (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 R^2 in the magazine ad exposure regression is 0.6808. Both R^2s indicate a substantial amount of residual variation in the exposure measures.[19]

In Table III, we show that our procedure balances the sociodemographic characteristics of groups defined by different amounts of advertising exposure. The table contains the mean advertising exposure by sociodemographic characteristics using three related measures. We show the percentage of each demographic category that has no advertising exposure, the mean of their advertising exposure, and the mean of their advertising exposure conditional on exposure to at least one ad. Panel A reports the TV ad exposure, and Panel B reports the mean magazine ad exposure. In general, respondents are unbalanced on their advertising exposure across demographic groups.

[19] 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 IV and VI. In Tables A.1 and A.2 in the appendix, we show that our results in Tables IV and VI are not affected when the NRT measure is excluded. The same comment applies to results (available on request) that delete NRT ads from the estimates in Table V.

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 related to advertising exposure. The p-value associated with this test is 0.000 in the first regression, 0.000 in the 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 III 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 are 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.[20]

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 = 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

[20] 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.

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

$$d = 1 - a = 1 - q - f, \qquad (3)$$

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.[21]

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 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.[22]

[21] 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 IV.

[22] 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 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

Finally, we estimate logit models in which the outcomes are the method-specific attempt or success rates defined in Panel B of Table I. 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-cigs. The latter logits contain an important specification or falsification test. If e-cig advertising encourages successful quitting, that effect should be largest for those who use e-cigs to quit relative to those who attempt to quit using other methods.

IV. Results

Marginal effects of e-cig 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 IV.[23] Five specifications are shown. In the first, the only fixed effects included 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. In all models the TV advertising exposure measure assumes that viewing patterns in the past month are representative of those in the past six months.

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.[24] 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.

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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.

[23] 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 IV and in all tables that follow it. 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.

[24] 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-cigs to quit smoking. Such targeting is consistent with e-cig manufacturers attempting to attract new populations of users.

The quit rate in their sample of 10 percent is approximately the same as the 9 percent rate in our sample. Note that Avery et al. are examining quit behavior in a much earlier period than in our study—one in which NRT was a relatively newer product than in the period observed here. The advertising literature stresses that producers of a mature product advertise mainly to increase their market shares rather than to attract individuals who currently do not use the product (for example, Schmalensee 1972; Leone 1995; Dave and Kelly 2014).

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 below.

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 and attempt effects are positive, significant, and quite large in the first three models but are 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 IV indicate that exposure to TV ads raises the quit probability but exposure to magazine ads does not. This may reflect the much larger audience reached by TV ads since a TV set is present in almost every household in the U.S. and can be watched at no additional charge once it is purchased. On the other hand, most exposure to magazines results from actual purchase of the magazine in question. Moreover, magazine circulation continues to decline, while TV watching has not done so (Lynch 2015).

In Table V, we examine the sensitivity of the results in Table IV to the assumptions that past month viewing patterns are representative of the past six months and that advertising effects last for six months and then fully depreciate. In the first two columns of Table V, we replicate the models estimated in columns (4) and (5) of Table IV under the assumption that the viewing patterns can be extrapolated to the past four months. In columns (5) and (6), we retain the six-month window, but assume that exposure depreciates at a compounded daily rate of 0.74 percent so that 20 percent of exposure to a message seen on the first day of the first month preceding completion of the Simmons survey has depreciated by the end of that month and 74 percent of an ad seen on the first day of the beginning of the six-month period has depreciated by the end of the six-month period. In columns (7) and (8), we retain the assumed depreciation rate but extrapolate past month viewing patterns to the past year. That implies that 93 percent of a message seen on the first day of the first month of the viewing period has depreciated by the end of the period. For comparative purposes, we repeat the estimates obtained with the six-month viewing period in columns (3) and (4). In the even-numbered columns, all of the fixed effects are included as regressors. In the odd-numbered columns, all of these effects except those pertaining to programs are included.[25]

Focusing on the marginal effect of an additional TV ad on the probability of quitting, one sees that it is significant at the 1 percent level and very similar in magnitude in each of the eight columns. It ranges from 0.08 percentage points in column 3 to 0.16 percentage points in column 8. The marginal failure effect never is significant. The marginal attempt effect always is positive and achieves significance at the 5 percent level in column (1) and at the 10 percent level in columns (2), (5), (7), and (8). Like the range in the marginal quit effect, the range in the marginal attempt effect has a fairly narrow range: from 0.07 percentage points in column (4) to 0.18 percentage points in column (5).

Since the mean of the exposure variable is sensitive to the assumptions made about the length of the viewing period and about depreciation and since the quit effect always is significant, we compute the elasticity of the quit probability with respect to exposure in the row in Table V directly below mean exposure. With a minimum value of 0.03 and a maximum value of 0.05, there is little difference in this elasticity.

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. This conclusion pertains to all four models that use alternative assumptions about the length of TV viewing patterns. Hence, there is no evidence of crowd-out. Instead, TV advertising for e-cigs appears to encourage smokers to attempt to quit by each of the four methods that we

[25] As indicated in Section III.B, we treat NRT advertising on TV in the same manner as we treat e-cig advertising on TV in the models in Table V. The coefficients of the former variable remain insignificant in all models in the table. Also as indicated in Section III.B, we do not experiment with alternative estimates of the number of magazine ads read for reasons specified in that section.

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 VI we specifically assess how ad exposure impacts the conditional probability of success when a six-month viewing pattern is assumed. 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.[26] 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. The same comment applies to NRT advertising on TV.

Focusing on the results for all attempts, one sees that an increase in exposure to e-cig 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 IV 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 $q = a\pi$,

$$(q_x/q) = (a_x/a) + (\pi_x/\pi), \qquad (4)$$

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 IV and VI our results imply that an additional exposure to an e-cig 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.[27] Put differently, the increase in the success

[26] We report estimates from linear probability models (LPM), rather than from binary logit models, 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.

[27] Since the magnitudes of the numbers employed in this computation are very small, we employ more decimal places than those reported in Tables IV and VI.

rate accounts for 80 percent of the increase in the quit rate. This underscores that 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.

Models with alternative assumptions about the length of viewing patterns and the rate of depreciation for all e-cig attempters are shown in the first two rows of Table A.3 in the appendix. The estimates in columns (1), (3), (5), and (7) include all the fixed effects except for those associated with programs are included as regressors. In columns (2), (4), (6), and (8), the program fixed effects are included.

The results in Table A.3 are very similar to those in Table VI. The TV advertising effect always is positive and significant. The inclusion of program fixed effects has almost no impact on the estimated coefficient in each of the two models with the same exposure measure. The marginal effect varies from 0.2 percentage points to 0.3 percentage points. The increase in the success rate accounts for approximately 71 percent of the increase in the quit rate when the length of the exposure period is four months. The corresponding percentages in the six-month period with deprecation and in the twelve-month period with depreciation are both approximately 74 percent.[28]

Why is most of the quit effect accounted for by the success effect? Presumably, all smokers who attempt to quit because they have seen ads for e-cigs, which are a new product, have at least some information about the product. It may be the case, however, that additional ads provide more information about the product. Another potential mechanism is that exposure to more ads by attempters reinforces their commitment to quit smoking or increases their preferences relative to cigarettes or reinforces the benefits of e-cigs compared to cigarettes. This mechanism is related to one in the literature on direct-to-consumer advertising (DTCA) of prescription drugs. Namely, Donohue et al. (2004); Bradford et al. (2006); and Encinosa, Bernard, and Dor (2010) find positive and significance effects of increased exposure to these ads on adherence by individuals who have been prescribed the drug being advertised.[29]

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[28] All these results are based on models with the complete set of fixed effects in Table V and in Table A.3.

[29] Our results do not imply that all the additional successes associated with smokers who view more ads come from those who would not have attempted to quit had they not seen the ads. Instead, many of these smokers may replace

The remainder of the estimates in Table VI 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-cig 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,

$$\pi = k^e\pi^e + k^n\pi^n + k^c\pi^c + k^o\pi^o, \qquad (5)$$

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-cig attempts. We find that exposure to additional ads has no effect on the attempt-specific fractions just defined. Hence,

$$(\partial\pi/\partial x) = k^e{*}(\partial\pi^e/\partial x). \qquad (6)$$

The fraction of attempts accounted for by e-cig attempts (k^e) equals 0.241 (Table I), and in the fourth specification in Table VI, $\partial\pi^e/\partial x = 0.0062$. Therefore, the estimated value of the right-hand side of equation (6) is 0.0015. That is very similar to the actual value of $\partial\pi/\partial x$ of 0.0019 in the fourth specification of the success rate regression for all attempters in Table VI. Put differently, the explained effect (0.0015) accounts for 79 percent of the actual effect (0.0019)

The estimates in Table A.3 tell a similar story. In the four-month model, the explained effect accounts for 85 percent of the actual effect. In the six-month model with depreciation, it accounts for 73 percent of the actual effect. The corresponding figure in the twelve-month model with depreciation is 67 percent. In summary, the lack of effects for attempt methods other than with e-cigs 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.

An important conclusion from the results in Tables V and A.3 is that the estimates are not sensitive to the assumptions made about the length of viewing patterns and the nature of

attempters in the failure category, while those who would have been in that category had they not seen the ads become successful quitters.

depreciation. In all models, e-cig ads seen on TV have a positive effect on the overall quit rate that is significant at the 1 percent level. In addition, the advertising effect is positive and significant when the success rate (the probability of quitting conditional on attempting) is the outcome. Moreover, most of the quit effect is accounted for by the success effect regardless of the exposure measure employed. The advertising effect always is positive and significant when e-cig success rates are the outcomes but not when success rates by attempters who use other methods are the outcomes. Finally, the success effect for e-cig attempters explains most of the corresponding effect observed for all attempters. For these reasons and for those indicated in Section III.B, we have emphasized the results that employ a six-month viewing pattern and no depreciation in this section and continue to do so in the rest of the paper.

Our estimate that exposure to an additional TV e-cig 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 I, 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-cig 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-cig 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.[30]

[30] 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. Although the marginal advertising effect in the six-month model with depreciation is twice as large as the one with no depreciation, the magnitudes of the effects in the two policy

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-cigs or their use as a method to stop smoking.

V. Heterogeneity and Identification Checks

Viscusi (2016) finds that while all adults overestimate the health risks associated with the use of e-cigs, the degree of overestimation is greater among older adults. This suggests that the effect of TV ad exposure may be larger for younger adults. When we stratify by age (comparing adults ages 18-34 vs. those ages 35+; see Table A.4 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.[31]

While e-cig 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 their relatively weaker habit formation related to the actual experience of smoking conventional cigarettes. It may also reflect their willingness to use e-cigs more intensively and for longer periods of time. This implies that the long-run impacts of the ads will exceed their short-run impacts since current older smokers who die will not be replaced in the population at large. It is another factor to be kept in mind in evaluating the magnitudes of the effects in the two policy simulations outlined at the end of the previous subsection.

A threat to our identification strategy is that advertisers may make future advertising decisions based on current characteristics of the viewers of specific programs. For example, e-cig producers may choose to place a relatively large number of ads next year on programs whose audience consists of a relatively large number of quitters or attempters this year. In that case, our

simulations are similar. That is because the mean number of messages of e-cig messages and NRT messages seen are smaller in the depreciation model.

[31] Due to reduced sample sizes, we cannot estimate models with program fixed effects and those in which attempt-specific success rates are the outcomes.

results could be attributed to reverse causality from quit or attempt propensities to the ads. To examine whether our results are due to these types of targeting decisions, we introduce measures of advertising exposure in year t+1 into the models in Table IV. Clearly, causality can run only from current quit or attempt behavior to future ad placement in these estimates.

The results of this investigation, which are contained in Table A.4 in the appendix, show no evidence of reverse causality due to targeting. The marginal effects of future exposure all are statistically insignificant and close to zero, whether or not current exposure is held constant. Moreover, the effects of current exposure do not change when future exposure is included in the logit functions.

VI Discussion

The title of this paper poses the question whether e-cig 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 quit rate by about one-tenth of a percentage point, roughly 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. Given the short period of time that e-cigs 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-cigs 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 I can be "explained" by the increase in e-cig 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.[32]

Our results and those by Majeed et al. (2017) should give pause to those who advocate a complete ban on e-cig advertising. Majeed and colleagues examine whether the perceived harm of e-cigs among U.S. adults changed between 2012 and 2015. They find that it did. In 2015, approximately 36 percent of adults perceived that e-cigs 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-cigs 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-cigs. Medical researchers need to investigate the long-term health consequences of the use of the product. Economists need to investigate the role of e-cigs in initiation in the use of nicotine by youths. Do youths who otherwise would start to smoke cigarettes substitute e-cigs 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?

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[32] 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 I. 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 reduce 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-cigs as a method to quit smoking.

Some of these questions revolve around whether e-cigs and combustible cigarettes are substitutes or complements. Friedman (2015) and Pesko, Hughes, and Faisal (2016) find that state bans on e-cig 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-cigs 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-cig sales to minors actually lower youth smoking participation rates. They also present suggestive evidence that the bans lower youth e-cig participation rates. These results suggest that the two sources of nicotine are complements, although the findings for e-cigs 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-cigs.

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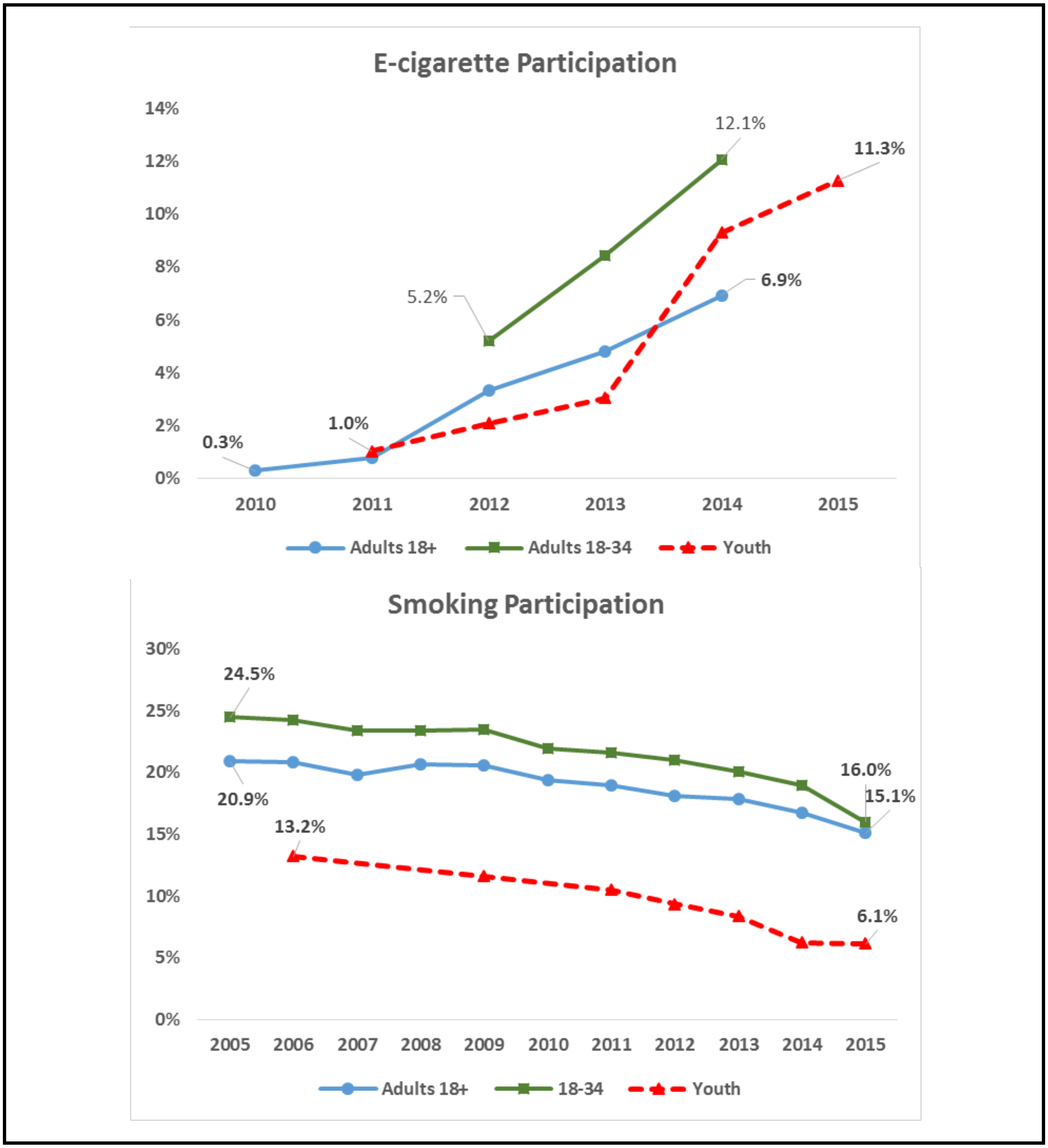
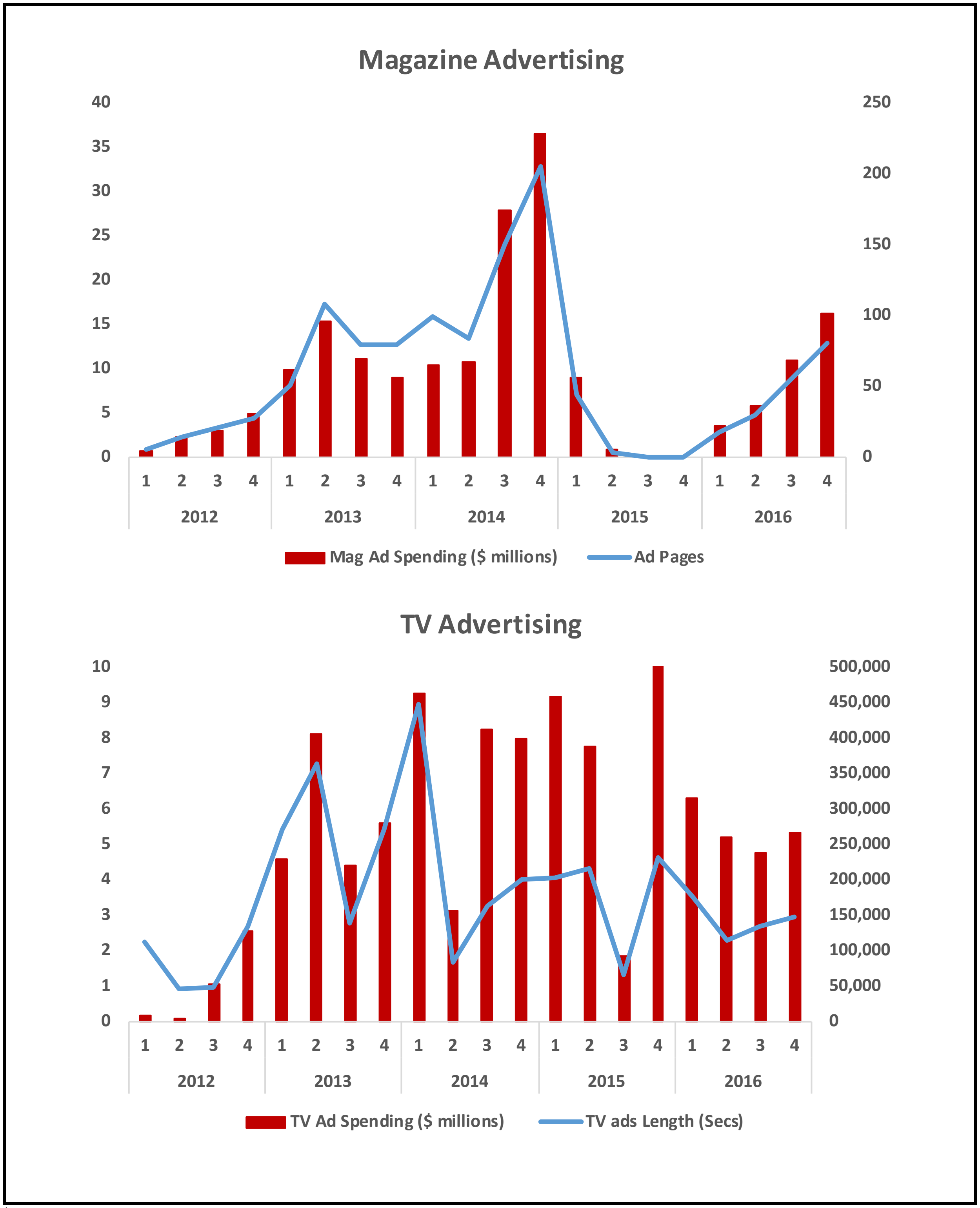
Figures and Tables

Figure I
E-Cigarette[1] and Traditional Cigarette Use[2] Trends, Adults, Young Adults, and Youth[3]



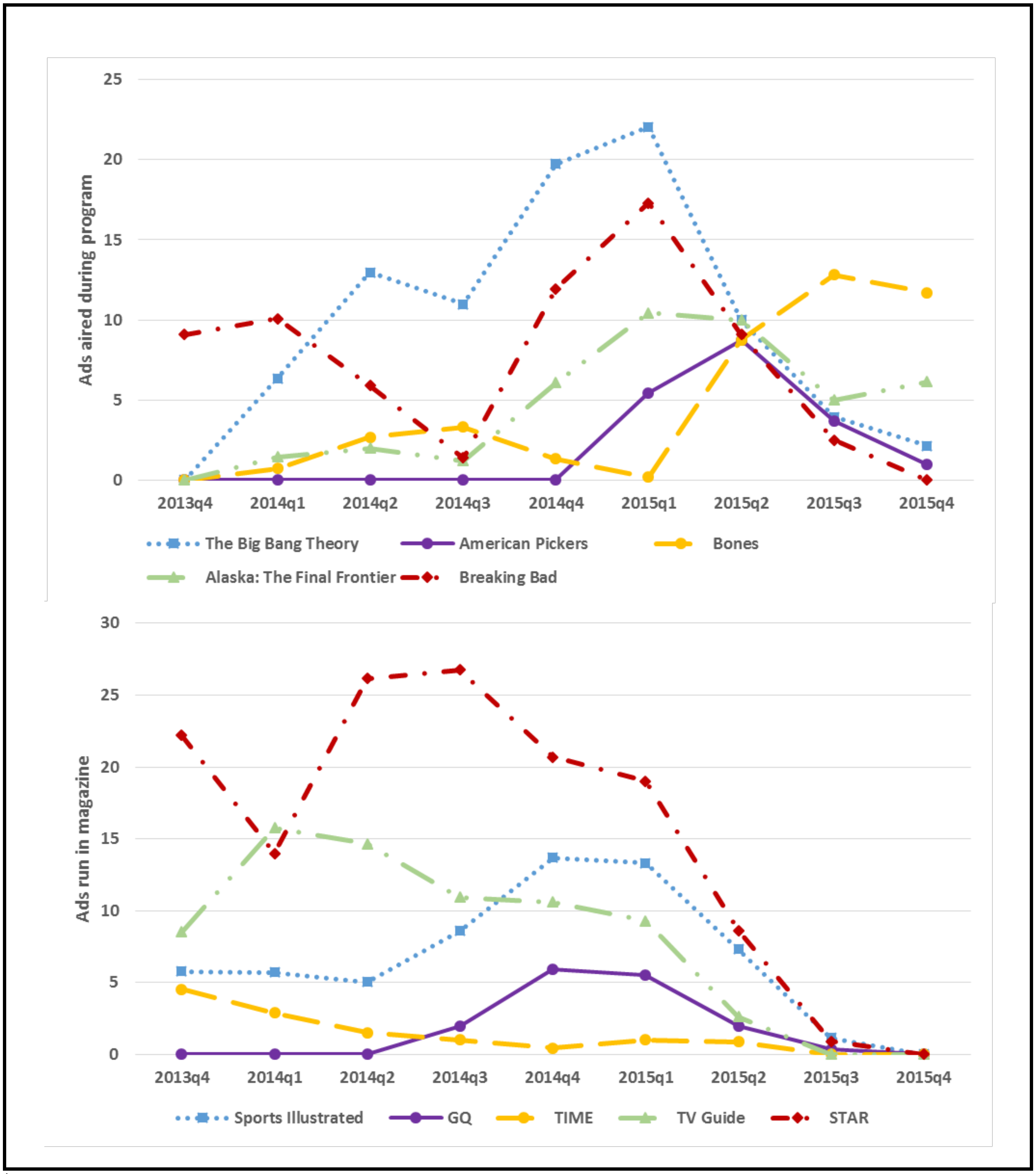
[1]Source: National Adult Tobacco Survey (2012-2014); McMillen et al. (2015) for 2010 and 2011. Figures for overall population comparable from both sources for 2012-2013
[2]Source: National Health Interview Survey (2005-2015)
[3]Source: National Youth Tobacco Survey (2006-2015)

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



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

Figure III
E-Cigarette Television Advertising by Program & Magazine Advertising by Magazine [1]



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

Table I: 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 II: Means of Independent Variables by Quitters, Failures, Non-attempters and Overall

Variable/Outcome	Quitters (Q)	Failures (F)	Non-Attempters (D)	Overall
Gender				
Male	55.2%	41.8%	51.0%	51.2%
Female	44.8%	58.2%	49.0%	48.8%
Education				
Less than HS	12.2%	17.9%	22.2%	20.1%
HS	30.4%	34.4%	36.6%	35.4%
Some College	34.9%	33.4%	28.2%	30.3%
*College or more	22.5%	14.3%	13.0%	14.2%
Insurance Status				
Private or Medicare	69.3%	58.8%	50.9%	54.8%
Medicaid	8.6%	15.1%	11.6%	12.3%
No Insurance	22.1%	26.1%	37.5%	32.9%
Age				
18-24	9.2%	7.9%	8.7%	8.5%
25-34	18.9%	15.5%	17.0%	16.7%
35-44	18.5%	17.2%	18.3%	18.0%
45-54	20.2%	22.4%	23.8%	23.1%
55-64	17.0%	23.0%	20.2%	20.7%
65+	16.2%	13.9%	12.1%	12.9%
Income				
<$15k	7.6%	15.0%	13.7%	13.5%
15k-34.99k	13.7%	18.5%	19.5%	18.7%
35k-49.99k	13.3%	14.8%	15.8%	15.3%
50k-99k	34.7%	30.6%	31.4%	31.4%
100k+	30.8%	21.1%	19.6%	21.0%
Race				
White or other races	73.8%	65.0%	60.8%	63.1%
Black	6.5%	11.4%	10.3%	10.3%
Hispanic	19.7%	23.6%	28.9%	26.6%
Marital Status				
Married	51.9%	44.7%	44.0%	44.9%
Divorced or separated	18.5%	21.0%	21.1%	20.8%
Widow	3.5%	6.9%	5.0%	5.4%
Single	26.1%	27.5%	30.0%	28.9%
Employment Status				
Employed Full-time	51.0%	42.9%	45.3%	45.1%
Employed Part-time	10.8%	10.5%	12.0%	11.5%
Retired	15.5%	14.7%	13.1%	13.8%
Unemployed	6.8%	9.6%	11.2%	10.3%
Disabled	7.9%	14.3%	10.9%	11.6%
Student	1.7%	1.5%	1.2%	1.3%
Homemaker	6.2%	6.5%	6.3%	6.3%
E-cig TV Ad Exposure	4.5	3.7	2.9	3.3
NRT TV Ad Exposure	16.5	17.9	14.1	15.4
Magazine Ad Exposure	3.8	4.8	3.3	3.8
N	747	2,324	5,220	8,291

Table III: Means of Advertising Exposure by Demographics

Panel A: Mean E-cig TV Advertising Exposure

Variable	**No Advertising Exposure (%)**	**Mean Advertising Exposure**	**Mean Conditional Advertising Exposure[1]**
Gender			
Male	76.8	2.9	12.5
Female	76.6	3.7	15.6
Education			
Less than HS	80.5	2.8	14.3
HS	76.0	3.4	14.3
Some College	75.0	3.6	14.3
College or more	76.8	2.9	12.4
Insurance Status			
Private or Medicare	75.4	3.4	13.8
Medicaid	74.2	4.4	16.9
No Insurance	79.8	2.6	13.1
Age			
18-24	78.3	3.6	16.5
25-34	75.8	4.2	17.3
35-44	75.5	3.6	14.8
45-54	76.1	2.9	12.3
55-64	77.1	3.2	13.8
65+	78.9	2.2	10.4
Income			
<$15k	77.8	3.0	13.5
15k-34.99k	79.3	3.0	14.5
35k-49.99k	76.5	2.8	11.9
50k-99k	75.7	3.5	14.3
100k+	75.4	3.7	15.1
Race			
White or other races	76.0	3.4	14.1
Black	71.9	3.6	12.7
Hispanic	80.2	2.9	14.5
Marital Status			
Married	77.3	3.0	13.4
Divorced or Separated	77.9	3.2	14.6
Widow	77.1	2.5	10.7
Single	74.8	3.8	15.1
Employment Status			
Employed Full-time	77.0	3.3	14.6
Employed Part-time	77.8	3.0	13.4
Retired	78.7	2.3	10.9
Unemployed	74.4	3.4	13.2
Disabled	73.4	4.3	16.0
Student	76.6	4.0	17
Homemaker	77.5	3.2	14.4

[1]Conditional on having potential exposure to an ad.

Table III: Means of Advertising Exposure by Demographics

Panel B: Mean E-cig Magazine Advertising Exposure

Variable	**No Advertising Exposure (%)**	**Mean Advertising Exposure**	**Mean Conditional Advertising Exposure[1]**
Gender			
Male	54.1	4.2	9.1
Female	60.1	3.3	8.3
Education			
Less than HS	64.1	3.8	10.7
HS	60.0	3.4	8.6
Some College	51.5	4.1	8.4
College or more	51.1	3.7	7.7
Insurance Status			
Private or Medicare	55.4	3.7	8.2
Medicaid	57.3	4.6	10.8
No Insurance	59.6	3.6	8.9
Age			
18-24	55.1	4.2	9.5
25-34	55.8	4.5	10.2
35-44	56.4	4.3	9.8
45-54	57.8	3.7	8.7
55-64	57.0	3.3	7.7
65+	59.3	2.6	6.5
Income			
<$15k	58.7	4.3	10.5
15k-34.99k	59.0	3.7	9.0
35k-49.99k	56.9	3.6	8.4
50k-99k	56.8	3.6	8.3
100k+	54.4	3.8	8.4
Race			
White or other races	57.0	3.4	7.9
Black	54.4	4.6	10.0
Hispanic	57.9	4.4	10.4
Marital Status			
Married	59.7	3.0	7.6
Divorced or Separated	55.2	4.2	9.3
Widow	57.0	4.1	9.5
Single	54.1	4.5	9.8
Employment Status			
Employed Full-time	57.3	3.6	8.5
Employed Part-time	56.9	4.3	9.9
Retired	59.2	2.4	5.8
Unemployed	55.6	4.1	9.2
Disabled	56.9	4.5	10.4
Student	46.8	5.9	11.1
Homemaker	54.8	4.5	9.9

[1]Conditional on having potential exposure to an ad.

Table IV: Multinomial Logit Model, Marginal Effects of E-cig Ads on Smoking Outcomes [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]
E-cig 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. Sample size is 8,291.

Table V: Multinomial Logit Model, Sensitivity of Smoking Outcomes to Assumed Length of TV Viewing Patterns [S.E.][1]

Independent Variable **Outcome**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
E-cig TV Ads								
Q	0.0010 [0.0004]	0.0010 [0.0004]	0.0008 [0.0003]	0.0009 [0.0003]	0.0015 [0.0005]	0.0016 [0.0005]	0.0014 [0.0005]	0.0016 [0.0005]
F	0.0005 [0.0007]	0.0003 [0.0007]	0.0000 [0.0005]	-0.0002 [0.0006]	0.0003 [0.0004]	-0.0000 [0.0010]	0.0002 [0.0008]	0.0000 [0.0008]
A	0.0015 [0.0008]	0.0013 [0.0008]	0.0008 [0.0005]	0.0007 [0.0006]	0.0018 [0.0009]	0.0016 [0.0010]	0.0016 [0.0008]	0.0015 [0.0009]
Length of TV Viewing Patterns	4-months	4-months	6-months	6-months	6-month depreciation[2]	6-month depreciation[2]	12-months depreciation[2]	12-months depreciation[2]
Mean Ad exposure	2.3	2.3	3.3	3.3	1.9	1.9	2.2	2.2
Elasticity w.r.t. E-cig Ads on Probability of Q	0.026	0.032	0.030	0.039	0.032	0.041	0.035	0.048
Year-qtr. fixed effects, and demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DMA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time slot fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Channel and Magazine fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Program Fixed Effects	No	Yes	No	Yes	No	Yes	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.

[2] The 6 month depreciation model assumes that the stock of advertising for 6 months depreciates with the following functional form. $Adstock_{it} = \sum_{j=0}^{183}(Ads_{t-jk})(1-r)^j$, where j is the number of days before the interview of person i on day t that an ad aired and r = 0.0074 is the daily compounded rate of depreciation of the ad. Similarly for the 12 month depreciation model the $Adstock_{it} = \sum_{j=0}^{365}(Ads_{t-k})(1-r)^j$. See text for more details concerning the two models that allow for depreciation.

Table VI: LPM, Marginal Effects of E-cig Ads on Successful Quitting Given Attempting [S.E.][1]

Independent Variable Sub-population	(1)	(2)	(3)	(4)	(5)
E-cig TV Ads					
All Attempters	0.0014 [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 [0.016]	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 [0.0020]	0.0003 [0.0033]	2
Other Method Attempters	0.0010 [0.0012]	0.0007 [0.0013]	0.0005 [0.0014]	0.0003 [0.0015]	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.

[2] Models cannot be estimated because of insufficient sample size

[3] N=3,071 for All attempters, N=740 for E-cig Only, N=559 for NRT Only, N=545 for Cold Turkey Only, N=1,227 for Other Method.

Appendix

Table A.1: Multinomial Logit Model, Marginal Effects of E-cig Ads on Smoking Outcomes (w/o NRT Control) [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]
E-cig 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.

Table A.2: LPM, Marginal Effects of E-cig Ads on Successful Quitting Given Attempting (w/o NRT Control) [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.

[2] Models cannot be estimated 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 A.3: Linear Probability Models, Sensitivity of Successful Quitting results to Assumed Length of TV Viewing Patterns [S.E.][1]

Independent Variable Sub-population	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
E-cig TV Ads								
All Attempters	0.0020 [0.0011]	0.0021 [0.0011]	0.0019 [0.0008]	0.0018 [0.0009]	0.0030 [0.0013]	0.0030 [0.0015]	0.0027 [0.0012]	0.0027 [0.0013]
E-cig Only Attempters	0.0070 [0.0031]	2	0.0062 [0.0025]	2	0.0090 [0.0043]	2	0.0073 [0.0038]	2
NRT Only Attempters	0.0041 [0.0030]	2	0.0031 [0.0021]	2	0.0056 [0.0040]	2	0.0049 [0.0037]	2
Cold Turkey Attempters	-0.0014 [0.0042]	2	0.0003 [0.0033]	2	0.0000 [0.0059]	2	0.0008 [0.0056]	2
Other Method Attempters	0.0003 [0.0017]	2	0.0003 [0.0015]	2	0.0006 [0.0023]	2	0.0002 [0.0020]	2
Length of TV Viewing Patterns	4-month	4-month	6-month	6-month	6-month depreciation[4]	6-month depreciation[4]	12-month depreciation[4]	12-month depreciation[4]
Year-qtr. fixed effects, and demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DMA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time slot fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Channel and Magazine fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Program Fixed Effects	No	Yes	No	Yes	No	Yes	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.

[2] Models cannot be estimated 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.

[4] The 6 month depreciation model assumes that the stock of advertising for 6 months depreciates with the following functional form. $Adstock_{it} = \sum_{k=0}^{183}(Ads_{t-k})(1-d)^{k/30}$ where k is the number of days before the interview of person i on day t that an ad aired and d takes the value 0.2. Similarly for 12 month depreciation model the $Adstock_{it} = \sum_{k=0}^{365}(Ads_{t-k})(1-d)^{k/30}$. For both models the ad stock fully depreciates at the end of the period.

Table A.4: Multinomial Logit Model, Marginal Effects of E-cig Ads on Smoking Outcomes by Age Group (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.

[2]Sample size of 18-34 sample is 3,587 and for 35+ is 4,704. For age 18-34 A is 37.2%, Q is 10.8% and F is 26.4%. For age 35+ A is 37.3%, Q is 8.6%, and F is 28.7%.

Table A.5: Multinomial Logit Model, Marginal Effects of Current and Future E-cig Ads on Smoking Outcomes [S.E.][1]

Independent Variable **Outcome**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
E-cig TV Ads [t]					
Q	0.0006 [0.0003]	0.0006 [0.0003]	0.0007 [0.0003]	0.0008 [0.0003]	0.0009 [0.0003]
F	0.0001 [0.0005]	0.0001 [0.0005]	0.0001 [0.0005]	0.0000 [0.0005]	-0.0001 [0.0006]
A	0.0007 [0.0006]	0.0007 [0.0006]	0.0008 [0.0006]	0.0009 [0.0006]	0.0008 [0.0006]
E-cig TV Ads [t+1][2]					
Q	-0.0001 [0.0002]	-0.0001 [0.0002]	-0.0001 [0.0002]	-0.0001 [0.0002]	0.0000 [0.0002]
F	-0.0002 [0.0004]	-0.0002 [0.0004]	-0.0002 [0.0005]	-0.0002 [0.0005]	-0.0001 [0.0005]
A	-0.0003 [0.0005]	-0.0003 [0.0005]	-0.0003 [0.0005]	-0.0002 [0.0005]	-0.0001 [0.0005]
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.

[2] Results are also a precisely estimated 0 when current e-cig advertising is excluded.