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Does e-cigarette advertising encourage adult smokers to quit?

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ABSTRACT

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%.

1. 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 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 Fig. 1, participation among adults grew from 0.3% in 2010 to 6.9% in 2014. Participation by 18–34 year olds was 1.5 times higher than that of adults of all ages by 2014. The figure depicts similar trends for youth. Participation by youths in grades 6 through 12 increased from 1.0% in 2011 to 11.3% 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%) and television (27%) with national reach (Kim et al., 2014; U.S. Surgeon General, 2016). Fig. 2 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% of adults had been exposed to e-cig marketing in a 2013 sample of Florida residents (Kim et al., 2014). Youth and young adult expo-

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[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.

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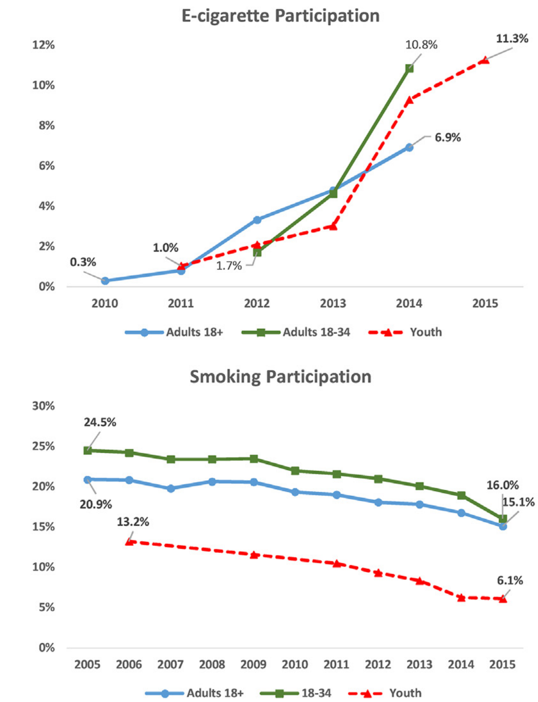
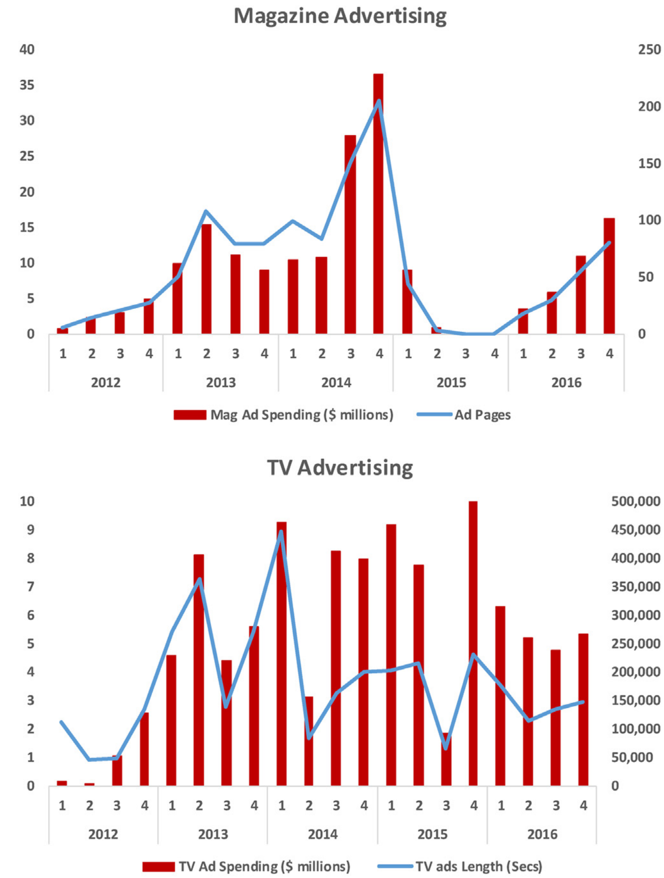


Notes: National Adult Tobacco Survey (2014) for e-cigarette participation by adults and young adults for 2012–2014. McMillen et al. (2015) for e-cigarette participation by adults for 2010 and 2011. Figures for both overall population comparable from both sources for 2012–2013. National Health Interview Survey (2015) for smoking participation by adults and young adults. National Youth Tobacco Survey (2015) for e-cigarette participation and smoking participation by youth.

Fig. 1. E-Cigarette and Traditional Cigarette Use Trends, Adults, Young Adults, and Youth (National Adult Tobacco Survey, 2014; McMillen et al., 2015; National Health Interview Survey, 2015; National Youth Tobacco Survey, 2015).



Note: Kantar Media, purchased from the source.

Fig. 2. E-Cigarette Magazine and Television Advertising Trends.

sure was at least equal to 10% 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 (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).

The recent trends in U.S. smoking rates provide hints that the growth of e-cig participation might be helping to reduce smoking. The lower portion of Fig. 1 highlights the well-known downward trend in adult smoking. The rate fell from 20.9% in 2005 to 15.1% 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. 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. Adolescent nicotine exposure via e-cigs may have lasting adverse consequences for cognitive development (U.S. Surgeon General, 2014). 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 (U.S. Surgeon General, 2016).

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 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% relative to a mean quit rate of 9%.

2. 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.

More definitive evidence on this issue is contained in a randomized controlled trial (RCT) conducted by Hajek et al. (2019). They randomly assigned 886 smokers to use e-cigarettes or conventional NRT products. One-year quit rates were almost twice as large in the former group compared to the latter group (18% vs 10%).

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 (forthcoming) 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% of e-cig ads viewed in our data appear at the national level.

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 et al., 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 et al., 2012); and vitamins (Eisenberg et al., 2017). Each of these studies uses detailed information on consumer TV viewing and/or magazine reading patterns in the Simmons National Consumer Survey (NCS, http://www.simmonssurvey.com) combined with comprehensive measures of advertising in these two media primarily from Kantar Media (https://www.kantarmedia.com/us). Most of these studies find positive effects of advertising on the outcomes being considered. The one by Avery et al. (2007) is especially relevant because they find that an increase in exposure to magazine advertisements of nicotine replacement therapy (NRT) products is associated with higher quit rates among cigarette smokers.

The NCS is a nationally representative proprietary marketing survey whose media usage and consumer demographic information are utilized by virtually all major marketing and advertising firms in the U.S. (Avery et al., 2013). Hence, the use of the NCS allows one to observe the same consumer information and characteristics as the advertiser, minimizing the "targeting bias" that would result from ads potentially being targeted based on factors not observed by the researcher (Avery et al., 2007). Furthermore, the in-depth information on media usage allows one to construct detailed and salient measures of advertising exposure that vary at the individual level to identify plausibly causal effects of this exposure. For instance, even readers of the same magazine may be exposed to different levels of e-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 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. Hence, we provide evidence of a mechanism to extend the quit effects of e-cigarettes in the RCT conducted by Hajek et al. (2019) to the population of smokers at large.

3. Analytical framework and empirical implementation

3.1. Conceptual foundation

Following Avery et al. (2007), we assume that a fully rational current cigarette smoker who is attempting to quit selects the optimal quantity of a smoking cessation product (s) by equating the marginal benefit in dollars of *s* to its price (*p*):

$$b \equiv hq_s = p. \tag{1}$$

In Eq. (1), h is the monetary value of the perceived health benefits of quitting smoking, q denotes the probability of a successful quit, and q_s is the perceived marginal product of s in the production of a successful quit. Of course, the specific product to be used also must be selected. Suppose there are three types: electronic cigarettes *e* with corresponding price p_e; nicotine replacement therapy n with price p_n; and "cold turkey" t with price (the monetary value of marginal disutility in this case) p_t. The consumer will select e if $b_e > p_e$ when $e = n = t = 0$, and $b_e = p_e$ at the value of e (e^*) that satisfies the above equation, while $b_n < p_n$ and $b_t < p_t$ continue to hold when $e = e^*$ and $n = t = 0$.

Advertising of e-cigarettes provides information about the device that raises its marginal product and potentially lowers its full price because p_e is less than p_n, and/or it informs consumers that they do not have to give up nicotine when they quit. Finally, advertising may increase marginal benefits of *e*, as well as for the other two methods because it reminds smokers of the harmful effects of their habit. The realization of an expectation that a switch from combustible cigarettes to e-cigarettes has been achieved with little or no reduction in nicotine may cause the ads to have a positive effect on quits by those who make attempts with that method, even if the ads have a much smaller effect on attempts. That is, exposure to ads for e-cigarettes could raise quits by raising successful attempts.

3.2. 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. That yields an approximate sample size of 58,000 individuals. Respondents report their current smoking status,[3] any smoking cessation attempt over the past year, and methods used to attempt smoking cessation over that period.[4] Based on information on respondents' current smoking status for those who attempted to quit smoking over the past year, we can define whether the respondent successfully quit or whether the cessation attempt was unsuccessful.

One limitation of the NCS is that information on e-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.

[3] 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.

[4] 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.

Table 1
Definitions and Means of Key Outcomes.[a]

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[b]	40.0%	17.1%

[a] Sample (N = 8291) 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.

[b] Includes gradual reduction only and mixed methods.

Given the structure of the survey, we limit our sample to individuals who are either past-year quitters or current smokers (N = 8291). There are three groups in the sample: successful quitters or simply quitters (Q = 747), unsuccessful quitters or simply failures (F = 2324), and non-attempters (D = 5220). The last two groups form the larger group of current smokers.

Panel A of Table 1 contains the basic outcomes that we consider in our empirical analysis and the mean of each outcome. The quit rate in the sample ($q = Q/N$) expressed as a percentage is 9.0%, and the failure rate ($f = F/N$) is 28.0%. Hence, the attempt rate ($A/N = a = q + f$, where $A = Q + F$) is 37.0%, or almost 40% 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%.

Panel B of Table 1 contains outcomes related to those in Panel A that we also examine. They are the percentage of attempts accounted for by each of four specific methods of quitting and the success rate of each method. The methods are the use of e-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% compared not surprisingly to 40.0% for mixed methods). Attempts using e-cigs have the second highest success rate (28.9% compared to 31.2% 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.

3.3. 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. 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.

Our matching algorithms are described in the first section of the online appendix. Here we make a number of key points about the measures that emerge from these algorithms. Magazine advertising exposure is based on the number of issues of each of 32 magazines that contain e-cig ads a respondent read in the past six months and is weighted by the number of issues they read out of every four issues.

TV advertising exposure is based on 326 programs, 131 channels, and 62 time slots that in combination identify all e-cig commercials aired in the past six months. Respondents provide information on programs watched and frequency of viewing them in the past month. They also indicate the times on which they watched specific channels during the past week. For spot ads that appear only in certain designated market areas (DMAs), there is the additional restriction that we only assign persons as exposed if they live in the DMA in which the ad appeared. 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 Media. There are virtually no NRT ads in magazines, and hence we do not control for magazine ad exposure. TV ad exposure for NRT is constructed with the algorithm just described.

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 to recall error, this is minimized by limiting the recall period to the past month.

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 2 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). In the appendix we show that our results are not sensitive to alternative assumptions about the length of the period to which past month viewing patterns are extrapolated and when exposure is allowed to depreciate gradually.

3.4. Definitions of other variables and sample characteristics

All models estimated in Section 4 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 2, 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 2.

It 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). 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% level.

3.5. Identification strategy

At several points in this paper, we have mentioned that firms are likely to target ads for their products to individuals who have certain characteristics. Hence, efforts to identify the causal effects 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. We employ what may be termed a “saturated fixed effects identification strategy” to obtain causal estimates of the effects of random variation in e-cigarette advertising on the decision to quit smoking. These estimates control for unobservable characteristics that may be correlated with both outcomes such as

Table 2
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
E-cig Magazine Ad Exposure	3.8	4.8	3.3	3.8
N	747	2324	5220	8291

quitting and the key independent variable of interest–advertising exposure.

In addition to the variables in Table 2, the most complete specifications in Section 4 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. 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 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 time-period, frequency and time-slot of consumption.

We show one major source of variation that identifies the effects of e-cig TV advertising exposure in Fig. 3. 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, program, and magazine 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 2 (age, gender, race/ethnicity, education, household income, employment status, insurance status, and marital status) and on year-quarter, channel, program, time slot, and magazine fixed effects. In the TV ad exposure regression, the R^2 is 0.5126. The corresponding R^2 in the magazine ad exposure regression is 0.6808.[5] Both R^2s indicate a substantial amount of residual variation in the exposure measures.[6]

The regressions just specified can also highlight that our procedure balances the sociodemographic characteristics of groups defined by different amounts of advertising exposure. When we limit the independent variables in the two regressions to the set of sociodemographic variables, this set always is significant (p-value equals 0.000 in each case) in each case. This suggests a considerable amount of imbalance among the groups. But in the saturated fixed effects regressions, the sociodemographic variables are not significant (p-value equals 0.603 in the case of TV exposure and p-value equals 0.648 in the case of magazine exposure).

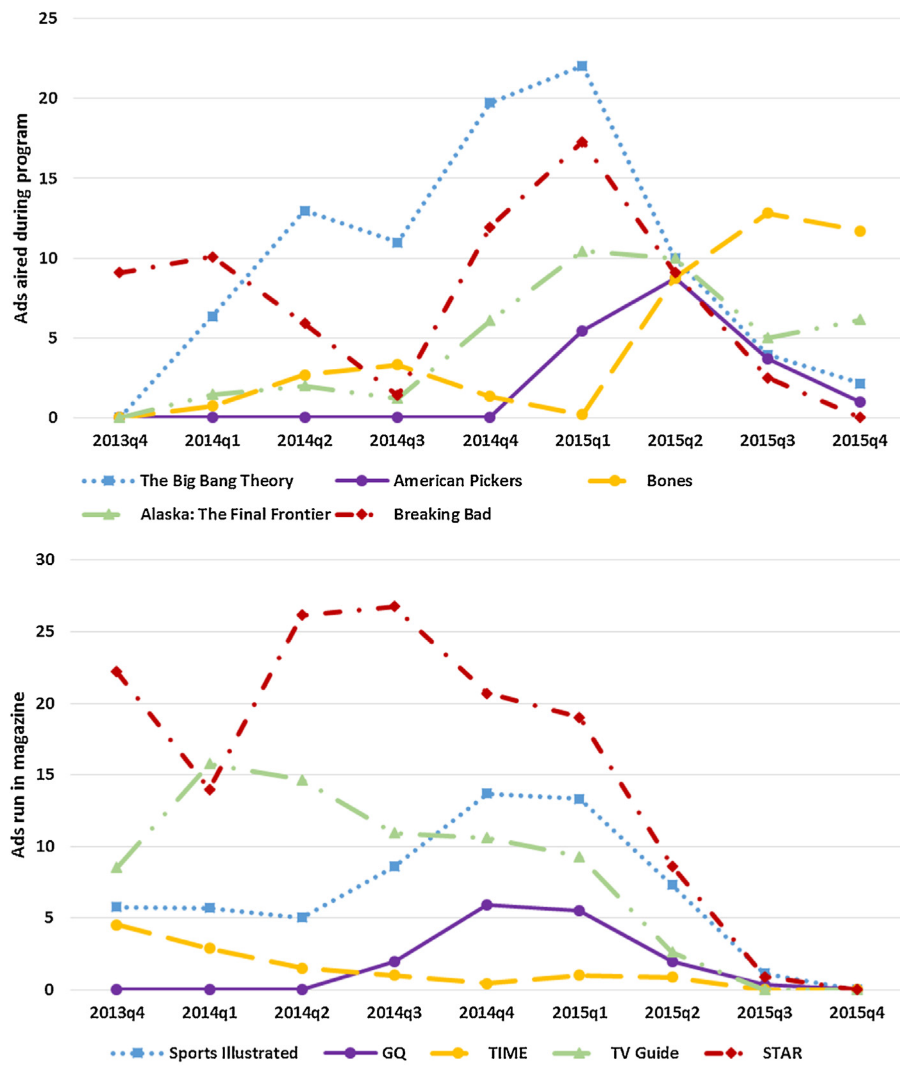
We conclude that the groups defined by different amounts of advertising exposure are balanced on observables once we control for fixed effects that pertain specifically to TV viewing and magazine reading patterns. This finding strengthens our identification strategy because there may be additional individual 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.

3.6. Empirical specifications

Recall that the sample consists of individuals who are either past-year quitters or current smokers (N = 8291) and that there are three groups in it. These are successful quitters or simply quitters (Q = 747), unsuccessful quitters or simply failures (F = 2324), and non-attempters (D = 5220). We begin by estimating a multinomial logit function with three outcomes: successfully quitting smoking or simply quitting, attempting to quit and failing or simply failing, and not attempting to quit. The mean probability of quitting (q, expressed as a percentage) is 9.0%. The comparable probabilities of

[5] Note also that our results in Section 4 are not due to influential observations. We know this because a winsorization at the 5th and 1st percentile levels of the residuals in a Frisch-Waugh-Lovell theorem type LPM regression yield similar marginal effects to our results.

[6] 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 Tables 3 and 5.



Note: Kantar Media, purchased from the source.

Fig. 3. E-Cigarette Television Advertising by Program & Magazine Advertising by Magazine.

failing (f) and not attempting (d) are 28.0% and 63.0%, 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

$$d = 1-a = 1-q-f, \quad (2)$$

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.

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. We do this by deleting all the individuals who do not attempt to quit and then estimating a binomial logit model with two outcomes: quits or failures.

Finally, we estimate logit models in which the outcomes are the method-specific attempt or success rates defined in Panel B of Table 1. The former logits are limited to individuals who attempt to quit and allow us to determine whether exposure to advertising induces crowd-out from other methods of quitting, especially nicotine replacement therapy, to the use of e-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. The second section of the appendix contains a detailed discussion of our estimation methods.

4. 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 3.[7] Five specifications are shown. In the first, the only fixed

[7] 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 3 and in all tables that follow it. Since 51% of the observations have only one individual per household and 33% have two observations per household, standard errors that ignore clustering are extremely similar to those that take it into account. We do not discuss marginal effects of NRT TV ads because these effects never are significant in the regressions in this section and in the appendix. Appendix Table 1 reports the NRT marginal effects for the models in Table 3.

Table 3
Multinomial Logit Model, Marginal Effects of E-cig Ads on Smoking Outcomes [S.E.].[a]

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

[a] Sample size is 8291. Each column represents a separate multinomial logit model with the three outcomes being successful quits (Q), failures (F), and non-attempters (D), the latter being the reference category. Marginal effects are reported, with standard errors clustered at the household level in brackets. Instead of reporting the marginal effect on D (non-attempters), we report the marginal effect of the regressor on A (attempts) since this is just the negative of the marginal effect of the regressor on D, and thus the sum of marginal effects of the regressor on Q and F. *p < 0.10, **p < 0.05, ***p < 0.01.

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.

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% level in the first two models and at the 1% 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.[8] 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% relative to the mean quit probability). The magnitude of this effect is identical to the impact of an increase in exposure to one additional magazine ad for an NRT product in a study by Avery et al. (2007). They use Simmons NCS data for fall and spring quarters from the fall of 1995 through the fall of 1999. The quit rate in their sample of 10% is approximately the same as the 9% 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.[9]

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 3 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).[10]

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 consider.[11] This result is similar to one reported by

[8] 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.

[9] With respect to the content of magazine vs. TV ads, both types of ads tend to emphasize “comparative claims” with respect to conventional cigarettes, for instance themes emphasizing that e-cigarettes do not produce tobacco smoke or odor or ash, and that they could be used to circumvent smoke-free policies; these ads also implicitly represent e-cigarettes as a healthier or “smarter” alternative to cigarettes or a cessation aid and emphasize the technological innovation of the product (Haardörfer et al., 2017; Payne et al., 2016; Banerjee et al., 2015). Hence, it is prima facie unclear that the differential effects for magazine vs. TV ads relate to differences in content, though more research is needed on this point.

[10] It may also be relatively easy to avoid magazine ads by skipping the pages. With regard to the literature on the effects of magazine advertising on cigarettes and alcohol, Kenkel et al. (2018) find no effect of menthol and non-menthol cigarette advertising on the demand for each type of product. Molloy (2016) reports similar null results in the case of alcohol consumption by young adults. His results pertain to ads in both media. Saffer et al. (2016) find small positive effects of TV alcohol advertising on consumption by persons ages 18 through 29. Their exposure measure varies only by year-quarter and designated market area. Hence it is much more limited than the measure that we employ. They do not consider advertising in magazines. Some caution should be exercised in comparing our results for e-cigarettes to those for cigarettes and alcohol. The latter products are established ones while e-cigarettes are a new entry into the marketplace. Studies summarized by Dave and Kelly (2014) underscore that much of the advertising of established products has been found to affect brand shares rather than total consumption.

[11] Kim et al. (2015) find that 75% of a sample of Florida adult smokers reported that seeing a TV ad for e-cigarettes “made me think about quitting smoking”, even though

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.

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 4), 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.[12]

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 policy simulations we outline below.

In Table 5 we specifically assess how ad exposure impacts the conditional probability of success. The table reports the results of linear probability models in which the conditional probability of success (quits conditional on attempts denoted by π) is the outcome.[13] 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 3 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 $q = a\pi$,

$$(3)\,(q_x/q) = (a_x/a) + (\pi_x/\pi),$$

where x is the advertising variable and a subscript denotes a partial derivative. The means of q, a, and π are 9.0%, 37.0%, and 24.3%, respectively. Based on the fifth and most comprehensive specification in Tables 3 and 5 our results imply that an additional exposure to an e-cig advertisement on TV raises the quit rate by about 1%, the attempt rate by 0.2%, and the success rate by 0.8%.[14] Put differently, the increase in the success rate accounts for 80% 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%.

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 et al. (2010) find positive and significance effects of increased exposure to these ads on adherence by individuals who have been prescribed the drug being advertised.[15]

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

The only case in which success effects are positive, generally significant, and generally stable pertains to e-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,

$$\pi = k^e\pi^e + k^n\pi^n + k^c\pi^c + k^o\pi^o, \tag{4}$$

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,

$$(5)\,(\partial\pi/\partial x) = k^e * (\partial\pi^e/\partial x).$$

The fraction of attempts accounted for by e-cig attempts (k^e) equals 0.241 (Table 1), and in the fourth specification in Table 5, $\partial\pi^e/\partial x = 0.0062$. Therefore, the estimated value of the right-hand side of Eq. (5) 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 5. Put differently, the

current FDA regulations do not allow e-cigarette ads to explicitly mention that the product can be used for smoking cessation or are less harmful than combustible cigarettes.

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

[13] 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.

[14] Since the magnitudes of the numbers employed in this computation are very small, we employ more decimal places than those reported in Tables 3 and 5.

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

Table 4
Multinomial Logit Model, Marginal Effects of E-cig Ads on Smoking Outcomes by Age Group (w/ NRT) [S.E.].[a]

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

[a] Sample size of 18–34 sample is 3587 and for 35+ is 4704. 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%. Each column represents a separate multinomial logit model with the three outcomes being successful quits (Q), failures (F), and non-attempters (D), the latter being the reference category. Marginal effects are reported, with standard errors in brackets. Instead of reporting the marginal effect on D (non-attempters), we report the marginal effect of the regressor on A (attempts) since this is just the negative of the marginal effect of the regressor on D, and thus the sum of marginal effects of the regressor on Q and F. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 5
LPM, Marginal Effects of E-cig Ads on Successful Quitting Given Attempting [S.E.].[a]

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]**	[b]
NRT Only Attempters	0.0021 [0.016]	0.0022 [0.0017]	0.0028 [0.0014]**	0.0031 [0.0021]	[b]
Cold Turkey Attempters	−0.0017 [0.0015]	−0.0015 [0.0016]	−0.0020 [0.0020]	0.0003 [0.0033]	[b]
Other Method Attempters	0.0010 [0.0012]	0.0007 [0.0013]	0.0005 [0.0014]	0.0003 [0.0015]	[b]
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

[a] N = 3071 for All attempters, N = 740 for E-cig Only, N = 559 for NRT Only, N = 545 for Cold Turkey Only, N = 1227 for Other Method. Each cell represents a separate linear probability model on successfully quitting smoking. Samples are restricted to those who attempted smoking cessation (when considering overall quit probability) and to those who attempted smoking cessation with a specific method (when considering method-specific success). Standard errors clustered at the household level are reported in brackets. *p < 0.10, **p < 0.05, ***p < 0.01.
[b] Models cannot be estimated because of insufficient sample size.

explained effect (0.0015) accounts for 79% of the actual effect (0.0019)

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% to 8.7%. Based on the smoking participation rates that underlie the lower portion of Fig. 1, this reduction in the quit rate translates into approximately 105,000 fewer quitters in 2015.

A policy that has the potential to encourage advertising would be to eliminate the FDA mandate requiring that all e-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%, which would have resulted in an additional 350,000 quitters in 2015.[16]

Results from Table 4 suggest that the impact of TV ad exposure on cessation is larger for younger adults. Given that the excess mortality risk from smoking is not significantly different for those who quit prior to age 35 relative to never smokers (Jha et al., 2013), the population health implications of early cessation are also greater than that of later cessation. Simulations specifically for younger adults indicate that if the FDA were to ban advertising of e-cigarettes on TV, then this would result in 63,000 fewer quitters in this age group. Jha et al. (2013) find that those who stopped smoking between the ages of 25–34 gain 10 extra years of life, thus having

[16] With respect to banning advertising, we predict successful quits with the multinomial logit based on actual values for each of the covariates for each individual, and then re-predict it by setting ad exposure to 0. In the case of the policy simulation where e-cigarette advertising is encouraged (or at least not discouraged), we first make predictions based on actual exposure (with the other covariates set at the actual values for each respondent), and then re-predict the outcome by raising each respondent's ad exposure such that the mean exposure rises to 14 e-cigarette ads – the mean number of NRT ads seen over the sample period. We note that the policy simulations are not assuming a constant marginal effect, since they take account of the non-linearities that are inherent in the multinomial logit specification.

essentially the same life expectancy as never smokers.[17] Combining the estimated reduction in the number of quitters, from a complete ban on TV e-cigarette ads, with the life years gained from quitting results in a reduction of 630,000 life-years. With respect to a policy that would encourage e-cigarette advertising to the level of NRT ads, this would result in an additional 210,000 quitters between the ages of 25–34, and an increase in 2.1 million life-years gained.

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.

5. Identification checks

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 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 3. 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 6, 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.

Other specification checks are contained in the appendix. There we show that our results are not sensitive to the exclusion of NRT advertising from our models, or to the inclusion of controls for cigarette taxes and the advertising of combustible cigarettes in magazines.[18] Additionally, we show that our estimates are robust to controlling for proxies for exposure to online e-cigarette ads. They also are not sensitive to shortening the extrapolation of past month TV viewing patterns from six months to four months or to lengthening it to one year. In addition they are not affected by the use of a six-month or one-year period combined with an assumed monthly rate at which exposure depreciates of approximately 20%. In order to minimize potential recall errors, we also test an alternate measure of ad exposure based only on magazines and TV programs that are consumed regularly by a given respondent, which yields very similar estimates. We discuss the assumption of the independence of irrelevant alternatives (IIA), underlying the multinomial logit framework, in the appendix and present alternate estimates from the two-part model, which separately specifies the decision to attempt vs. not attempt smoking cessation and then, conditional on making an attempt, the choice between successfully quitting vs. a failed attempt. Finally, we ascertain that our results are not unduly driven by outliers or respondents who are heavily exposed to either type of ad. In general, all of these checks continue to confirm our main findings.

The appendix also contains further analyses of heterogeneity in the response to ad exposure across various margins. First, we assess whether the quit effects are stronger among groups with a higher ex ante probability of attempting to quit smoking. Here we find some suggestive evidence that the positive effects of exposure to TV ads on attempts and successful quits may be larger among smokers who are less likely to have otherwise previously attempted smoking cessation. This may reflect the possibility that e-cigarettes may be helping those to quit who have an especially hard time quitting through other means (cold turkey, NRT, etc.) because e-cigarettes more closely resemble the experience of smoking. Additional stratification analyses further show that the effects of TV ad exposure is significantly higher among low-educated adults. Finally, we explicitly test for non-linear effects of the ad exposure at the extensive and intensive margins.

6. 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% relative to a mean quit rate of 9% 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%, while a policy that would not discourage it would raise the quit rate by slightly more than 10%. 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 Fig. 1 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%. In the latter year, it fell to 15.11% 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%, 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% of the observed decline.[19] 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.

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% of adults perceived that e-cigs had the same level of harm as cigarettes compared to only 12% 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% in 2012 to 4% 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.

[17] This estimate adjusts for differences in education, alcohol consumption, and body mass index.

[18] Conventional cigarettes are banned from advertising on TV.

[19] This computation and the formula that underlies it are outlined in the fourth section of the appendix.

Table 6
Multinomial Logit Model, Marginal Effects of Current and Future E-cig Ads on Smoking Outcomes [S.E.].[a]

Independent Variables 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][b]					
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

[a] Sample size is 8291. Each column represents a separate multinomial logit model with the three outcomes being successful quits (Q), failures (F), and non-attempters (D), the latter being the reference category. Marginal effects are reported, with standard errors clustered at the household level in brackets. Instead of reporting the marginal effect on D (non-attempters), we report the marginal effect of the regressor on A (attempts) since this is just the negative of the marginal effect of the regressor on D, and thus the sum of marginal effects of the regressor on Q and F. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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

The introduction and diffusion of Juul exacerbates the dilemma concerning the regulation of e-cigarette advertising. On the one hand, our results indicate that TV advertising encourages adult smokers to switch to a product that is less harmful to their health. On the other hand, even if youths who start to use e-cigarettes do not transition to combustible cigarettes, the addictive properties of nicotine have been demonstrated to impair cognitive development, and other potentially harmful effects of e-cigarettes currently are under investigation. The emergence of Juul underscores the need for additional studies like ours on the effects of advertising on the behavior of adult smokers and for new research on their effects on decisions by youths to begin to use e-cigarettes. 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?

Some of these questions revolve around whether e-cigs and combustible cigarettes are substitutes or complements. Friedman (2015) and Pesko et al. (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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Online appendix. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jhealeco.2019.102227.

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