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ABSTRACT

Smoking is the leading preventable cause of death in the U.S. Because e-cigarettes do not involve the combustion of tobacco, vaping offers the potential to prevent most of the health consequences of smoking. We study the impact of an information shock created by an outbreak of lung injuries apparently related to e-cigarettes. We use data from multiple sources: surveys of risk perceptions conducted before, during, and after the outbreak; an in-depth survey we conducted on risk perceptions and vaping and smoking behavior; and national aggregate time-series sales data. We find that after the outbreak, consumer perceptions of the riskiness of e-cigarettes sharply increased, so that in contrast to almost all experts, the majority of consumers perceive e-cigarettes to be relatively and absolutely riskier than cigarettes. From our estimated e-cigarette demand models, we conclude that the information shock reduced e-cigarette demand by about 30 percent. We also estimate that the information shock decreased the use of e-cigarettes for smoking cessation, again by about 30 percent. Over time, the reduced smoking cessation due to the information shock will in turn increase smoking-related illness and death.

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A data appendix is available at http://www.nber.org/data-appendix/w30255

1. Introduction

For goods like tobacco that are detrimental to health, consumers consider both the monetary price and the health price – the marginal cost to their own health (Cutler 2002). Information, or misinformation, about the marginal health cost can thus play a critical role in driving consumer demand for health-related goods and behaviors. A line of empirical studies in economics use information shocks to explore the role of health information in consumer demand. Some studies focus on information shocks due to new health risks including AIDS (Philipson and Posner 1993), Mad Cow disease (Adda 2007), and COVID-19 (Bundorf et al. 2021). Instead of economy-wide shocks, Smith et al. (2001) and Darden (2017) study how individuals respond when they receive new information about their own health, for example because of a new diagnosis. Other studies focus on information shocks created when profit-maximizing firms respond to changes in public policies and take actions such as advertising high-fiber cereals (Ippolito and Mathios 1990), advertising smoking cessation products (Avery et al. 2007), and posting calories in restaurant menus (Courtemanche et al. 2020). While most prior studies tend to focus on shocks that improve consumer information, recent research focuses on the challenges of improving consumer health information in an information- and misinformation-dense polarized media environment (Allcott et al. 2020, Faia et al. 2021).

Cigarette smoking provides a powerful lens with which to understand the role of product risk information on consumer behavior and health. For many years, smoking has been the leading preventable cause of death in the U.S. and is estimated to lead to almost 500,000 deaths per year (U.S. Department of Health and Human Services 2020). Medical research studies and official government reports on the health consequences of smoking published in the 1950s and 1960s created information shocks to consumer demand for combustible cigarettes. Schneider, Klein, and Murphy (1981) estimate that by 1971 the cumulative effect of the information shocks was to reduce per capita cigarette demand by about 25 percent. Over the even longer run, the fraction of smokers in the U.S. population fell from 40 percent in 1965 to 14.2 percent in 2019. Information on the risks of smoking cigarettes also increased consumer demand for tobacco products that might carry lower risk, such as filtered and lower-tar cigarettes. Although these innovations were successful in the market, they did little to prevent smoking-related illnesses and death.[1]

In sharp contrast, innovative products like e-cigarettes and other non-combustible tobacco products now offer the potential to prevent most of the health risks of smoking. The toxicants and carcinogens in smoke that are linked to serious health consequences come from the combustion of tobacco. By avoiding combustion, e-cigarettes and other non-combustible products deliver nicotine without these toxicants. The consensus report of the National Academies of Science, Engineering, and Medicine (NASEM) concludes that: "There is *conclusive* evidence that completely substituting e-cigarettes for combustible tobacco cigarettes reduces users' exposure to numerous toxicants and carcinogens present in combustible tobacco cigarettes" (NASEM 2018, emphasis in original to indicate highest evidence standard). The Food and Drug Administration recognizes the lower health risks of non-combustible tobacco products and has authorized the sale of a form of smokeless tobacco, a heated tobacco product, nicotine-containing discs and chews, and some brands of e-cigarettes as appropriate for public health due to the potential health benefits to smokers who switch (see for example, FDA 2021).

[1] The U.S. market share of filtered cigarettes grew rapidly, from 58 percent in 1963 to 99.8 percent in 2020; the market share of cigarettes with machine-read tar levels of 15 mg or less grew from 2 percent in 1967 to 94.7 percent in 2011 (Federal Trade Commission 2021). Thun, et al. (2013) examine trends in smoking-related mortality in three cohorts from the 1960s, 1980s, and the 2000s. They estimate that the relative risk for death from all causes among current smokers as compared with never smokers was higher in the 2000s cohort than in the 1960s and 1980s cohorts. They also note that an unexplained increase in mortality from chronic obstructive pulmonary disease might be due to cigarette design changes that promoted deeper inhalation of smoke. Tanner, et al. (2019) estimate higher all-cause mortality rates for unfiltered cigarette smokers than for filtered cigarette smokers but did not find any difference in mortality rates between smokers of light (low-tar) versus regular cigarettes.

Despite the scientific consensus that non-combustible tobacco products are less risky, there is less consensus about the degree of risk reduction. McNeil et al. (2018) present evidence that vaping e-cigarettes is five percent as risky as smoking. In a survey of public health experts, the median of the 137 responses is that the impact of vaping on life expectancy is 25 percent as large as the impact of smoking; the interquartile range is 10 to 60 percent (Allcott and Rafkin 2022).[2] The range of expert opinions creates consumer uncertainty about the relative risk of vaping and might make consumers especially sensitive to information shocks.

In this paper, we study the impacts of an information shock on consumer risk perceptions and on consumer demand for e-cigarettes and smoking cessation. We exploit quasi-experimental variation in risk perceptions from an outbreak of lung injuries in the late summer and fall of 2019, which the CDC termed "E-cigarette, or Vaping, Associated Lung Injuries" (EVALI). The outbreak was exogenous with respect to the market for e-cigarettes and was created by illegal manufacturers who added a harmful ingredient into vaping products that contained THC, the main psychoactive component of marijuana.[3] Because eventually it was determined that nicotine e-cigarettes did not cause the outbreak, EVALI might be better termed a "misinformation shock." We use the term "misinformation" as synonymous with "incorrect information" and do not mean to imply that there were intentional attempts to mislead. Although e-cigarettes were not the cause of the outbreak, the CDC and other public health officials at the time provided strong warnings about the dangers of vaping and some States passed restrictive regulations on e-cigarette sales. For example, in response to EVALI Massachusetts declared a public health

[2] The FDA's preliminary regulatory impact analysis of a proposed ban on menthol cigarettes uses the assumption that the mortality risk of e-cigarettes is 15 percent of the mortality risk of smoking (FDA 2022, p.86).
[3] We follow conventional usage and refer to products that contain nicotine as "e-cigarettes" and the use of those products as "vaping;" we mention THC to distinguish THC-containing vaping products from nicotine-containing e-cigarettes. Section 2 provides more discussion of the lung injury outbreak.

emergency and temporarily banned the sale of both nicotine-containing e-cigarettes and THC-containing vaping products.

We use data from multiple sources: surveys of risk perceptions conducted before, during, and after the outbreak; an in-depth survey we conducted on risk perceptions and vaping and smoking behavior; and national aggregate time-series sales data. Our analysis establishes four empirical findings: 1) after EVALI, consumer perceptions of the riskiness of e-cigarettes sharply increased; 2) in contrast to almost all experts, the majority of consumers perceive e-cigarettes to be relatively and absolutely riskier than cigarettes; 3) in individual-level cross-sectional data, perceptions of the riskiness of e-cigarettes are strongly associated with lower consumer demand for e-cigarettes; and 4) after EVALI, retail e-cigarette sales dropped and a strongly positive time trend in sales reversed and became strongly negative. From these empirical findings, we conclude that the misinformation shock from the EVALI outbreak reduced e-cigarette demand by about 30 percent.

Given that some prior research finds that e-cigarettes and cigarettes are substitutes, we also explore the impact of EVALI on smoking. From our cross-sectional model we estimate that the information shock decreased the use of e-cigarettes for smoking cessation, also by about 30 percent. Because evidence from randomized clinical trials suggests that e-cigarettes are twice as effective for smoking cessation than pharmaceutical nicotine replacement products (Hajek et al. 2019), the reduced use of e-cigarettes can be expected to reduce smoking cessation. Over time, the reduced smoking cessation due to the EVALI information shock will in turn increase smoking-related illness and death. Based on a population health model, we predict that the 68 deaths directly due to EVALI will be compounded into 450,000 life years lost due to deterred smoking cessation.

Our empirical demand models rely on variation across individuals at the same point in time to identify the relationship between risk perceptions and the demand for e-cigarettes and smoking cessation. In this research design, threats to validity stem from the possible endogeneity of perceived harm: those who perceive more harm from e-cigarettes may be otherwise inclined to vape less. We conduct two exercises to corroborate the cross-sectional estimates by comparing them to interrupted time-series analysis of aggregate e-cigarette sales. In the first exercise, we combine estimates of the change in consumer risks perceptions due to EVALI with our cross-sectional e-cigarette demand model. Our demand model predicts that the EVALI information shock reduces vaping by 24 percent. After taking into account other policy events around the same time as EVALI, from our interrupted time series analysis we estimate that EVALI reduced e-cigarette sales by between 24 and 36 percent. Hence, the change in risk perceptions from EVALI that we document can explain between 67 and 100 percent of the observed decline in e-cigarette sales. Our second corroboration exercise is analogous to the method of two-sample two-stage least squares. We use the first-stage estimate of the effect of EVALI on risk perceptions to re-scale the reduced-form time series estimate of the impact of EVALI on e-cigarette sales. The re-scaled time-series estimate of the effect of risk perceptions on e-cigarette sales is over twice as large as the comparable cross-sectional estimate. The findings from both corroboration exercises suggest that the cross-sectional estimates if anything understate the causal effect of risk perceptions on vaping.

Our study contributes to a rapidly growing body of research on the economics and regulation of e-cigarettes. Over the past 50 years, policy makers have used a variety of tools to reduce consumer demand for combustible cigarettes, including health information campaigns, taxes, restrictions on advertising, and restrictions on smoking in public places (DeCicca, Kenkel, and Lovenheim 2022). Policy makers are beginning to use many of the same tools to reduce e-cigarette demand. Extending his earlier work on smokers' risk perceptions (Viscusi 1990), Viscusi (2016, 2020, 2022) uses a Bayesian learning model to explore how people form their perceptions of the riskiness of e-cigarettes. A set of studies exploit cross-state differences in e-cigarette and cigarette taxation to estimate own- and cross-price effects (Cotti et al. 2021, Pesko, Courtemanche, and Maclean 2020, Abouk et al. 2021).[4] The welfare economics of e-cigarette regulation are complex and depend partly on whether e-cigarette consumers are making well-informed decisions. Allcott and Rafkin's (2022) analysis of optimal e-cigarette regulation supports the recent trend for higher e-cigarette taxes; from 2019 to March 2021 the number of states that tax cigarettes tripled, from 10 to 30. However, Allcott and Rafkin also find that if consumers overestimate the health risks of vaping, the optimal policy is to subsidize, not tax, e-cigarettes. Another implication of the EVALI information shock is that instead of new taxes, policy makers might need to re-examine the case for e-cigarette subsidies to overcome consumer misinformation.

The remainder of the paper is organized as follows. Section 2 provides background about the market for e-cigarettes and the EVALI outbreak. Section 3 describes the various data sets used in our empirical analysis. Section 4 presents trend data and cross-sectional evidence on the impact of the EVALI outbreak on consumer perceptions of the relative and absolute riskiness of e-cigarettes. Section 5 presents empirical results from our cross-sectional models of demand for e-cigarettes. Section 6 presents corroborating empirical results from interrupted time-series models of e-cigarette sales. Section 7 presents estimates of the impact of the EVALI information shock on smoking cessation and public health. Section 8 provides a brief conclusion.

[4] See DeCiccca, Kenkel, and Lovenheim (2022) for a detailed review of this literature.

2. Background

E-cigarettes were introduced into U.S. markets around 2007. Annual sales grew rapidly, from $500 million in 2012 to $6.6 billion in 2018 (Cowen and Company Equity Research, 2019). In early 2019, e-cigarette sales were predicted to total $9 billion in 2019 and continue to grow by 15 to 20 percent annually through 2023 (Herzog 2019). In the 2019 National Health Interview Survey (NHIS), 4.5 percent of adults report that they currently use e-cigarettes every day or some days (Cornelius et al. 2020). In the 2019 National Youth Tobacco Survey (NYTS), 27.5 percent of high school students report using e-cigarettes within the past 30 days (Wang et al. 2019). The fractions of adults and high school students vaping in 2019 were at all-time highs.

Although vaping e-cigarettes is more common among youth, because of their larger population share and more frequent vaping, adult vapers dominate the e-cigarette market. Table 1 shows the fractions of all vaping days accounted for by different age groups and by smoking status. In order to describe the market before the 2019 information shock, we use self-reported data on youth vaping days from the 2019 National Youth Tobacco Survey (NYTS) combined with self-reported data on adult vaping days from the 2018 National Health Interview Survey (NHIS).[5] We estimate that adults aged 18 and over account for 81 percent of vaping days.[6] Cut differently, current and former smokers account for 73 percent of vaping days.[7]

[5] The information shock was in the late summer and fall 2019. The 2019 NYTS was completed in the spring of 2019 before the shock. Because the NHIS is conducted year-round, the 2019 NHIS is partly post-information shock; Table 1 uses the 2018 NHIS data. Even with the information shock, the 4.5 percent prevalence of adult vaping in 2019 exceeded the 2018 NHIS adult vaping rate of 3.2 percent. Compared to the NYTS, the NHIS appears to understate young adult vaping. We adjusted the number of vaping days in the NHIS for young adults to make the two series more consistent; see Appendix A for details.

[6] Beginning in 2020, federal legislation increased the legal purchase age for all tobacco products including e-cigarettes to 21. Table 1 presents our estimate that in 2019 adults aged 18-20 accounted for 21.2 percent of vaping days.

[7] We use data on vaping days because it is the only common metric available in most datasets for youth and adults in recent years. The Population Assessment of Tobacco and Health (PATH) study includes more detailed puff topography measures of the number of vaping times per day and the number of puffs per vaping episode. However, Soule, et al. (2021) note limitations to puff topography measures including accuracy of recall and extreme self-reported values.

From their introduction until recently, e-cigarettes have been regulated in the U.S. as ordinary consumer products. In 2016 the FDA issued the deeming regulation, in which it deemed e-cigarettes to be under the FDA statutory authority over tobacco products created by the 2009 Tobacco Control Act. In August and September 2021 the FDA began issuing marketing denial orders and marketing approval orders for e-cigarettes. Prior to the 2021 FDA actions, e-cigarette manufacturers were allowed to advertise their products, but the advertisements were not allowed to make health claims or therapeutic claims that e-cigarettes are helpful for smoking cessation. E-cigarette television advertising expenditures were mainly stable from 2013 through the first quarter of 2017, were very low through the rest of 2017 and 2018, and were much higher in the first three quarters of 2019 (Duan, Wang, Emery, et al. 2021).

As the e-cigarette market developed, the FDA and non-profit health organizations have sent mixed and often negative messages about the health risks of e-cigarettes. The FDA provides an illustrative example. In July 2017 the FDA Commissioner Scott Gottlieb announced a new comprehensive plan that emphasized "striking an appropriate balance between regulation and encouraging development of innovative tobacco products that may be less dangerous than cigarettes." (Gottlieb 2017). However, in reaction to new data showing a sharp increase in teen vaping, in November 2018 Gottlieb pledged to "take whatever action is necessary to stop these trends from continuing." (Gottlieb 2018). In one action, in 2018 the FDA expanded its youth smoking prevention campaign into the "Real Cost Youth E-Cigarette Prevention Campaign," which includes television and online advertisements, social media, and school-based materials. Based on their qualitative content analysis, Xuan and Choi (2021) criticize the campaign for its reliance on fear-based messages about vaping.

In the late summer of 2019, the media began to report an outbreak of lung injuries apparently linked to e-cigarettes. The EVALI outbreak peaked in mid-September and ended by early 2020 (Figure 1, Panel A). EVALI cases were reported to the CDC from all 50 states and D.C. By the time of the CDC's final update in February 2020, 2,807 EVALI hospitalizations had been reported, including 68 confirmed deaths.[8] The information was more shocking because, unlike COVID-19 and other serious lung diseases, many patients with serious EVALI symptoms were young. The median age of hospitalized EVALI patients was 24 years; 15 percent of hospitalized EVALI patients were under 18 years old. EVALI was more likely to be fatal among somewhat older patients; the median age of deceased patients was 49.5 years. Eventually, the CDC's investigation concluded that EVALI cases were linked to products that contained THC, the main psychoactive component of marijuana, that were obtained from informal sources including dealers. EVALI cases also were strongly linked to Vitamin E acetate, which was used as an additive in THC-containing products.[9] Commercially produced nicotine e-cigarettes are not linked to EVALI.

CDC warnings, national media stories, social media, and the Internet informed the public about the EVALI outbreak. Throughout most of the EVALI outbreak, the CDC provided mixed messages about the role of THC products and at times issued strong warnings against the use of all e-cigarettes, not just THC products. Jeong et al. (2021) analyze e-cigarette news articles published in leading U.S. print and online sources in 2019. They find that the frequency of e-cigarette articles increased from less than 100 per month from January through July to a peak of

[8] https://www.cdc.gov/tobacco/basic_information/e-cigarettes/severe-lung-disease.html.

[9] THC vaping devices use oil-based liquids because THC dissolves most readily in oil. Nicotine vaping devices use water-based liquids because nicotine dissolves in water. As a result, THC- and nicotine-vaping devices have different coils and wicks and operate at different temperatures. Moreover, users of THC vaping devices do not generally refer to them as "e-cigarettes," but use other terms including "vape pens," "THC carts [cartridges]," and "weed vapes." Given common terminology, the CDC's acronym that links the term "e-cigarettes" to lung injuries might have been and might continue to be confusing to users.

over 500 news articles in September 2019, almost all of which discussed EVALI. Jeong et al. find that two-thirds of the EVALI-related articles mentioned THC vaping, but often in the second half of the article. The EVALI-related articles also mentioned other health risks including that nicotine is addictive/harmful (26 percent), exposure to toxins/carcinogens (14 percent), and that health effects are unknown (11 percent). Only 18 percent of EVALI-related articles mentioned that e-cigarettes are less risky than cigarettes. Google Searches for the terms "vaping deaths" and "vaping illness" also peaked in mid-September, as shown in Figure 1 (Panel B). Hassan et al. (2022) collected Twitter data from April 1 through December 31, 2019 and use machine learning to identify common topics. They find evidence that around September 2019 the EVALI outbreak disrupted usual social media commentary and prompted discussion on Twitter about the illnesses and deaths.

Several other events in the fall of 2019 increased media and public interest in e-cigarettes and contributed to the EVALI information shock. Preliminary results released from the 2019 NYTS showed a sharp rise in the rate of teen vaping from 2018; a year earlier FDA Commissioner Gottlieb had already termed the 2018 rate of teen vaping an "epidemic" (Gottlieb 2018). The 2019 NYTS also documented the continued popularity of fruit, menthol or mint, and candy flavored e-cigarettes among teens. On September 11, the FDA announced plans to prioritize enforcement actions to limit the availability of flavored e-cigarettes (FDA 2019). Flavored e-cigarettes were banned in Michigan (September 18), Washington State (October 10), and Oregon (October 15). The bans on flavored e-cigarettes were originally responses to the high rates of teen vaping but gained additional momentum from EVALI. Jeong et al. (2021) find that 40 percent of EVALI-related news articles also discussed the prevalence of teen vaping and 27 percent discussed the appeal of flavors to teens. Google Searches show spikes in searches for "vaping epidemic" and "vaping flavors" in mid-September 2019 but at much lower frequencies than "vaping deaths."[10] In mid-September 2019 major media companies stopped advertising e-cigarettes (Graham 2019). Concern about the EVALI outbreak, teen vaping, and flavored e-cigarettes might tend to be tangled together in public perceptions. When we refer to the EVALI information shock, we recognize that the shock also reflected news about teen vaping and the policy responses by the FDA and some States.

In line with or perhaps exceeding industry expectations, weekly e-cigarette sales grew rapidly in the first half of 2019 and in mid-August reached $89.35 million, a 39 percent increase over the first week of January 2019 (Figure 1, Panel C). The data, which will be discussed in more detail below, are from the NielsenIQ retailer scanner data. In late August and the first two weeks of September – when EVALI hospitalizations, EVALI-related news articles, Google Searches, and tweets about vaping deaths peaked – e-cigarette weekly sales fell from their August peak by $13 million or by 15 percent. E-cigarette sales continued to fall through the end of 2019 and in early 2020. In the remainder of this paper, we develop several lines of evidence to conclude that the drop in e-cigarette sales was the causal effect of the information shock created by the EVALI outbreak.

3. Data

We combine data from multiple sources that were collected before, during, and after the EVALI outbreak. First, we use data from two sets of repeated cross-sectional surveys to track trends in consumer information about the riskiness of e-cigarettes. We combine data from the Health Information National Trends Survey (HINTS) and a series of online Google Surveys (GS) that we commissioned. HINTS is an ongoing nationally representative survey conducted

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[10] When the peak in searches for "vaping deaths" is indexed at 100, the peak in searches for "vaping epidemic" is 10 and the peak in searches for "vaping flavors" is 4.

annually for the National Cancer Institute. GS is a commercial organization that recruits respondents from Internet users who visit websites that use a “surveywall” where the site’s content is blocked until the user completes the survey. Academic research in marketing and social sciences increasingly rely on online opt-in surveys, and methodological studies suggest these data are of high quality.[11] Starting in September 2019, we commissioned a series of ongoing Google Surveys about adults’ perceptions of the risks of e-cigarettes relative to combustible cigarettes. Our GS use the same question asked in the 2012, 2014, 2015, 2017, 2018, 2019, and 2020 HINTS. The sample sizes from the repeated HINTS cross-sections range from 1736 to 5438. The sample sizes of our GS repeated cross-sections range from 2656 to 3679. Dave et al. (2020) provide more discussion of the HINTS and our GS data through January 2020.

Second, we use cross-sectional data from a NielsenIQ Custom Survey (NCS) conducted for us in May 2020. The 2020 NCS sample of 2,442 adults is a sub-sample of participants in the NielsenIQ Homescan Consumer Panel (NHCP). NHCP households are provided with a scanner and are asked to scan all items they purchase. To be eligible for our NCS, NHCP households must have made at least one purchase of an e-cigarette or cigarette in the prior year. However, the NCS may be completed by a non-smoking or non-vaping adult member of the household.[12] The NCS includes detailed questions about vaping, smoking, and consumer risk perceptions, including the same HINTS/GS question about the relative harmfulness of e-cigarettes. The NCS sample is not representative of the U.S. adult population, but its demographics are generally similar to the demographics of adult past-year smokers and past-year vapers in the 2018-2019

[11] Several studies have been conducted of the accuracy and biases of online opt-in survey data (Mercer et al., 2018; Sostek 2019). Santoso et al. (2016) discuss GS methods in more detail and report the results of several methodological studies. They conclude that there is no evidence that GS is either more or less representative than other online opt-in survey datasets.
[12] Our analysis sample includes 399 respondents, or 16 percent of the sample, who self-report that they have never been regular smokers or vapers. Due to the NCS eligibility screen, this fraction is much lower than the fraction of U.S. adults who have never smoked.

Tobacco Use Supplement (TUS) to the CPS (Appendix Table C1). One exception is the age composition.[13] The NCS sample includes almost no young adults aged 21-24; the NCS sample is comprised of only five percent of adults aged 25-34, compared to 21 percent in the TUS-CPS sample. Otherwise, the demographics of the NCS sample are comparable to middle-aged and older adult smokers and vapers. Because the NCS sample is restricted to adults, we are not able to study teen and young adult demand for e-cigarettes.

Third, we use data on sales of e-cigarettes and cigarettes from the NielsenIQ retailer scanner (NRS) data. The NRS data are from about 50,000 participating grocery, drug, mass merchandise, and convenience and other stores that provide NielsenIQ with their scanner data; NielsenIQ projects sales from non-participating establishments in these retail channels. We use data on weekly sales from July 2018 through March 2020.[14] We only use data through early March 2020 to avoid confounding the impact of EVALI with the later impact of COVID-19.

4. Impact of the Information Shock on Consumer Risk Perceptions

Relative Risk Perceptions

In this section, we explore the impact of EVALI on consumer perceptions of the riskiness of e-cigarettes. We first explore differences in the perceived relative riskiness of e-cigarettes in surveys conducted before and after EVALI (Table 2). The patterns suggest that after EVALI, many consumers shifted from being uninformed to being misinformed about e-cigarette risks. Panel A compares the responses to the 2019 HINTS conducted before EVALI to responses to the 2020 HINTS. Between 2019 and 2020, the fraction of don't knows fell by 11 percentage points

[13] Another exception is that the NCS sample includes 73 percent females. The households in the NHCP panel include a balanced number of males and females, but a female household member was more likely to complete the Custom Survey.

[14] The data are for the tobacco alternatives vapor categories and cover the 88-week period starting July 7, 2018 and ending March 7, 2020 for the U.S. national market, retailer (xAOC + convenience) channels. NielsenIQ does not collect data on sales in vape shops, specialized tobacco shops, or online, and NielsenIQ does not project sales for these retail channels.

while the fraction of respondents who reported that e-cigarettes are more harmful increased by 6 percentage points and the fraction who reported much more harmful increased by 9 percentage points. The fractions of respondents who reported that e-cigarettes are less or much less harmful fell a few percentage points. Panel B compares responses in a weighted sub-sample of the 2019 HINTS to responses in our 2020 NCS. To improve comparability between the samples, the 2019 HINTS sub-sample is restricted to current smokers or vapers and is weighted to match the gender composition of the 2020 NCS. Across the 2019 HINTS sub-sample and the 2020 NCS, the fraction of don't knows again decreased while the fractions reporting that e-cigarettes are more or much more harmful increased. The patterns in Panels A and B are consistent with EVALI creating an information shock that caused consumers to perceive e-cigarettes as relatively riskier, with a stronger impact on previously uninformed consumers (the don't knows).

Panel C of Table 2 further explores the possible impact of EVALI on consumer relative risk perceptions by comparing two sub-samples of the 2020 NCS. After the question about the relative harm of e-cigarettes, the 2020 NCS included a subsequent question about EVALI: "Thinking back over the last 6 months to a year, what have you heard about vaping and lung injuries?" Panel C compares the minority of the sample who had not heard anything about EVALI to the majority who had heard about EVALI. Compared to the Not Heard NCS sample, the fractions of respondents in the Had Heard NCS sample who reported that e-cigarettes are more or much harmful were 9 and 7 percentage points higher, mirroring the differences in Panels A and B between surveys conducted in 2019 pre-EVALI and in 2020 post-EVALI.

Next, we examine longer-run time trends in relative risk perceptions. Figure 2 uses data from additional surveys conducted before and after EVALI; each point in Figure 2 corresponds to a separate survey, including the 2019 and 2020 HINTS and the 2020 NCS used in Table 2. For

Figure 2 we focus on the combined response categories of "more harmful" and "much more harmful" to simplify the figure and because based on current scientific evidence these perceptions are unambiguously incorrect. Figure 2 shows that in the HINTS data collected over the seven years before EVALI, the fraction reporting that e-cigarettes are more or much more harmful than cigarettes increased by more than 2 percentage points per year, from 3 percent to 20 percent.[15] This upward trend itself is interesting, as it shows that counter to the scientific consensus, the public perceives increased relative risk from vaping. This trend likely reflects conflicting opinions about vaping risk among public health experts.

Figure 2 includes our GS data on relative risk perceptions, which start in mid-September 2019, around the peak of the EVALI outbreak. The fractions of the GS samples reporting that e-cigarettes are more or much more harmful than cigarettes are more than 15 percentage points higher than the May 2019 HINTS and are above the predicted trend line. We find that most of the increased risk perceptions persisted after the EVALI outbreak into 2020. For the first half of 2020, the increase in risk perceptions is consistent with our previous estimate that the EVALI outbreak is associated with an increase of 16 percentage points in the fraction of consumers who perceive e-cigarettes as more or much more harmful (Dave et al. 2020, based on our GS data through January 2020). In the data from GS conducted in late 2020 and early 2021 – about a year after the EVALI outbreak – the fractions perceiving more or much more harmful are beginning to return to the pre-EVALI trend. In the most recent GS conducted in October 2021 – about two years after EVALI – 24 percent of the sample perceived e-cigarettes as more or much more harmful, which is about on the pre-EVALI trend and is 4 percentage points higher than in

[15] In Figure 3 and for most of the analysis reported in this section, people who responded "don't know" are dropped from the samples. Appendix Figure B1 provides a version of Figure 3 based on samples that include the "don't know" respondents. Appendix Figure B2 shows the fractions in each sample who responded, "don't know."

the pre-EVALI 2019 HINTS. Interestingly, the GS data after the onset of the COVID-19 pandemic – another major lung disease – show no evidence that COVID-19 changed consumer perceptions of the relative risks of vaping.

Absolute Risk Perceptions

Although we do not have trend data on absolute risk perceptions, we included questions about the absolute risks of smoking and vaping in our May 2020 NCS. Compared to expert estimates, on average NCS respondents have accurate perceptions of the life expectancy loss of smoking but substantially overestimate the life expectancy loss due to vaping. Among NCS respondents, the mean perceived life expectancy loss due to smoking is 9.7 years and the median is 9 years; the mean perceived life expectancy loss due to vaping is 13 years and the median is 12 years. Among public health researchers, a commonly cited estimate of the life expectancy loss due to smoking is 10 years (Jha et al. 2013).[16] There is not a strong consensus about the life expectancy loss due to vaping, but most expert estimates are much lower than consumer perceptions in the NCS. The expert estimates that e-cigarettes are between five (McNeil et al. 2018) and 25 percent (Allcott and Rafkin 2022) as risky as smoking imply that the life expectancy loss due to vaping is between 0.5 to 2.5 years, substantially less than the mean or median perceptions among NCS respondents that vaping reduces life expectancy by more than 10 years.

We next compare our measure of absolute risk perceptions with our measure of relative risk perceptions (Table 3). On average, the NCS respondents who perceive e-cigarettes as relatively riskier do so because they think that vaping causes a larger life expectancy loss, not

[16] Darden, Gilleskie, and Strumpf (2018) use data from a long panel to jointly model smoking and health and allow for correlated unobservable heterogeneity. Their estimates imply that smoking causes 4.3 years of life expectancy loss, which implies that the public health consensus and the NCS respondents both over-estimate the loss due to smoking.

because they think that smoking causes a smaller loss. In fact, compared to respondents who perceive e-cigarettes as much less or less harmful than smoking, respondents who perceive e-cigarettes as more harmful also on average perceive one to two more years of life expectancy loss due to smoking. That is, they perceive higher risk from both tobacco products, but they perceive an even larger life expectancy loss due to vaping. Respondents who perceive e-cigarettes as much less harmful on average perceive that the life expectancy loss due to vaping is 65 percent as large as the loss due to smoking, which is still much higher than expert estimates from 5-25 percent (Neil et al. 2018, Allcott and Rafkin 2022).[17] Respondents who perceive e-cigarettes as much more harmful perceive that the life expectancy loss due to vaping is twice the loss due to smoking. The average perceived life expectancy loss due to vaping among those who responded “don’t know” to the relative harm question is similar to those who responded that e-cigarettes are just as harmful as smoking.

To provide another perspective on consumer information, Table 4 describes what NCS respondents reported having heard about EVALI. Respondents were asked to choose all that applied out of a list of seven statements. The listed statements included correct and incorrect statements that correspond to common themes in media and Internet discussions (Jeong, Singh, Wackowski et al. 2021). Almost all (83 percent) respondents had heard something about EVALI. About half were well-informed about the broad parameters of the EVALI outbreak, i.e. that there were hospitalized cases including deaths. But many respondents were un- or mis-informed about the role of THC products: only 15 percent reported that EVALI cases were mainly linked to THC products, while 32 percent reported that the cases were linked to the use of all vaping products. 19 percent of respondents were misinformed and thought that EVALI cases were linked to

[17]In a survey of UK residents, Viscusi (2022) also finds that even respondents who perceive e-cigarettes to be relatively less risky under-estimate the absolute risk reduction.

flavored e-cigarettes. In the NCS we also asked respondents if they agreed with the incorrect statement that: "The nicotine in cigarettes is the substance that causes most of the cancer caused by smoking." The question earlier in the survey about the relative harmfulness of e-cigarettes specified that they deliver nicotine through vapor, so the incorrect belief that nicotine causes cancer might be associated with e-cigarette risk perceptions. Almost half of the NCS respondents strongly agreed or agreed with the incorrect statement that nicotine causes cancer.

In our last empirical exercise to describe consumer information about e-cigarettes, we estimate models that use the perceived relative risk and the perceived life expectancy loss from vaping as dependent variables (Table 5). Although our models do not identify causal relationships, the estimated associations describe possible sources of consumer information about e-cigarette risks. The first set of explanatory variables are indicators for the statements heard about EVALI. Relative to the reference group who reported that they had not heard about EVALI, respondents who had heard the correct statement that there were some hospitalized cases including deaths were 7.4 percentage points more likely to perceive that e-cigarettes are more or much more harmful (column 1) and perceived 2 more years life expectancy loss (column 2). Respondents who had heard the correct statement that the cases were linked to THC products were 6.2 percentage points less likely to perceive that e-cigarettes are more or much more harmful and perceived 1.1 fewer years life expectancy loss. Relative harm and life expectancy loss perceptions also are statistically significantly associated with having heard some of the incorrect statements about EVALI. Respondents who agreed with the incorrect statement that nicotine causes cancer are a statistically insignificant 3.4 percentage points more likely to perceive that e-cigarettes are more or much more harmful than cigarettes, but they perceive a statistically and practically significant 2.5 more years of life expectancy loss from vaping. The small difference in perceived relative harm makes sense because both e-cigarettes and cigarettes contain nicotine.[18]

The third column of Table 5 report the results of a regression that explores the Bayesian learning model about vaping risks proposed by Viscusi (2016, 2020, 2022). Viscusi hypothesizes that consumer perceptions of the risk of vaping are based on their prior beliefs about the risks of smoking. Consistent with this hypothesis, we find that each additional perceived year of life expectancy loss due to smoking is associated with 0.7 more years of perceived life expectancy loss due to vaping. After controlling for differences in the perceived life expectancy loss due to smoking, we continue to find statistically significant and quantitatively important associations between the perceived life expectancy loss due to vaping and having heard specific correct and incorrect statements about EVALI. Table 5 also reports estimates that perceived relative harm of vaping and perceived life expectancy loss due to vaping vary across demographic groups. The strongest demographic pattern is a negative gradient with schooling. In the Bayesian learning framework, these results can be interpreted as suggesting that respondents who had heard different statements, and different demographic groups, update their prior beliefs to different extents.

The estimates in the column (3) model of Table 5 suggest that differences in Bayesian updating can lead to substantial differences in perceptions about the life expectancy loss due to vaping. For example, compared to someone in the baseline reference group, a consumer with a graduate degree who had heard the correct statements that there were hospitalizations and some deaths and that the cases were linked to THC products, and the skeptical statement that reports were exaggerated, is predicted to perceive 7.9 fewer years life expectancy loss due to vaping. If

[18] In results available upon request, we did not find any statistically significant or meaningfully large interaction terms between the indicator for belief about nicotine and the indicators for having heard statements about EVALI.

their prior belief is that the life expectancy loss due to smoking is 10 years, the model predicts that this relatively well-informed and highly educated consumer would perceive 6.4 years of life expectancy loss due to vaping. The predicted perception that vaping is 64 percent as risky as smoking is again above the expert estimates that vaping is between 5-25 percent as risky (McNeil et al. 2018, Allcott and Rafkin 2022).

To sum up, in this section we reported novel data on consumer risk perceptions collected before, during, and after the EVALI outbreak. Multiple lines of evidence suggest that the EVALI outbreak created an information shock that shifted many consumers from being uninformed about e-cigarette risks to being misinformed. Although the misinformation shock appears to be fading over time, on average consumers substantially over-estimate the life expectancy loss due to vaping. In the following sections, we explore evidence about the impact of the misinformation on consumer demand for e-cigarettes, smoking cessation, and public health.

5. Cross-Sectional Analysis of Individual Risk Perceptions and E-cigarette Demand

We next report estimates of individual-level demand functions for e-cigarettes. We use self-reported measures of vaping from our 2020 NCS to create the dependent variables of the demand functions. On the extensive margin of demand, vaping participation in the 2020 NCS sample is 14 percent. By comparison, in data from the 2019 U.S. National Health Interview, 4.5 percent of adults were current users of e-cigarettes (Cornelius et al. 2020). The higher prevalence of vaping in our NCS sample is not surprising, given the screening criterion of at least one e-cigarette or cigarette purchase in the past year. On the intensive margin, current users of e-cigarettes on average vaped 17.4 days in the past month. DeCicca, Kenkel, and Mathios (2008) point out that for addictive goods like e-cigarettes, changes in the stock of current participation depend on the flows of cessation and initiation. To explore flows, we use self-reported data from our NCS on when former vapers quit, attempts to quit vaping, intentions to quit vaping in the future, and on when current vapers first initiated regular vaping.[19]

The key explanatory variables in the demand functions are the indicators for perceptions about the relative risk of e-cigarettes and the perceived life years loss due to smoking. These variables capture the health price of e-cigarettes and the cross-health price of smoking. The demand models also include sex, age, race/ethnicity, completed schooling, and the presence of children in the household and measures of policies in the individual's state of residence, including state e-cigarette and cigarette taxes and state policies that restrict e-cigarette use or sales. The models control for whether the survey was completed on a desktop computer or mobile device. Appendix Table C2 provides descriptive statistics.

Table 6 presents the estimated e-cigarette demand functions. The first column reports the results of the unconditional demand model of the number of days vaped in the past month. The unconditional demand model is estimated by ordinary least squares (OLS) using the entire sample of non-vapers with zero consumption and vapers with positive consumption. The next two columns report estimates of the two-part model of demand on the extensive and intensive margins: a linear probability model (LPM) on the extensive margin of vaping participation, and an OLS model on the intensive margin of the number of days vaped in the past month, conditional on vaping. In the next columns, we present the results from LPMs of past-year vaping cessation, past-year quit attempts, quit intentions, and past-year vaping initiation.

The results in Table 6 show strong associations between e-cigarette demand and the perceptions of the relative risk of e-cigarettes. The magnitudes of many of the associations are

[19] In addition to the regression models reported in Table 6, we also visually examined the data on the reported timing of vaping cessation over the past 12 months, a time period which included the peak of the EVALI outbreak. With a relatively small number of quits, the only apparent pattern is a spike in vaping cessation during the first week of January, presumably reflecting New Year's resolutions.

large. For example, in the unconditional demand model, perceiving that e-cigarettes are much less harmful is associated with an increase of 9.6 more days vaping in the past month, which is almost four times larger than the sample mean. Differences in unconditional demand reflect differences in vaping participation and demand conditional on vaping; differences in vaping participation in turn reflects differences in vaping cessation and initiation. The perception of vaping being much less harmful than cigarettes is associated with a 40 percentage point increase in the probability of vaping participation, a 17 percentage point decrease in the probability of past-year vaping cessation, a 24 percentage point decrease in the probability of past-year attempts to quit vaping, a 19 percentage point decrease in the probability of intentions to quit vaping in the next six months, and a 12 percentage point increase in the probability of past-year vaping initiation among smokers.[20]

In general, the magnitudes and signs of the coefficients in Table 6 vary as expected across the risk perception categories from much less, less, more, and much more harmful. The coefficients on the "don't know" response are small and are not statistically significantly different from zero at conventional levels; the "don't know" response is similar to the response that e-cigarettes are just as harmful as smoking (the omitted reference category). Interestingly, controlling for relative perceived risk, e-cigarette demand is not strongly influenced by perceptions about the life-years lost due to smoking. The models include controls for demographic characteristics and state policies related to vaping, but there are not many strong patterns.

The estimates in Table 6 specify e-cigarette demand as a function of relative risk perceptions in order to match with the HINTS and GS data on harm perceptions before, during,

[20] The marginal effects from probit models are similar to the LPM results reported. The probit results are available upon request.

and after EVALI. Appendix Table C3 reports the results from specifications of e-cigarette demand as a function of the perceived absolute risks of e-cigarettes and smoking, measured by the perceived number of life-years lost. To allow for non-linearities, we use indicators of the deciles of the absolute risk variables. The results in Table C3 show strong associations between e-cigarette demand and the perceived absolute risk of e-cigarettes. In several models, the relationships are non-linear, with most of the effects concentrated in the lower deciles of perceived absolute risk. The strong effects at these lower deciles are consistent with the pattern in Table 6 of large coefficients on the "much less" and "less" categories of relative risk. The results in Appendix Table C3 show weaker associations between e-cigarette demand and the perceived absolute risk of smoking.

The demand models in Table 6 rely on cross-sectional variation to identify the causal effects of consumer risk perceptions on e-cigarette demand. In Section 4 we presented evidence that the cross-sectional variation in risk perceptions might reflect heterogeneity in the impact of the EVALI information shock. The evidence shows a large change in risk perceptions in surveys conducted before, during, and after EVALI. In the cross-sectional data used in the Table 6 demand models, risk perceptions reflect the fact that some consumers did not hear about EVALI, while others heard various incorrect and/or correct statements. Other unobserved exogenous sources of heterogeneity include possible exposure to anti-vaping mass media campaigns such as those sponsored by the FDA.[21] However, the Table 6 demand function estimates also are potentially subject to endogeneity bias. Consumer risk perceptions reflect their investments in health information, which in turn might be associated with unobserved heterogeneity in

[21] The FDA's "Real Cost" campaign was aimed at teens aged 12-17, but Hall, Saffer, and Noar (2019) report that in an online sample of young adults aged 18 – 29, about half had seen at least one Real Cost advertisement in the past three months.

preferences over health, risk, and time. Controls for demographics including sex, age, schooling, and income should help reduce the potential role of unobservables. In addition, the e-cigarette demand functions include a control for the perceived life expectancy loss due to smoking, which is a closely related health risk. Nevertheless, there might be other sources of unobservable heterogeneity such as confirmation bias that will tend to bias the estimated coefficients on the perceived risk variables away from zero. [22] Given the novelty of our data on risk perceptions and e-cigarette demand, we believe the evidence in Table 6 makes a useful contribution to an under-studied question. We next explore of a much different type of data – time-series data on e-cigarette sales – to see whether the patterns corroborate the cross-sectional estimates.

6. Impact of the Information Shock on E-Cigarette Sales

Interrupted Time-Series Analysis of E-Cigarette Sales

In this section we use aggregate weekly time-series sales data from the 2018 – 2020 NRS to corroborate our estimated consumer demand functions. We first report estimates from an interrupted time-series analysis (ITSA) of the impact of EVALI on the level and growth of aggregate e-cigarette retail sales. The model includes an event-time interaction to allow EVALL to have delayed impacts on sales, for example due to infrequent e-cigarette purchases, consumer learning over time, or consumers adjusting their stocks of addictive capital.[23] Based on tests for autocorrelation in the error distribution, we report Newey-West standard errors with one lag.

[22] Confirmation bias occurs when consumers seek out and pay more attention to information that confirms their prior beliefs. For example, Faia et al. (2021) provide experimental evidence that people with more pessimistic prior beliefs about the COVID-19 pandemic are more likely to prefer pessimistic news articles.

[23] Becker and Murphy (1988) model addiction as involving adjacent complementarity between consumption at time t and t+1. As a result, it usually is optimal for consumers to gradually adjust their consumption to an unexpected shock. The model allows for unstable steady states, in which case an unexpected shock might move the consumer from a high-consumption to a low-consumption steady state; that it, the shock might cause some addicts to quit. Below in Section 6, our empirical analysis of individual-level data explores the determinants of vaping cessation.

Column (1) of Table 7 presents the results of the ITSA model of e-cigarette sales; Panel A of Figure 4 compares the actual weekly sales to the predicted values from the estimated ITSA model. The EVALI outbreak is associated with an estimated immediate reduction in e-cigarette sales of $11.6 million, which is 13 percent of the pre-EVALI peak in mid-August of $89 million per week. Moreover, after EVALI the previous positive time trend in e-cigarette sales becomes negative. The time trend and event-time interaction show that before EVALI, e-cigarette sales are estimated to increase by $0.7 million per week, while after EVALI e-cigarette sales are estimated to decrease by $0.5 million per week. Compared to the pre-EVALI time trend, by the end of the sample period in early March 2020, 24 weeks of the changed time trend implies a decrease in weekly sales of $28 million. The estimated total weekly decrease due to the immediate impact and the time trend change is $39.7 million, which is 36 percent of the predicted counter-factual sales of $109 million with no EVALI impact.[24] The changes in e-cigarette sales mainly reflect changes in quantities, not price; the levels and trends in most e-cigarette prices did not change much during EVALI (see Appendix D for more details).

The close correspondence between the timing of the EVALI outbreak and the changes in the level and time trend in e-cigarette sales suggests that EVALI had a sharp negative causal impact on e-cigarette demand. In column (2) of Table 7, we extend the ITSA analysis to include four additional events: the November 2018 voluntary withdrawal of the leading brand Juul's fruit-flavored e-cigarettes from the market, the November 2019 voluntary withdrawal of mint-flavored Juul e-cigarettes, the December 2019 increase in the Federal legal purchase age to 21 for all tobacco products including e-cigarettes, and the February 2020 FDA compliance policy that effectively banned the sales of pod-based flavored e-cigarettes, other than tobacco or

[24] With no EVALI impact on the level or time trend in sales, counter-factual sales are predicted as the pre-EVALI time trend (0.708) multiplied by 88 weeks, plus the estimated constant term (46.71).

menthol. As can be seen in Panel B of Figure 4, the additional parameters improve the fit of the model but do not substantively change the estimated impacts of the impact of EVALI on e-cigarette sales. The results show little evidence that the policy events were associated with sustained reductions in total e-cigarettes sales. When sales are disaggregated by flavors, the results (reported in columns 3-6 of Table 7) show that when sales of certain flavors were restricted, the drop in that category's sales was offset by increases in the remaining flavor categories. Linden (2015) cautions that identification of a causal impact in an ITSA model is difficult when there are multiple events in a narrow time window. However, the close correspondence between the timing of the policy changes that restricted flavors and the changes in sales of different categories of flavored e-cigarettes again supports causal inferences from the ITSA results.

We use as our preferred estimate that EVALI reduced e-cigarette sales by 36 percent, which is the estimated reduction in e-cigarette sales through early March 2020. [25] Our preferred estimate avoids misattributing to EVALI most of the effects of the February 2020 FDA policy change and all of the effects of COVID-19. On the one hand, given the evidence we present above that the EVALI information shock persisted into 2020, our preferred estimate might miss longer-term effects of EVALI on e-cigarette demand. On the other hand, our analysis faces the inherent difficulty of disentangling the post-EVALI negative time trend that started in September 2019 from the effects of the policy changes in November and December 2019. As further evidence that the ITSA model identifies the causal impact of EVALI, we note that the immediate

[25] Similar to our estimate that uses national data, in time-series analysis of NielsenIq Scantrack sales data for a subset of 23 states, Liber et al. (2021) find that by January 2020 e-cigarette sales declined by 29 percent from their pre-EVALI peak. They also find that the temporary ban from September 24 to December 23 2019 on all e-cigarette sales in Massachusetts reduced e-cigarette sales in that state. The temporary Massachusetts ban cannot account for much of our estimated reduction in national sales. Prior to the ban, Massachusetts e-cigarette sales accounted for only 2.2 percent of national sales. Moreover, in Appendix D we provide evidence that the drop in Massachusetts e-cigarette sales was substantially offset by an increase in sales in neighboring states, especially New Hampshire.

drop and the change in the time trend of e-cigarette sales preceded the other policy changes by several months.

Perhaps the most significant policy change that provides an alternative explanation for the reduction in e-cigarette sales is the late December 2019 increase in the Federal legal tobacco purchase age to 21. We use the ITSA estimated model to consider two scenarios for counter-factual sales without the increase in the Federal legal purchase age. The first scenario is that the sales decline after December 20 was due to the legal age, so that without the legal age change sales would have been flat through early March. Under that scenario, the impact of the legal age is to decrease e-cigarette sales by 5 percent of the predicted counter-factual level of $109 million with no EVALI impact. The second scenario is that without the legal age change, e-cigarette sales would have resumed their pre-EVALI positive growth. Under that scenario, the impact of the legal age is to decrease e-cigarette sales by 12 percent. Based on these two scenarios, our estimate of the impact of EVALI on e-cigarette sales falls from 36 percent to between 24 and 31 percent.[26]

[26] Other evidence supports our estimate that the Federal legal purchase age reduced e-cigarette sales by at most 12 percent. From Table 1, teens and young adults under the age of 21 account for 40.2 percent of vaping days. However, based on the histories of legal purchase ages for alcohol, combustible cigarettes, and e-cigarettes, the increase in the legal age is not likely to have eliminated underage vaping. If the legal age caused total vaping days to drop by 12 percent, the implied reduction in vaping days by teens and young adults is 30 percent. There is suggestive evidence that the legal age reduced teen vaping by less than 30 percent. In data from the Monitoring the Future (MTF) survey, the rate of past 30-day vaping among teens did not statistically significantly change between 2019 and 2020 (Miech, Leventhal, Johnston et al. 2021). However, the 2020 MTF surveys were discontinued at the beginning of the COVID-19 pandemic. Using data from the NYTS, we estimate that teen vaping days fell by 25 percent between 2019 and 2020. The 25 percent decline in teen vaping reflects the combined effects of EVALI, the changes in the availability of flavored e-cigarettes, the increase in the legal purchase age, and the beginning of the COVID-19 pandemic. The effect of the legal age on underage young adult vaping was probably less than its impact on teens, because young adults aged 18-20 are more likely to be able to obtain e-cigarettes from social sources, e.g. friends aged 21 and older. From Table 1, young adults aged 18-20 account for 21.2 percent of all vaping days.

Comparing the Cross-Sectional and Time-Series Estimates

To corroborate our cross-sectional results in light of the potential endogeneity concerns, we use the results from our cross-sectional e-cigarette demand model to predict the effects of the EVALI information shock and then compare the prediction to the estimated changes in e-cigarette sales in the time-series data. We use the results from Panel B of Table 2 to quantify the effects of EVALI on relative risk perceptions; post-EVALI, the fraction who perceive e-cigarettes to be much less harmful decreased by 2.5 percentage points, the fraction who perceive less harmful decreased by 2.7 percentage points, the fraction who perceive more harmful increased by 2.9 percentage points, and the fraction who perceive much more harmful increased by 11 percentage points.[27]

The next step is to multiply the pre-/post-EVALI changes in relative risk perceptions by the estimated coefficients from the unconditional demand model. We predict that the changes in risk perceptions reduced unconditional e-cigarette demand by 0.6 vaping days, which is 24 percent of the sample mean. Most of the predicted reduction is due to an over 20 percent predicted decrease in vaping participation, with the remaining predicted reduction due to a decrease in conditional demand. The predicted reduction in vaping participation reflects predictions that the changes in risk perceptions increased past-year vaping cessation by 4 percentage points and reduced past-year vaping initiation among smokers by 1 percentage point.

Our prediction from the cross-sectional demand model is that the EVALI information shock reduced e-cigarette demand by 24 percent. Our preferred estimate from the ITSA model of the time-series data is that EVALI reduced e-cigarette sales by 36 percent; if we use our upper-

[27] The fraction reporting just as harmful fell by 2.3 percentage points and the fraction don't know fell by 6.4 percentage points, so the changes sum to zero.

bound estimate of the impact of the change in the Federal legal age for tobacco products, our time-series estimate of the impact of EVALI falls to 24 percent. Hence, the change in risk perceptions from EVALI that we document can explain between 67 and 100 percent of the observed decline in e-cigarette sales.

Another way to compare our cross-sectional and time-series estimates is in terms of the causal relationship between consumer perceptions and e-cigarette demand. The cross-sectional demand model provides a direct estimate of this relationship. We have two sources of time-series evidence. Our analysis of the NRS data provides a reduced-form estimate of the impact of EVALI on e-cigarette sales. Our analysis of the HINTS/GS data provides a "first stage" estimate of the impact of EVALI on consumer perceptions of the harmfulness of e-cigarettes relative to cigarettes. Analogous to the method of two-sample two-stage least squares, we use the first-stage estimate of the effect of EVALI on harm perceptions to re-scale the reduced-form ITSA estimate of the impact of EVALI on e-cigarette sales. The re-scaled ITSA estimate of the effect of consumer perceptions on e-cigarette sales is over twice as large as the comparable cross-sectional estimate.

In contrast to our cross-sectional estimates, our ITSA estimates of the reduced-form relationship between EVALI and e-cigarettes sales and the first-stage relationship between EVALI and harm perceptions are identified based on before-and-after variation due to the exogenous shock of EVALI. The result that the re-scaled ITSA estimate is larger than the comparable cross-sectional estimate does not support the expected endogeneity bias away from zero in the cross-sectional estimates. Although our cross-sectional and time-series identification strategies are both subject to potential biases, the convergent evidence suggests that the information shock created by EVALI reduced e-cigarette demand by 24 – 36 percent.

7. Impact of the EVALI Information Shock on Smoking Cessation and Public Health

Cross-Sectional Analysis of Individual Risk Perceptions and Smoking Cessation Demand

We next report estimates of individual-level demand functions for smoking cessation. For the models of smoking cessation we restrict the NCS sample to past-year smokers, i.e. current smokers and former smokers who reported having quit within the past-year. Table 8 reports cross-sectional models of the determinants of smoking cessation demand. The explanatory variables are the same as those used in the models of e-cigarette demand reported in Table 6. The first column of Table 8 reports a linear probability model of the joint probability of past-year quitting and using e-cigarettes to quit. The second and third columns report linear probability models of the probability of past-year quitting and, conditional on past-year quitting, the probability of using e-cigarettes to help them quit. Columns four through six provide the analogous models of considering quitting in the next six months.

The Table 8 results show statistically significant associations where respondents who believe that e-cigarettes are much less harmful or less harmful are more likely to have quit with the help of e-cigarettes or, among current smokers, to consider quitting with the help of e-cigarettes. In general, the magnitudes and signs of the coefficients vary as expected across the harm perception categories. The coefficients on the more and much more harmful categories tend to be small (in absolute value) and often are not statistically significantly different from zero. The harm perceptions are more strongly associated with the conditional probabilities of using e-cigarettes to help past-year and next-six-month quitting.

The next step is to use the results from our cross-sectional smoking cessation demand functions to predict the effects of the EVALI information shock. When we multiply the pre-

/post-EVALI changes in relative risk perceptions by the estimated coefficients from the model of past-year quitting with the help of e-cigarettes, we predict a decrease of 0.4 percentage points, which is 32 percent of the sample mean. Similarly, we predict that the impact of the EVALI information shock is to decrease the probability of considering quitting with the help of e-cigarettes by 1.7 percentage points, which is 28 percent of the sample mean. Because past-year quitting is infrequent, the absolute magnitude of the effects of the EVALI information shock on past-year quitting is small. However, the percentage reduction in past-year quitting with the help of e-cigarettes is comparable to the percentage predicted reductions in e-cigarette demand reported in Section 5. In other words, our models suggest that the drop in e-cigarette demand corresponds with a comparable decrease in the use of e-cigarettes as a method to quit smoking combustible cigarettes.

Impact of the EVALI Information Shock on Public Health

Although the EVALI outbreak ended by early 2020, the changes in e-cigarette demand and smoking cessation induced by the misinformation shock will have long-run impacts of population health. To predict these long-run impacts, we extend a population health model of smoking and health (Jin et al. 2015) to include vaping.[28] The model begins with estimates of the adult population by smoking and vaping status in 2010. The model uses estimates of birth rates, smoking status- and vaping status-specific mortality rates, and age-specific smoking and vaping initiation and cessation rates to simulate the number of adults smoking and vaping each year through 2070. The smoking and vaping populations evolve as new cohorts initiate use while current users either continue use, switch the product they use, quit use of both products, or die.

[28] The simulation model of Jin et al. (2015) is based on the model developed by Mendez, Warner and Courant (1998), which they use to accurately predict smoking prevalence through 2010 (Warner & Mendez, 2012).

Appendix E provides a more detailed explanation of the population health model, the key parameters, and the data sources.

Based on the estimate developed above, in the population health model we assume that the EVALI information shock reduced quitting with the help of e-cigarettes in 2019 by 32 percent. We view our estimate in Sections 5 and 6 that EVALI reduced the demand for e-cigarettes by 24 to 36 percent as corroborative evidence for this assumed decrease. Given the evidence in section 4 that the information shock persisted from 2019 into the first half of 2020 and then faded, we assume that in 2020 the rate of quitting with the help of e-cigarettes decreased by 16 percent. After that, the rate of quitting with the help of e-cigarettes is assumed to return to its pre-EVALI level. Randomized clinical trials provide evidence that smokers who quit with the help of e-cigarettes are more likely to succeed than smokers who use other methods (Hajek et al. 2019). To capture this, the population health model assumes that the decreased 2019 and 2020 rates of quitting with the help of e-cigarettes translate into decreased smoking cessation rates.

Figure 4 shows the cumulative life years lost due to the EVALI-induced decrease in smoking cessation. Because of the timing of smoking-related mortality over the life course, the life years lost from the temporary decrease in smoking cessation in 2019 and 2020 grow steadily over time. By 2070, the accumulated life years lost add up to 451,203. For comparison, from their study of the impact of e-cigarette advertising, Dave et al. (2019) estimate that a complete ban on television advertisements would have led to 105,000 fewer quits in 2015; combined with estimates of the health consequences of smoking, Dave et al. estimate that the reduced quitting by young adults under the age of 35 would lead to an additional 630,000 life years lost due to smoking.

The parameters in our population health model are uncertain due to sampling uncertainty in our estimate of the impact of EVALI on smoking cessation and due to scientific uncertainty about other parameters. Appendix E presents sensitivity analysis that explores the impact of parameter uncertainty on our prediction of 450,000 life-years lost due to EVALI.[29] When we use the 95 percent confidence interval bounds on our estimate of the impact of e-cigarette harm perceptions on smoking cessation by e-cigarettes (column 1 of Table 8), the predicted life years lost range from 210,000 to 850,000.

As an additional exercise, we use our population health model to predict the impact if the CDC and other public health organizations had reacted differently to the EVALI outbreak. We use Britain's alternative approach to e-cigarette risk communication to develop a plausible counterfactual. Our counterfactual assumes that with different risk communication policies the U.S. could have limited the mistaken increase in risk perceptions to the same rate observed in Britain. During much of the EVALI outbreak, the CDC sent mixed messages about the roles of nicotine-versus THC-vaping products as the likely underlying cause. In contrast, during the EVALI outbreak Public Health England (2019) stressed that reports from the U.S. linked EVALI to illegally produced THC products and issued the statement: "Our advice on e-cigarettes remains unchanged - vaping isn't completely risk-free but is far less harmful than smoking tobacco." British consumers' perceptions of the relative harm of vaping increased after EVALI, but not by as much as in the U.S. (Tattan-Birch et al. 2020).

[29] As an example of an alternative approach, Allcott and Rafkin (2022) use Monte Carlo simulations to capture sampling variation in the estimated parameters in their formula for the optimal e-cigarette tax rate. The Monte Carlo approach is less useful in our context due to the scientific uncertainty about key parameters. To capture that source of uncertainty in the Monte Carlo approach, we would need to make arbitrary assumptions about the standard deviations of the parameter distributions.

From our cross-sectional demand model, we predict that if U.S. consumers' perceptions of the relative riskiness of e-cigarettes had same relative change as in Britain, the rate of quitting with the help of e-cigarettes would have decreased by 16 percent instead of 32 percent.[30] Our population health model predicts this would have led to 228,093 fewer life-years lost.

8. **Discussion**

We estimate that the misinformation shock created by the EVALI outbreak reduced e-cigarette demand by 24-36 percent. Our results echo earlier research that finds that information shocks in the 1950s and 1960s reduced cigarette demand (Schneider, Klein, and Murphy 1981). However, in the 1950s and 1960s many consumers were unaware of the health consequences of smoking and altered their behavior when accurate information on health risks became available. The earlier information shocks thus helped to correct consumer mistakes and improved consumer health and welfare. In contrast, in the 2010s many consumers were either uninformed or already mistakenly believed that e-cigarettes were riskier than smoking. The EVALI information shock exacerbated consumer mistakes and likely worsened consumer health and welfare. Based on a population health model, we predict that over the next 50 years the EVALI information shock will lead to 450,000 life years lost due to deterred smoking cessation. As points of comparison, the CDC reports that seat belts saved almost 13,000 lives in 2009 and an estimated 255,000 lives from 1975 through 2009.[31] Preventing EVALI entirely might have been very difficult, but a

[30] In the UK, the proportion of people who believed that e-cigarettes are less harmful than cigarettes decreased by 16.5% (from 37% to 30.9%) and those who believed e-cigarettes are more harmful increased by 35.4% (from 12.7% to 17.2%) (Tattan-Birch et al. 2020). The study did not differentiate the perception of less harmful vs. much less harmful, and more harmful vs. much more harmful. We assume that the proportion of people in the US who believed that e-cigarettes are much less harmful decreased by 16.5% (from 6.1% to 5.1%), less harmful decreased by 16.5% (from 13.1% to 10.9%), more harmful increased by 35.4% (from 7.6% to 10.3%), and much more harmful increased by 35.4% (from 5.1% to 6.9%). Multiplying out these changes with the coefficients from column 1 of Table 8, we estimate 0.2 percentage point, or 16 percent, decrease in the cessation rate by e-cigarettes.

[31] https://www.cdc.gov/transportationsafety/seatbeltbrief/index.html.

different set of risk communication policies could have prevented some of the pre-existing misinformation and some of the EVALI misinformation shock.

Although analysis of optimal e-cigarette regulation is complex and requires often strong assumptions, experts mostly agree that the key tradeoff is between prevention of youth vaping versus the potential for e-cigarettes to help adult smokers to quit. Viewed as an information problem, the appropriate public health messages seem straightforward: vaping is addictive and might be risky so youth should not start, but vaping is much less risky than smoking and can help smokers to quit. Yet, as Balfour et al. (2021) discuss in more detail, the e-cigarette policy tradeoffs have polarized the tobacco control community "along a spectrum from fervent opponents to enthusiastic supporters." Public health experts disagree about the likelihood that teen vaping acts as a gateway to smoking combustible cigarettes and on the effectiveness of e-cigarettes as a smoking cessation method. In many discussions, beliefs about the different tradeoffs in e-cigarette regulation seem to be correlated. For example, the Campaign for Tobacco-Free Kids emphasizes the potential health harms of e-cigarettes and the gateway effect, while describing the evidence that e-cigarettes help people quit smoking as "limited."[32] The recent review by 15 past Presidents of the Society of Nicotine and Tobacco Research interprets the evidence on both of these points quite differently (Balfour, et al. 2022). The polarized debate has obvious parallels with debates about public policies and the COVID-19 pandemic.

The debates about e-cigarette policies and COVID-19 policies also parallel longer-standing debates about risk tradeoffs in public health. A key policy challenge is to effectively communicate the risk information that consumers need to make privately optimizing health tradeoffs. The EVALI outbreak provides an example where a misinformation shock that changed

[32] https://www.tobaccofreekids.org/what-we-do/global/electronic-cigarettes.

consumer health decisions might lead to large and lasting damage to public health. In a similar example, a later-discredited 1998 study that suggested a link between childhood vaccines and autism appears to have created sticky misinformation that reduced childhood vaccination rates in the 2000s and 2010s (Chang 2018, Quian, Chou, and Lai 2020). In many markets, profit-maximizing firms advertise to provide health information about their products, with the public sector playing an important role in guaranteeing the truth and accuracy of advertising claims.[33] However, under current FDA regulations e-cigarette advertisements cannot make health claims, while advertisements for COVID-19 and childhood vaccines are tightly related due to their prescription-only status. Given the reduced role of the private sector, it becomes even more important that public sector risk communication efforts explain that e-cigarettes, COVID-19 vaccinations, and childhood vaccinations are not risk-free, yet still on net substantially reduce serious health risks.

[33] As examples, Ippolito and Mathios (1990) study the market for cereals and Avery et al. (2007) study the market for smoking cessation products.

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Table 1: Fractions of all vaping days accounted for by different age groups and smoking status

	Age <18	Age 18-20	Age 21+	Total
Past-30-day vaping days by smoking status				
Never smokers	7.8%	10.9%	8.6%	27.3%
Current smokers	6.1%	2.3%	22.9%	31.3%
Years since quitting smoking <1	2.1%	2.9%	7.4%	12.4%
Years since quitting smoking 1 - 4	2.2%	5.1%	14.5%	21.8%
Years since quitting smoking >=5	0.7%	0.0%	6.5%	7.2%
Total	19.0%	21.2%	59.8%	100%

Notes: Data are from NHIS 2018 and NYTS 2019. Vaping days for adults are adjusted to improve the comparability of the NHIS and NYTS; see Appendix A for details.

Table 2: Perceptions of Perceived Risk of Using E-cigarettes Relative to Smoking (%)

	2019 HINTS	2020 HINTS	Difference, before-and-after EVALI
Much less harmful	3.8	2.7	-1.1
Less harmful	11.6	8.8	-2.8
Just as harmful	36.1	35.3	-0.8
More harmful	6.9	13.0	6.1
Much more harmful	6.0	15.3	9.3
I don't know	35.7	25.0	-10.7

	2019 HINTS Smokers or vapers	2020 NCS	Difference, before-and-after EVALI
Much Less Harmful	6.1	3.6	-2.5
Less Harmful	13.1	10.4	-2.7
Just as Harmful	36.7	34.5	-2.3
More Harmful	7.6	10.5	2.9
Much More Harmful	5.1	16.1	11.0
I don't know	31.3	24.9	-6.4

	Not heard about EVALI, 2020 NCS	Heard about EVALI, 2020 NCS	Difference, not-and-heard about EVALI
Much less harmful	3.8	3.6	-0.3
Less harmful	7.2	11.1	3.8
Just as harmful	31.8	35.0	3.3
More harmful	5.2	11.6	6.4
Much more harmful	10.4	17.3	7.0
I don't know	41.7	21.5	-20.2

Data: HINTS 2019 - 2020 and 2020 NCS.

Table 3: Perceived Absolute and Relative Risks of Vaping and Smoking

	%	Perceived life expectancy loss due to vaping (years)	Perceived life expectancy loss due to smoking (years)
Much less harmful	3.6	5.1*	7.8
Less harmful	10.4	6.6*	8.8
Just as harmful	34.5	12.2*	10.4
More harmful	10.5	16.3*	9.7
Much more harmful	16.1	21.4*	10.7
I don't know	24.9	11.2*	8.8

*statistically significant different from perceived life expectancy loss due to smoking at 0.05 level. Source: NielsenIQ Custom Survey, May 2020.

Table 4: Consumer Information Related to E-Cigarettes

Thinking back over the last 6 months to a year, what have you heard about vaping and lung injuries? (Select all that apply)	Sample Proportion
I haven't heard anything.	17
There were some hospitalized cases including deaths.	47
There were some cases but not deaths.	4
The cases were mainly linked to the use of vaping products that contain flavors like fruit and candy.	19
The cases were mainly linked to the use of vaping products that contain THC.	15
The cases were linked to the use of all vaping products whether or not they contain flavors or THC.	32
I feel the reports were exaggerated.	4
How much do you agree or disagree with the following statement — "The nicotine in cigarettes is the substance that causes most of the cancer caused by smoking."	
Strongly agree or agree	46

Source: NielsenIQ Custom Survey, May 2020.

Table 5: Models of Perceptions of the Relative Harm and Life Years Loss due to Vaping

	E-cigs harm	Vaper life loss	Vaper life loss
There were some hospitalized cases including deaths.	0.074***	1.987***	1.235**
	(0.018)	(0.496)	(0.415)
There were some cases but not deaths.	0.015	2.112	1.099
	(0.044)	(1.210)	(1.012)
Mainly linked to products that contain flavors like fruit	0.074**	0.739	0.405
	(0.023)	(0.629)	(0.526)
Mainly linked to products that contain THC.	-0.062*	-1.088	-1.542**
	(0.025)	(0.703)	(0.587)
The cases were linked to the use of all vaping products whe	0.136***	2.522***	2.263***
	(0.019)	(0.530)	(0.443)
The reports were exaggerated.	-0.141**	-5.917***	-3.181**
	(0.044)	(1.227)	(1.029)
Agree that nicotine causes cancer	0.034	2.477***	0.896*
	(0.018)	(0.502)	(0.422)
Perceived smokers' life expectancy loss (year)			0.702***
			(0.022)
Male	0.000	0.000	0.000
	(.)	(.)	(.)
Female	0.011	1.723**	0.238
	(0.020)	(0.566)	(0.475)
21-34 years old	0.000	0.000	0.000
	(.)	(.)	(.)
35-44 years old	0.014	-0.275	-0.010
	(0.049)	(1.366)	(1.141)
45-54 years old	0.034	-1.483	0.754
	(0.047)	(1.297)	(1.086)
55-64 years old	0.015	-2.265	1.265
	(0.046)	(1.283)	(1.077)
65+ years old	0.022	-2.225	2.315*
	(0.048)	(1.328)	(1.119)
White	0.000	0.000	0.000
	(.)	(.)	(.)
Black/African American	0.013	1.639*	1.166
	(0.029)	(0.793)	(0.663)
Asian	0.057	-1.781	-2.480
	(0.072)	(2.005)	(1.675)

Other	-0.027	-0.091	0.489
	(0.041)	(1.143)	(0.955)
Less than High School	0.000	0.000	0.000
	(.)	(.)	(.)
No Female/male Head or Unknown	-0.067	-2.370	-5.081*
	(0.094)	(2.615)	(2.186)
Graduated High School	-0.098	-2.060	-1.730
	(0.052)	(1.428)	(1.193)
Some College	-0.108*	-3.189*	-2.991*
	(0.051)	(1.417)	(1.184)
Graduated College	-0.118*	-3.998**	-3.707**
	(0.052)	(1.446)	(1.208)
Post College Grad	-0.098	-4.446**	-4.381**
	(0.060)	(1.653)	(1.381)
Constant	0.232**	15.063***	7.289***
	(0.082)	(2.267)	(1.909)
Observations	2,439	2,439	2,439
Adj R-squared	0.04	0.05	0.34
Dep Var Mean	0.27	12.96	12.96

Table 6: E-Cigarette Demand Functions

	Vaping demand	Vaping participation	Intensive vaping demand	Vaping cessation	Vaping initiation by smokers	try to quit vaping p12m	Consider quitting vaping in next 6m
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Much less harmful	9.583***	0.404***	6.940**	-0.170*	0.120**	-0.243**	-0.193*
	(0.791)	(0.036)	(2.276)	(0.068)	(0.046)	(0.082)	(0.088)
Less harmful	7.534***	0.359***	4.388*	-0.122*	0.141***	-0.133*	-0.111
	(0.511)	(0.023)	(1.714)	(0.050)	(0.025)	(0.062)	(0.066)
Just as harmful	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
More harmful	-1.195*	-0.074**	-2.185	0.227*	-0.024	0.053	0.125
	(0.502)	(0.023)	(4.132)	(0.101)	(0.021)	(0.149)	(0.160)
Much more harmful	-1.082*	-0.066***	-1.405	0.183*	-0.008	0.366**	0.374**
	(0.431)	(0.019)	(3.382)	(0.084)	(0.018)	(0.122)	(0.131)
I don't know	-0.044	-0.012	1.082	-0.041	0.009	0.006	0.046
	(0.378)	(0.017)	(2.094)	(0.059)	(0.017)	(0.076)	(0.081)
Perceived smokers' life expectancy loss (year)	-0.042**	-0.002*	-0.078	-0.000	-0.001	0.006*	0.010**
	(0.015)	(0.001)	(0.077)	(0.002)	(0.001)	(0.003)	(0.003)
Male	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Female	0.698*	0.017	2.732	-0.083	0.008	-0.051	-0.015
	(0.331)	(0.015)	(1.614)	(0.045)	(0.015)	(0.058)	(0.063)
21-34 years old	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
35-44 years old	-0.322	-0.078*	3.396	0.087	-0.004	-0.041	0.041
	(0.796)	(0.036)	(2.676)	(0.080)	(0.036)	(0.097)	(0.104)
45-54 years old	-1.649*	-0.130***	0.625	0.136	-0.027	0.054	0.020
	(0.756)	(0.034)	(2.638)	(0.078)	(0.034)	(0.095)	(0.102)
55-64 years old	-1.861*	-0.129***	-1.010	0.088	-0.011	0.091	0.129
	(0.748)	(0.034)	(2.647)	(0.078)	(0.034)	(0.096)	(0.103)
65+ years old	-2.707***	-0.171***	-3.259	0.041	-0.041	0.295**	0.124
	(0.775)	(0.035)	(3.073)	(0.091)	(0.036)	(0.111)	(0.119)
White	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Black/African American	-0.275	-0.014	0.576	0.055	0.019	0.235*	0.325**
	(0.463)	(0.021)	(2.615)	(0.072)	(0.020)	(0.095)	(0.101)
Asian	-0.503	-0.048	3.478	0.055	-0.043	-0.039	-0.533*
	(1.168)	(0.053)	(6.404)	(0.171)	(0.059)	(0.232)	(0.248)
Other	0.131	0.014	0.581	-0.003	0.004	-0.035	0.177
	(0.667)	(0.030)	(2.916)	(0.084)	(0.033)	(0.106)	(0.113)
Less than High School	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
No Female/male Head or Unknown	-0.448	0.080	-8.232	-0.059	0.112	-0.321	-0.373
	(1.528)	(0.069)	(5.977)	(0.159)	(0.071)	(0.216)	(0.231)
Graduated High School	-1.821*	-0.033	-7.554*	-0.055	-0.083*	-0.290*	-0.247
	(0.834)	(0.038)	(3.633)	(0.101)	(0.035)	(0.131)	(0.141)

Some College	-1.585	-0.032	-5.359	-0.002	-0.098**	-0.232	-0.098
	(0.827)	(0.037)	(3.552)	(0.099)	(0.035)	(0.129)	(0.138)
Graduated College	-0.913	-0.008	-3.342	-0.073	-0.060	-0.181	-0.121
	(0.844)	(0.038)	(3.594)	(0.101)	(0.036)	(0.130)	(0.139)
Post College Grad	-1.638	-0.039	-4.424	0.048	-0.093*	-0.256	-0.219
	(0.963)	(0.043)	(4.286)	(0.120)	(0.041)	(0.155)	(0.166)
Desktop	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Mobile	0.803**	0.039**	0.699	-0.077	0.040**	0.084	0.009
	(0.310)	(0.014)	(1.561)	(0.043)	(0.014)	(0.056)	(0.060)
Child under 6	-0.368	-0.015	-1.727	0.072	-0.056	-0.091	-0.022
	(0.796)	(0.036)	(3.573)	(0.097)	(0.034)	(0.129)	(0.138)
Child 6-12	-0.761	-0.009	-4.076	-0.020	0.018	0.041	0.002
	(0.548)	(0.025)	(2.394)	(0.070)	(0.024)	(0.087)	(0.093)
Child 13-17	0.088	0.007	-1.338	0.025	-0.004	-0.051	-0.097
	(0.550)	(0.025)	(2.442)	(0.070)	(0.023)	(0.088)	(0.095)
Living alone	0.026	0.016	-1.489	-0.028	0.028	0.027	-0.090
	(0.330)	(0.015)	(1.586)	(0.045)	(0.014)	(0.057)	(0.061)
cig_tax_st2018dol	0.281	0.012	1.088	-0.073**	0.001	0.058	0.057
	(0.182)	(0.008)	(0.929)	(0.027)	(0.008)	(0.034)	(0.036)
Exposed to state E-cigarette Tax	-0.352	-0.021	-0.368	0.080	-0.025	-0.094	-0.037
	(0.360)	(0.016)	(1.775)	(0.051)	(0.016)	(0.064)	(0.069)
Exposed to state E-cigarette Restriction in Restaurant	-0.103	-0.004	-0.890	0.034	-0.041*	-0.170*	-0.023
	(0.384)	(0.017)	(1.929)	(0.056)	(0.017)	(0.070)	(0.075)
Exposed to state E-cigarette Sales Minimum Age	0.175	-0.007	3.259	-0.056	0.014	0.091	0.018
	(0.677)	(0.031)	(3.031)	(0.087)	(0.032)	(0.110)	(0.117)
Exposed to state bans on flavored E-cigarettes	-0.336	-0.018	2.794	0.010	0.004	-0.084	-0.013
	(0.716)	(0.032)	(3.627)	(0.103)	(0.034)	(0.131)	(0.140)
Constant	4.046**	0.248***	14.763**	0.435**	0.131*	0.360	0.410*
	(1.346)	(0.061)	(5.361)	(0.155)	(0.061)	(0.194)	(0.208)
Observations	2,439	2,439	349	443	1,443	349	349
Adj R-squared	0.17	0.18	0.04	0.06	0.05	0.11	0.10
Dep Var Mean	2.49	0.14	17.42	0.21	0.06	0.32	0.46

Table 7: Interrupted Time Series Analysis of Impact of EVALI on E-cigarette Sales

	All Sales (1)	All Sales (2)	Fruit (3)	Mint (4)	Menthol (5)	Tobacco (6)
Time (week)	0.708^{***}	0.923^{***}	0.428^{***}	0.216^{***}	0.0451^{***}	0.226^{***}
	(0.0184)	(0.0191)	(0.0212)	(0.00678)	(0.00244)	(0.0258)
JUUL withdrawals most flavors		-4.705^{**}	-6.907^{**}	1.637^{*}	0.384^{*}	-0.248
		(1.492)	(2.247)	(0.676)	(0.151)	(0.470)
Interaction of time and the above event		-0.152^{**}	-0.690^{***}	0.485^{***}	0.0625^{***}	-0.0517
		(0.0574)	(0.0852)	(0.0367)	(0.00663)	(0.0300)
EVALI	-11.62^{***}	-13.02^{***}	3.354^{*}	-10.49^{***}	-1.335^{***}	-3.300^{***}
	(1.384)	(1.818)	(1.676)	(1.414)	(0.219)	(0.518)
Interaction of time and the above event	-1.168^{***}	-1.469^{***}	0.133	-1.275^{***}	-0.126^{***}	0.0178
	(0.0695)	(0.272)	(0.0921)	(0.165)	(0.0255)	(0.0610)
JUUL withdrawals mint flavor		5.931^{***}	0.757^{***}	5.666^{***}	0.107	-0.755^{*}
		(1.373)	(0.199)	(1.300)	(0.226)	(0.368)
Interaction of time and the above event		0.135	0.451^{***}	-2.259^{***}	1.549^{***}	0.334^{***}
		(0.301)	(0.0567)	(0.211)	(0.0669)	(0.0777)
T21		-0.704	0.861^{***}	-2.090	-0.155	-0.0215
		(1.232)	(0.251)	(1.178)	(0.187)	(0.145)
Interaction of time and the above event		-0.689^{*}	-0.779^{***}	0.863^{**}	-0.427^{***}	-0.311^{***}
		(0.268)	(0.0548)	(0.275)	(0.0656)	(0.0580)
FDA bans flavor in pods		-0.0792	-3.086^{***}	0.517	2.102^{***}	0.539^{***}
		(1.012)	(0.651)	(0.885)	(0.499)	(0.102)
Interaction of time and the above event		2.144^{***}	0.192	1.374^{***}	0.152	0.134^{***}
		(0.409)	(0.220)	(0.302)	(0.131)	(0.0244)
Constant	46.71^{***}	45.83^{***}	20.73^{***}	9.791^{***}	4.350^{***}	7.267^{***}
	(0.639)	(0.194)	(0.207)	(0.0583)	(0.0280)	(0.234)
Observations	88	88	88	88	88	88
F-statistic	549.54	1065.67	743.67	1499.68	11090.40	1464.37
Dep Var Mean	69.29	69.29	16.83	23.29	9.93	14.79

Table 8: Smoking Cessation Demand Functions

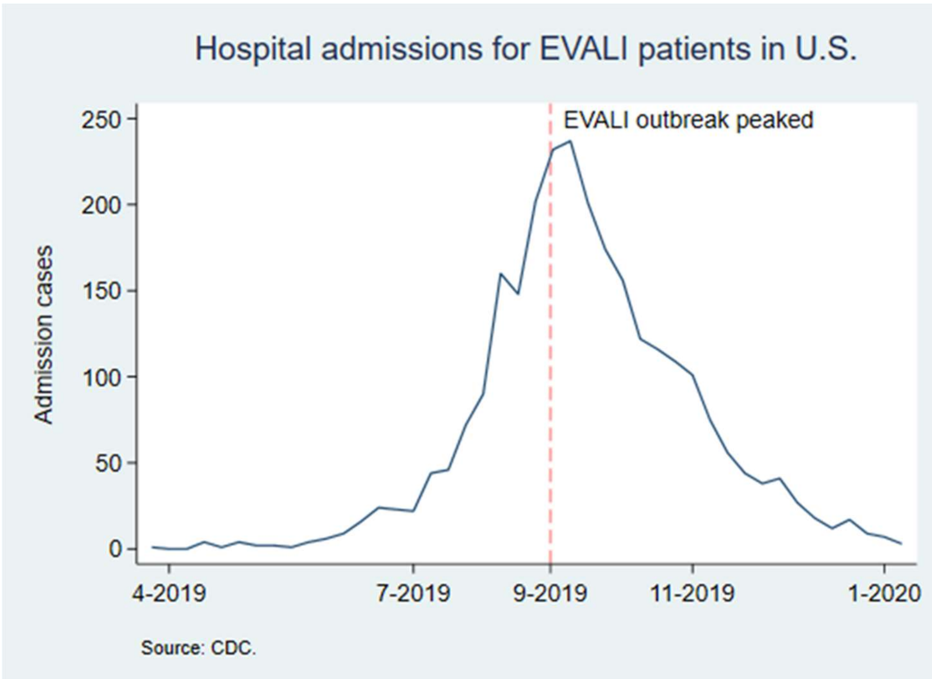
	Smoking cessation by E-cig	Smoking Cessation in past 12 mon.	Quitters: Smoking cessation by E-cig	Consider quitting smoking by E-cig	Consider quitting smoking in next 6 mon.	Attempters: Consider quitting smoking by E-cig
	b/se	b/se	b/se	b/se	b/se	b/se
Much less harmful	0.082***	0.039	0.655***	0.226***	0.058	0.357***
	(0.016)	(0.036)	(0.156)	(0.035)	(0.074)	(0.057)
Less harmful	0.045***	0.018	0.521***	0.204***	0.143**	0.298***
	(0.010)	(0.022)	(0.103)	(0.021)	(0.045)	(0.034)
Just as harmful	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
More harmful	-0.006	-0.033	-0.052	-0.035	0.020	-0.060
	(0.009)	(0.021)	(0.148)	(0.020)	(0.042)	(0.035)
Much more harmful	-0.006	-0.016	-0.130	-0.037*	0.020	-0.071*
	(0.008)	(0.019)	(0.106)	(0.018)	(0.038)	(0.031)
Don't know	0.004	0.000	0.039	0.014	-0.052	0.038
	(0.008)	(0.017)	(0.093)	(0.016)	(0.035)	(0.030)
Male	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Female	-0.002	-0.002	-0.009	0.029*	0.067*	0.031
	(0.007)	(0.015)	(0.078)	(0.014)	(0.030)	(0.025)
21-34 years old	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
35-44 years old	0.031*	0.007	0.568***	-0.015	0.011	-0.015
	(0.015)	(0.034)	(0.161)	(0.032)	(0.070)	(0.055)
45-54 years old	0.009	-0.020	0.482**	-0.045	0.023	-0.064
	(0.015)	(0.032)	(0.161)	(0.031)	(0.066)	(0.053)
55-64 years old	0.012	-0.031	0.541**	-0.026	0.015	-0.044
	(0.014)	(0.032)	(0.165)	(0.030)	(0.065)	(0.052)
65+ years old	0.005	-0.031	0.357*	-0.049	-0.024	-0.078
	(0.015)	(0.033)	(0.171)	(0.032)	(0.068)	(0.056)
White	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Black/African American	0.000	-0.002	0.122	-0.018	0.151***	-0.043
	(0.009)	(0.020)	(0.106)	(0.019)	(0.041)	(0.031)
Asian	-0.014	-0.031	-0.092	0.051	-0.008	0.048
	(0.025)	(0.056)	(0.359)	(0.052)	(0.113)	(0.097)
Other	0.012	0.012	0.049	-0.012	0.093	-0.023
	(0.014)	(0.031)	(0.155)	(0.029)	(0.063)	(0.049)
Less than High School	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
No Female/male Head or Unknown	0.103**	0.085	0.666*	0.013	0.201	-0.063
	(0.032)	(0.070)	(0.287)	(0.069)	(0.149)	(0.110)
Graduated High School	-0.008	-0.033	0.118	-0.044	0.005	-0.124*
	(0.015)	(0.034)	(0.175)	(0.032)	(0.070)	(0.060)
Some College	-0.006	-0.014	0.019	-0.053	0.047	-0.149*
	(0.015)	(0.034)	(0.168)	(0.032)	(0.069)	(0.059)
Graduated College	0.010	-0.011	0.282	-0.049	0.067	-0.134*
	(0.016)	(0.035)	(0.170)	(0.033)	(0.071)	(0.060)
Post College Grad	0.000	0.002	0.269	-0.034	0.077	-0.106
	(0.018)	(0.040)	(0.196)	(0.038)	(0.083)	(0.068)
Desktop	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)

Mobile	-0.002	-0.012	0.089	0.014	0.076**	0.008
	(0.006)	(0.014)	(0.075)	(0.013)	(0.028)	(0.023)
Child under 6	-0.021	0.018	-0.106	0.016	0.029	0.030
	(0.015)	(0.033)	(0.168)	(0.032)	(0.068)	(0.054)
Child 6-12	0.019	-0.038	0.175	-0.018	-0.018	-0.033
	(0.011)	(0.024)	(0.162)	(0.022)	(0.048)	(0.040)
Child 13-17	-0.016	-0.023	-0.122	0.025	0.021	0.042
	(0.010)	(0.023)	(0.139)	(0.022)	(0.047)	(0.038)
Living alone	-0.007	-0.005	-0.083	0.001	0.012	0.007
	(0.006)	(0.014)	(0.073)	(0.014)	(0.029)	(0.024)
cig_tax_st2018dol	0.008*	0.004	0.060	0.007	0.049**	0.007
	(0.004)	(0.008)	(0.048)	(0.008)	(0.016)	(0.013)
Exposed to state E-cigarette Tax	-0.009	-0.009	-0.024	-0.003	-0.044	0.001
	(0.007)	(0.016)	(0.093)	(0.015)	(0.032)	(0.026)
Exposed to state E-cigarette Restriction in Restaurant	-0.005	-0.003	0.017	-0.024	-0.027	-0.028
	(0.008)	(0.017)	(0.095)	(0.016)	(0.034)	(0.028)
Exposed to state E-cigarette Sales Minimum Age	0.018	0.018	0.053	0.007	0.003	0.013
	(0.014)	(0.030)	(0.183)	(0.029)	(0.061)	(0.049)
Exposed to state bans on flavored E-cigarettes	-0.005	0.015	-0.191	0.009	-0.001	-0.005
	(0.015)	(0.033)	(0.158)	(0.032)	(0.068)	(0.056)
Constant	-0.023	0.102	-0.660*	0.081	0.312**	0.212*
	(0.026)	(0.057)	(0.296)	(0.054)	(0.117)	(0.095)
Observations	1,625	1,625	108	1,517	1,517	817
Adj R-squared	0.04	-0.00	0.41	0.10	0.03	0.15
Dep Var Mean	0.01	0.07	0.20	0.06	0.54	0.12

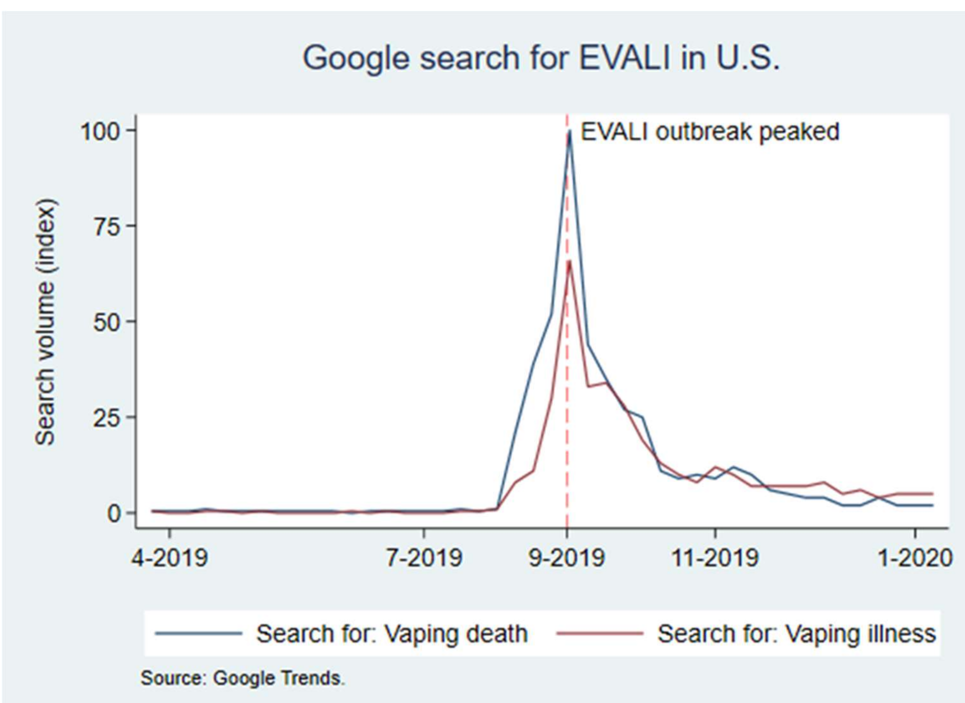
Source: NielsenIQ Custom Survey on tobacco use collected 5/15 - 6/7, 2020. Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Figure 1: Trends in Hospital Admissions, Google Searches, and E-cigarette Sales

Panel A: Trends in Hospital Admissions for EVALI Patients



Panel B: Google Searches Related to EVALI



Panel C: Retail E-cigarette Sales

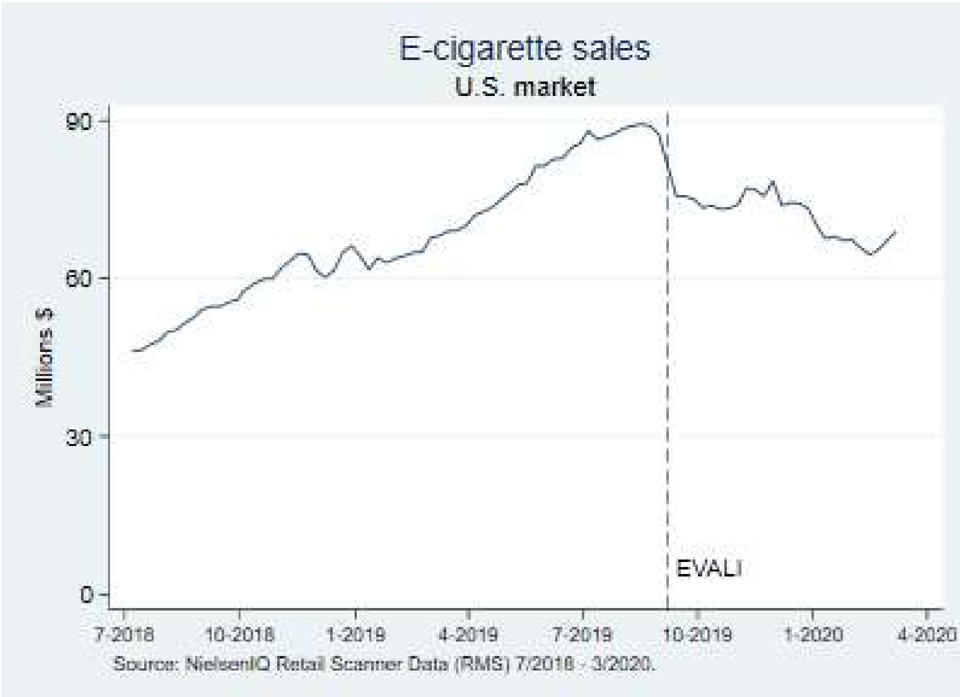


Figure 2: Trend in Perceived Harm of E-cigarette Relative to Combustible Cigarettes

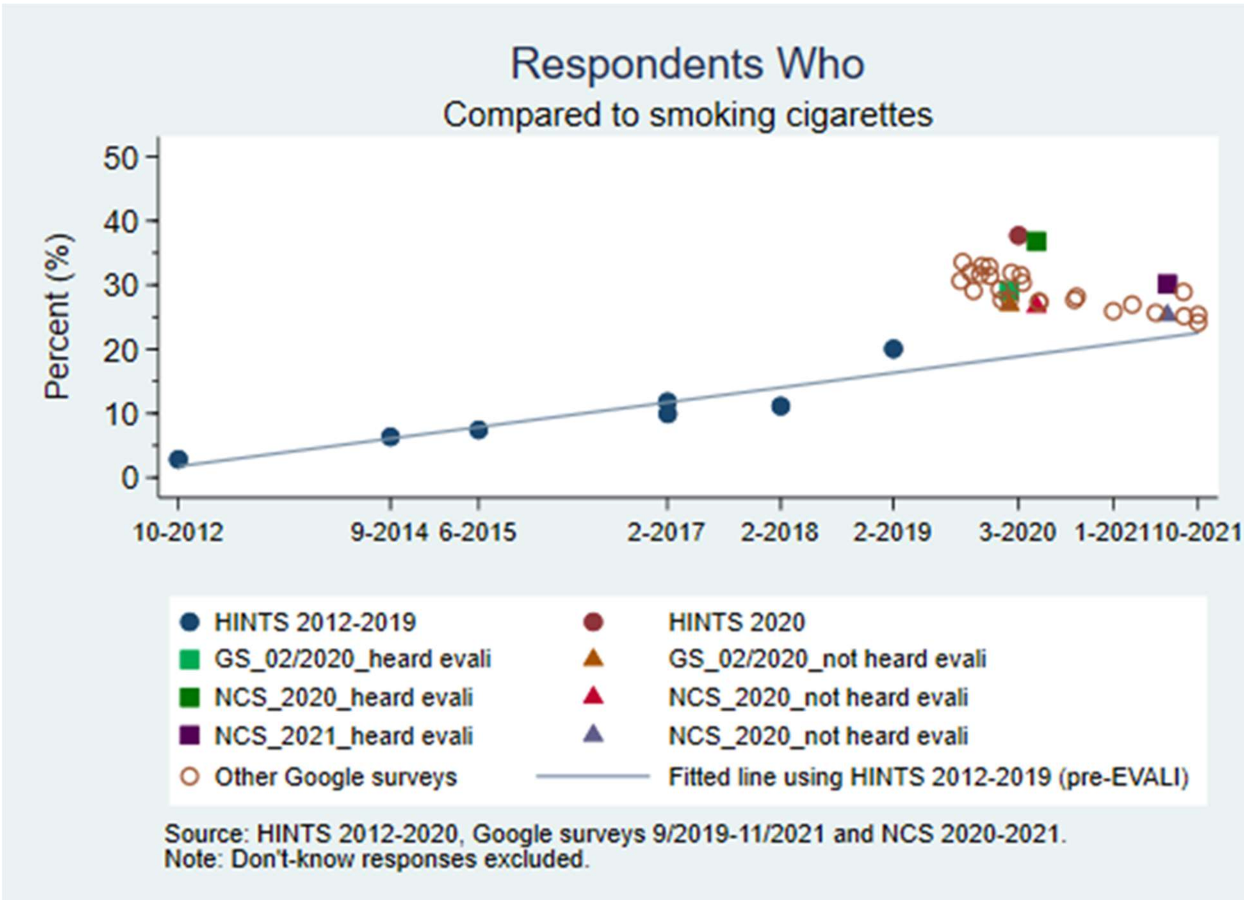
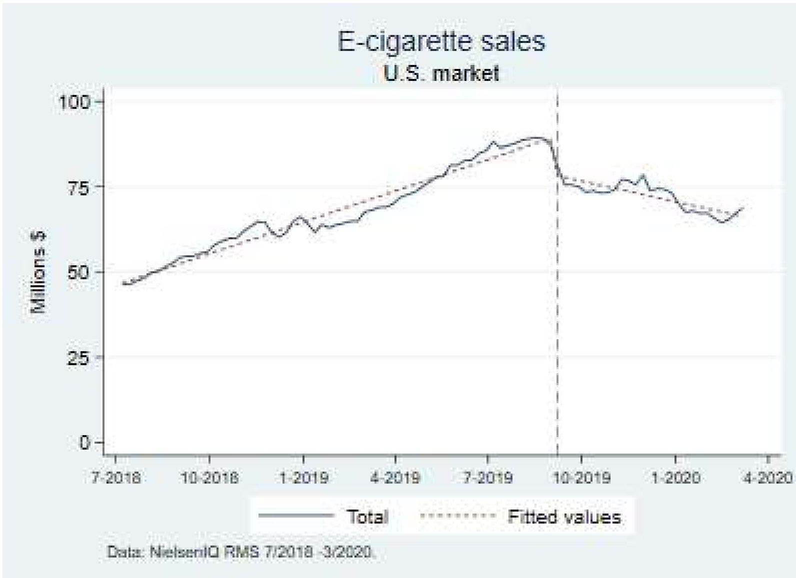


Figure 3: Estimated Impact of EVALI on E-cigarette Sales

Panel A: 1-Event ITSA Model



Panel B: 5-Event ITSA Model

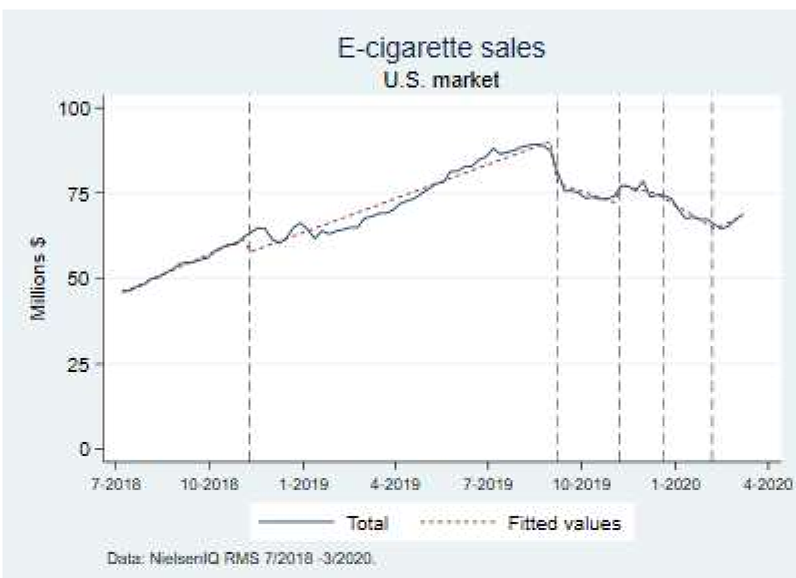


Figure 4: Predicted Life Years Lost Due to EVALI-induced Decrease in Smoking Cessation