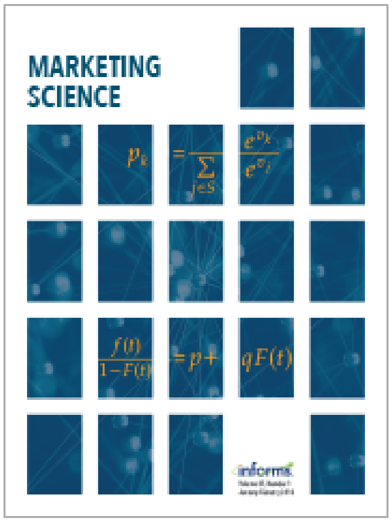

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Frontiers: Asymmetric Effects of Recreational Cannabis Legalization

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Abstract. Recently, as cannabis was legalized for recreational use in an increasing number of states, it has become more important to understand the effects of cannabis policies, especially on youth. Marketers of other recreational substances are also paying close attention to cannabis policy changes. Alcohol and tobacco companies typically view the cannabis industry as a potential threat and are often found among the opponents to its legalization. However, based on extant research, the treatment effects of recreational cannabis legalization (RCL) and its cross-commodity effects on the alcohol and tobacco industries remain inconclusive. Analyzing large-scale web-based behavioral data, we find that although RCL significantly increases cannabis search, the increase comes from adults only, but not youth. RCL also influences alcohol and tobacco industries asymmetrically: it reduces search volume and advertising effectiveness for alcohol but increases those for tobacco. Hence, cannabis appears to be a substitute for alcohol but not tobacco.

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Keywords: cannabis legalization • policy change • alcohol • tobacco

Introduction

Many U.S. states witnessed changes in cannabis legislations recently. Different parties hold divergent opinions about such changes, and the impact of recreational cannabis legalization (RCL) on people's attitudes toward and use of cannabis remains unclear (Zhao and Harris 2004, Hall and Kozlowski 2018). Because drug abuse may cause severe consequences (Tashkin 1993), potentially even more so among youth (Kandel 1975), one question inevitably arises in each state considering the legalization of cannabis for recreational use: if it becomes legal, would people (especially youth) want or use it more (Loria 2017)?

The common belief held by opponents of RCL is that people's interest in cannabis would increase drastically following legalization because of greater social acceptance, availability, and possibly affordability of the substance (Hopfer 2014, Bent 2016). However, according to previous studies, which are heavily based on self-reported surveys, the impact of cannabis policies is inconclusive. Although some suggest that they affect youth's attitude toward or consumption of cannabis (e.g., Chaloupka and Laixuthai 1997, Cerdá et al. 2016), others indicate weak or no effects (e.g., Thies and Register 1993, Pacula 1998, Rusby et al. 2018). The influences of RCL on adults are also largely open to question (Hall and Lynskey 2016, Budney and Borodovsky 2017). Moreover, prior research has rarely directly compared the potential difference in the effects of RCL on youth versus adults.

Marketers, policymakers, and researchers are also curious about the cross-commodity relationships among cannabis, alcohol, and tobacco (Barry et al. 2014, Borchardt 2017). Fearing the potential threat of recreational cannabis as a rival, big alcohol and tobacco companies often act as opponents of its legalization and sponsor anticannabis campaigns (Cohen 2014, Bloomberg 2016, Williams 2016). However, the literature provides inconsistent findings about whether cannabis and alcohol/tobacco are economic substitutes (e.g., Pacula 1998, Chaloupka et al. 1999, Farrelly et al. 1999, Cameron and Williams 2001, Zhao and Harris 2004; see Online Appendix I for a detailed summary of previous findings) and has not directly tested how RCL influences the alcohol and tobacco industries.

Despite their potential effects on public health and society, cannabis, alcohol, and tobacco businesses are, after all, businesses, and their economic significance cannot be ignored. The recent wave of RCL across the United States could generate $22 billion in sales per year (Huddleston 2016). Annual revenues of U.S. alcohol and tobacco industries combined are over $300 billion (Maloney and Chaudhuri 2017, Statista 2018). As with any other business, these businesses attempt to leverage marketing tools to build brand, attract and retain customers, and increase sales (Vara 2016). According to the most recent Federal Trade Commission releases, annual advertising and promotional spending of alcohol and tobacco companies topped \$3.5 billion and \$8.5 billion, respectively (Federal Trade Commission 2014, 2016). Cannabis marketers are also actively exploring means of promotion in the states that legalized its consumption (Schrank 2017). However, there is rarely any academic research on these substances from a marketing perspective (i.e., considering them as products and investigating the determinants of consumer interest and the performances of their marketing mixes).

In summary, regarding RCL, several important questions remain largely inconclusive or unanswered. For example, how does people's interest in cannabis change after RCL? Do youth react to the policy change differently from adults? Does RCL affect people's interest in alcohol and tobacco and the marketing performances of alcohol and tobacco companies?

A review of related literature reveals at least four major limitations/gaps. First, there are mixed results within each stream of literature (e.g., impact of cannabis policy on youth, the cross-commodity relationship between cannabis and alcohol, and the cross-commodity relationship between cannabis and tobacco; see Online Appendix I). Second, little is known about the net treatment effect of RCL. Prior studies typically relied on data from *either* before or *after* RCL and thus could not isolate its treatment effect. Third, most studies are based on retrospective surveys asking subjects to recall their drug use patterns in the past. Besides recall bias, social-desirability bias may also reduce the accuracy of self-reported measures because respondents may be conservative when answering questions about illegal drug use (Thompson and Phua 2005). Finally, there is a lack of direct insights for marketers. None of the related studies have examined marketing performance (e.g., advertising effectiveness) as the outcome variable.

Unlike prior studies, this study analyzes large-scale unobtrusive behavioral data before and after policy change to unveil the treatment effect of RCL using a difference-in-difference (DID) approach and examines various metrics relevant not only to policymakers but also to marketers (e.g., online searches and ad clicks, both of which could reflect consumer interest in the substance). We find a positive treatment effect of RCL on cannabis searched overall. However, the effect is significantly attenuated for youth; that is, RCL has asymmetric effects on adults versus youth. Specifically, RCL is likely to increase cannabis searches among adults only. Among youth, cannabis searches do not increase and tend in fact to decrease after RCL. Moreover, RCL has asymmetric effects on the alcohol versus the tobacco industry: it *reduces* search volume and ad effectiveness for alcohol but *increases* those for tobacco. These results indicate a substituting relationship between cannabis and alcohol but a complementing relationship between cannabis and tobacco. Our findings add novel and timely insights based on big data from a marketing perspective to the continuous debates in the literature and provide meaningful implications for policymakers and marketing practitioners in related industries.

2. Data and Method

We obtained large-scale data on online searches, ad impressions, and clicks from a leading U.S.-based web portal from January 2014 to April 2017. Table 1 lists the states that have legalized cannabis for recreational use. The policy changes in six of these states and the District of Columbia (for simplicity, we use the term *treated state* to refer to each of these states or the District of Columbia hereafter) allow us to adopt a DID natural experiment framework to test the treatment effect of RCL, which requires data from both before and after RCL took effect. In Colorado and Washington, RCL occurred in 2012, which is out of our data period. Hence, we do not consider these two states as treated states. To account for unobserved factors that could drive changes in people's interest in/consumption of cannabis over time, we use the 10 states without any form of cannabis policy change as *control states*.[1] The data provided by the portal cover more than 28 million searches and 120 million ad impressions related to the cannabis, alcohol, and tobacco industries in these states. In addition to behavioral data (e.g., searches and ad clicks), we also gained access to the web users' geographic locations, gender, age group,[2] and device indicators (more detailed personal identification information is unknown because of privacy-protection restrictions). Hence, for each state, we analyze aggregated data

Table 1. RCL Dates

State	Abbreviation	RCL took effect on
Alaska	AK	2/24/2015
California	CA	11/9/2016
Colorado	CO	12/10/2012
District of Columbia	DC	2/26/2015
Maine	ME	1/30/2017
Massachusetts	MA	12/15/2016
Nevada	NV	1/1/2017
Oregon	OR	7/1/2015
Washington	WA	12/6/2012

over time for each population group, which is a unique combination of gender (female or male), age group (youth or adult), and device (desktop, tablet, or mobile). For example, male adults on mobile devices constitute one population group. Youth is defined as 19 years of age or younger based on the literature (Sundh and Hagquist 2005, Steinberg 2011).

2.1. Mining Search Queries

To test the treatment effect of RCL, we need data *before and after* the treatment. However, there are no high-frequency longitudinal surveys that constantly track the dynamics of people's interest in cannabis, alcohol, or tobacco in any U.S. state, and such endeavors would be extremely costly/difficult to conduct. Moreover, there is a commonly documented bias in self-reported measures when survey participants are unwilling to reveal their true attitude because of social or legal concerns (Thompson and Phua 2005, Kim et al. 2018). For instance, before cannabis is legalized, people may be conservative when reporting their interest in it. A retrospective survey that asks participants to recall their level of interest in the past tends to have low accuracy and validity as the time lapse increases. Hence, we employ a non-survey-based unobtrusive measure to proxy consumer interest.

Extant research indicates that keyword search frequency on online search engines serves as a good proxy for people's interest in a subject. Marketing studies have used the search volume of a product to measure consumers' interest in it (Hu et al. 2014, Xiong and Bharadwaj 2014, Kim and Hanssens 2017), and finance studies have used the search volume of a firm's stock ticker symbol to measure investors' interest in the stock (Da et al. 2011, deHaan et al. 2015). Following this literature, we examine online search queries on cannabis, alcohol, and tobacco.

As detailed in Online Appendix III, we first compile a "seed list" of keywords from various sources of the lexicon for cannabis, alcohol, or tobacco and then expand it using word-embedding techniques. A person interested in cannabis may not necessarily search for the keyword *cannabis* but rather for its synonyms/slang names/spelling variations instead. Our algorithm ensures the comprehensiveness of the data on related search queries. The main idea of word embedding is to use a word's surrounding context to learn word representations in a low-dimensional, continuous vector space, which is also known as *Word2Vec*. In the embedding space derived, words/phrases that are semantically similar are close to one another. The technique leverages the key feature of distributed-language models (Turian et al. 2010, Mikolov et al. 2013), which have demonstrated success in natural-language-processing applications and various artificial intelligence tasks. Using this technique, we represent each search query with a vector of numbers, expand the seed list by examining the neighboring queries in the embedding space following Grbovic et al. (2016), and obtain the final list after manual cleaning and deduplication. Based on the expanded list of keywords, we compute the search volume (based on exact match) for each substance.[3] To adjust for the inherent online activeness of each population group at each time point, the search volume for each substance is scaled by the total volume of all searches in the data (including queries both related and unrelated to the focal substances) of the population group at the corresponding time in the corresponding state (×100 to represent percentage).

2.2. Advertising Metrics

Federal and state laws allow advertisements on the Internet for both alcohol and tobacco products.[4] We can thus compare the performances of alcohol and tobacco ads before and after RCL (to investigate the cross-commodity effects of RCL on alcohol and tobacco). We do not examine advertising for recreational cannabis because it was prohibited before the policy change and remained scarce after loosened state laws because of federal regulations and publishers' self-imposed policies (Jassy 2017).[5]

We compile data on alcohol and tobacco ads displayed on the web portal. We focus on the most commonly studied performance metric for online advertisers, clickthrough rate, following the literature (e.g., Dinner et al. 2014). When users are exposed to an online ad impression (i.e., when the ad is loaded and displayed to a user), they may or may not click on it. The *clickthrough rate* of an ad is the likelihood of clicking on it upon impression—that is, $\frac{\textit{number of clicks}}{\textit{number of impressions}}$. Typically, a user will not click on an ad unless he or she is interested in it, and the web portal has already filtered out the cases of accidental clicks ("fat fingers") from the data. Clickthrough rate is a meaningful measure for both adults and youth because, although youth cannot legally purchase alcohol online, they can click on an alcohol ad if they are interested in it. We also collect data on the dollar revenue that the publisher (web portal) generated from displaying the ads and compute revenue per impression (revenue divided by the number of ad impressions). Because a publisher typically does not charge the advertiser unless the ad is clicked on, its revenue per impression is also influenced by users' interest in the product.

2.3. Model

We estimate the following model for the weekly panel data on each population group (as defined at the beginning of Section 2) across the treated states and control states:

$$Y_{ijk} = \beta_0 + \boldsymbol{\beta_1 Treat_k \times Post_{j/k}} + \beta_2 Youth_i + \beta_3 Gender_i + \beta_4 Device_{1i} + \beta_5 Device_{2i} + \sum_s \gamma_s State_k^s + \sum_w \delta_w Week_j^w + \varepsilon_{ijk}, \tag{1}$$

where Y denotes the outcome variable (search frequency of cannabis, alcohol, or tobacco; clickthrough rate or revenue per impression of alcohol or tobacco ads) of each population group i at time (week) j in state k. $Youth$ (1 for youth; 0 for adult), $Gender$ (1 for female; 0 for male), and $Device_1$ and $Device_2$ (indicator for tablet and indicator for mobile, respectively; 0 for desktop) are included to account for the inherent heterogeneity across population groups. The set of dummy variables $State_k^s$ accounts for state-specific fixed effects (1 when $s = k$; 0 otherwise), and their coefficients are γ_s. Dummy variables $Week_j^w$ account for time-specific fixed effects ($Week_j^w = 1$ when $w = j$; 0 otherwise), and their coefficients are δ_w. $Treat_k \times Post_{j|k}$ becomes 1 when a treated state (i.e., a state with RCL during the observation period) enters its *posttreatment* period (i.e., after RCL took effect in this state) and is 0 otherwise.[6] Hence, $\boldsymbol{\beta_1}$ captures the overall/average treatment effect of RCL across all treated states. In an additional analysis reported in Online Appendix VI, we also estimate the treatment effect for each treated state separately.

To examine the moderating effect of *Youth*, we modify Equation (1) into

$$Y_{ijk} = \beta_0 + \boldsymbol{\beta_1 Treat_k \times Post_{j/k}} + \beta_2 Youth_i + \beta_3 Gender_i + \beta_4 Device_{1i} + \beta_5 Device_{2i} + \boldsymbol{\beta_6 Treat_k \times Post_{j/k} \times Youth_i} + \sum_s \zeta_s State_k^s \times youth_i + \sum_w \eta_w Week_j^w \times Youth_i + \sum_s \gamma_s State_k^s + \sum_w \delta_w Week_j^w + \varepsilon_{ijk}. \tag{2}$$

Here, $\boldsymbol{\beta_6}$ reflects the moderating effect of youth compared with adults. We estimate Equations (1) and (2) with analytic weights because the unit of analysis is population group. As a robustness check, we compute two-way clustered standard errors and find consistent conclusions (see Online Appendix VII).

3. Results

3.1. Effects of RCL on Cannabis Search

Table 2 summarizes the estimation results, with cannabis searches as the dependent variable. The coefficient of *Treat* × *Post* estimated from Equation (1) is positive and significant, indicating that RCL increases cannabis searches on average. This coefficient suggests a 16.5% increase in cannabis searches after RCL relative to the pretreatment average across the treated states.

Table 2. Effect of RCL on Cannabis Searches

Variable	Equation (1)	Equation (2)
Treat × *Post*	0.0721***	0.0837***
	(0.0080)	(0.0154)
Treat × *Post* × *Youth*		–0.1613***
		(0.0278)
Youth	0.1417***	0.2035**
	(0.0068)	(0.0826)
Gender	–0.0338***	–0.0395***
	(0.0038)	(0.0058)
$Device_1$	0.0090*	0.0145*
	(0.0054)	(0.0080)
$Device_2$	0.0111*	0.0131
	(0.0066)	(0.0100)

Notes. State and week fixed effects are also included. Entries are coefficients with robust standard errors in parentheses. We analyze aggregated data on population group level over time, and the number of observations is 35,496.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

However, this increase is mitigated among youth, as indicated by the negative and significant coefficient of *Treat* × *Post* × *Youth* estimated from Equation (2). The sum of the coefficients of *Treat* × *Post* and *Treat* × *Post* × *Youth* is –0.0776 ($p < 0.01$), suggesting a significant decrease in cannabis searches among youth after RCL. To further understand the treatment effects for youth versus adults, we divide the data set into a youth sub–data set and an adult sub–data set, estimate the effect within each sub–data set (Online Appendix IX), and find asymmetric results across these two sub–data sets. Specifically, RCL has a positive and significant treatment effect on cannabis searches among adults only, but not among youth.

3.2. Effects of RCL on Alcohol and Tobacco Industries

Table 3, panels A and B, reports the effects of RCL on alcohol and tobacco industries. The coefficient of *Treat* × *Post* on alcohol searches is negative and significant, indicating reduced interest in alcohol when cannabis is legalized and becomes more available. Based on the coefficient estimated from Equation (1), we can infer a reduction of 10.9% in alcohol searches after RCL relative to the average of the pretreatment period. Hence, cannabis and alcohol may be *substitutes* for each other. Moreover, the coefficients of *Treat* × *Post* on alcohol ad clickthrough rate and publisher's revenue per impression are also negative and significant, providing supplemental evidence on the substituting relationship between cannabis and alcohol.[7]

Table 3. Effect of RCL on Alcohol and Tobacco Industries

Panel A: Alcohol metrics as dependent variable

	Alcohol search		Alcohol ad click		Publisher revenue from alcohol ad	
Variable	Equation (1)	Equation (2)	Equation (1)	Equation (2)	Equation (1)	Equation (2)
Treat × *Post*	−0.1194***	−0.1383***	−0.0098***	−0.0112***	−0.0050***	−0.0055***
	(0.0124)	(0.0203)	(0.0016)	(0.0028)	(0.0013)	(0.0020)
Treat × *Post* × *Youth*		0.1605***		0.0169***		0.0063*
		(0.0342)		(0.0046)		(0.0033)
Youth	0.0893***	0.2033**	−0.0098***	−0.0144	−0.0113***	−0.0217***
	(0.0097)	(0.0948)	(0.0012)	(0.0133)	(0.0010)	(0.0097)
Gender	0.0010	-0.0039	0.0018**	0.0019*	0.0034***	0.0032***
	(0.0058)	(0.0072)	(0.0007)	(0.0010)	(0.0006)	(0.0007)
Device$_1$	0.0124	0.0136	−0.0018*	−0.0025*	−0.0017*	−0.0017*
	(0.0078)	(0.0099)	(0.0010)	(0.0014)	(0.0009)	(0.0011)
Device$_2$	0.0174*	0.0204	−0.0026***	−0.0026**	−0.0013*	−0.0014*
	(0.0099)	(0.0126)	(0.0008)	(0.0012)	(0.0007)	(0.0008)

Panel B: Tobacco metrics as dependent variable

	Tobacco search		Tobacco ad click		Publisher revenue from tobacco ad	
Variable	Equation (1)	Equation (2)	Equation (1)	Equation (2)	Equation (1)	Equation (2)
Treat×Post	0.0285***	0.0308***	0.0131***	0.0159***	0.0029**	0.0031*
	(0.0064)	(0.0100)	(0.0039)	(0.0047)	(0.0013)	(0.0017)
Treat×Post×Youth		−0.0712***		−0.0333***		−0.0038
	(0.0233)			(0.0103)		(0.0037)
Youth	0.0684***	0.2676***	−0.0153***	−0.0350	−0.0064***	−0.0115
	(0.0042)	(0.0554)	(0.0031)	(0.0261)	(0.0013)	(0.0094)
Gender	−0.0029	−0.0064*	0.0023	0.0018	−0.0006	−0.0007
	(0.0029)	(0.0039)	(0.0018)	(0.0018)	(0.0006)	(0.0007)
Device1	0.0084**	0.0099*	−0.0041	−0.0046*	−0.0017*	−0.0018*
	(0.0042)	(0.0055)	(0.0026)	(0.0026)	(0.0009)	(0.0010)
Device2	0.0091*	0.0101	−0.0037*	−0.0034	−0.0014**	−0.0014*
	(0.0050)	(0.0069)	(0.0020)	(0.0021)	(0.0007)	(0.0008)

Notes. State and week fixed effects are also included. Entries are coefficients with robust standard errors in parentheses. We analyze aggregated data on population group level over time and the number of observations is 35,496.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$ (two-tailed).

Considering (1) this substituting relationship between alcohol and cannabis and (2) the weakened role of RCL in increasing youth's interest in cannabis compared with that of adults, the effects of RCL on alcohol-related metrics should also be less negative among youth than among adults. This is supported by the positive coefficient of *Treat* × *Post* × *Youth*.

In comparison, the coefficient of *Treat* × *Post* is positive and significant on tobacco searches, indicating that RCL enhances consumer interest in tobacco products. This coefficient suggests an increase of 7.8% in tobacco searches after RCL relative to the pretreatment period. Hence, we find evidence for the *complementarity* (rather than substitutability) between cannabis and tobacco. Consistently, the treatment effects of RCL are also positive on tobacco ad performance (clickthrough rate and publisher's revenue per impression).

The coefficients of *Treat* × *Post* × *Youth* are negative, opposite to those of *Treat* × *Post*. Hence, the positive impact of RCL on tobacco-related metrics is also mitigated for youth (for similar reasons as in the case of alcohol).

Separate estimations with the adult sub–data set and youth sub–data set (Online Appendix IX) also confirm these patterns. In summary, for adults, RCL has significant negative treatment effects on alcohol-related metrics but significant positive effects on tobacco-related metrics, indicating substitutability between cannabis and alcohol and complementarity between cannabis and tobacco. In contrast, such effects are weakened or even reversed for youth.

3.3. Testing the DID Assumption

A key assumption in the DID analysis is that the observed effect does not occur prior to the treatment. If the effect occurred in the pretreatment period, something other than the treatment could have been responsible for the observed outcome. We test this assumption following a widely adopted approach in the literature (Angrist and Pischke 2008, Wang and Goldfarb 2017, Chen et al. 2018), which splits the key covariate into a series of time indicators (leads and lags) to reveal detailed effects over time. Specifically, for each outcome metric, we estimate the interaction effects of treatment and six time indicators (one for each 4-week period in the 12 weeks before treatment and the 12 weeks after treatment). The base is more than 12 weeks before treatment. Results in Figure 1 indicate (1) that the effects in the pretreatment period are nonsignificant and generally flat and (2) that significant effects started to occur only after the treatment. The results provide suggestive evidence that the DID assumption is satisfied and that the observed effects can be attributed to the treatment. They also suggest that reverse causality (i.e., pretreatment increase or decrease in the outcome causes the treatment) is unlikely (Wang and Goldfarb 2017).

3.4. Robustness Checks

We conduct additional analyses as robustness checks. First, we find largely consistent patterns when estimating the treatment effect for each treated state separately (Online Appendix VI). Second, we estimate an alternative model following Israeli (2018) by replacing the state-specific fixed-effect dummies in Equations (1) and (2) with a single dummy indicator for all treated states and controlling for state-level characteristics, including demographics (median household income, education, and racial composition) based on Census data and political orientation (Online Appendix VIII). The estimated treatment effects remain consistent. Third, we compute search volumes based on the seed lists before keyword expansion. The results lead to consistent conclusions (Online Appendix X).

4. Implications for Policymakers, Marketers, and Researchers

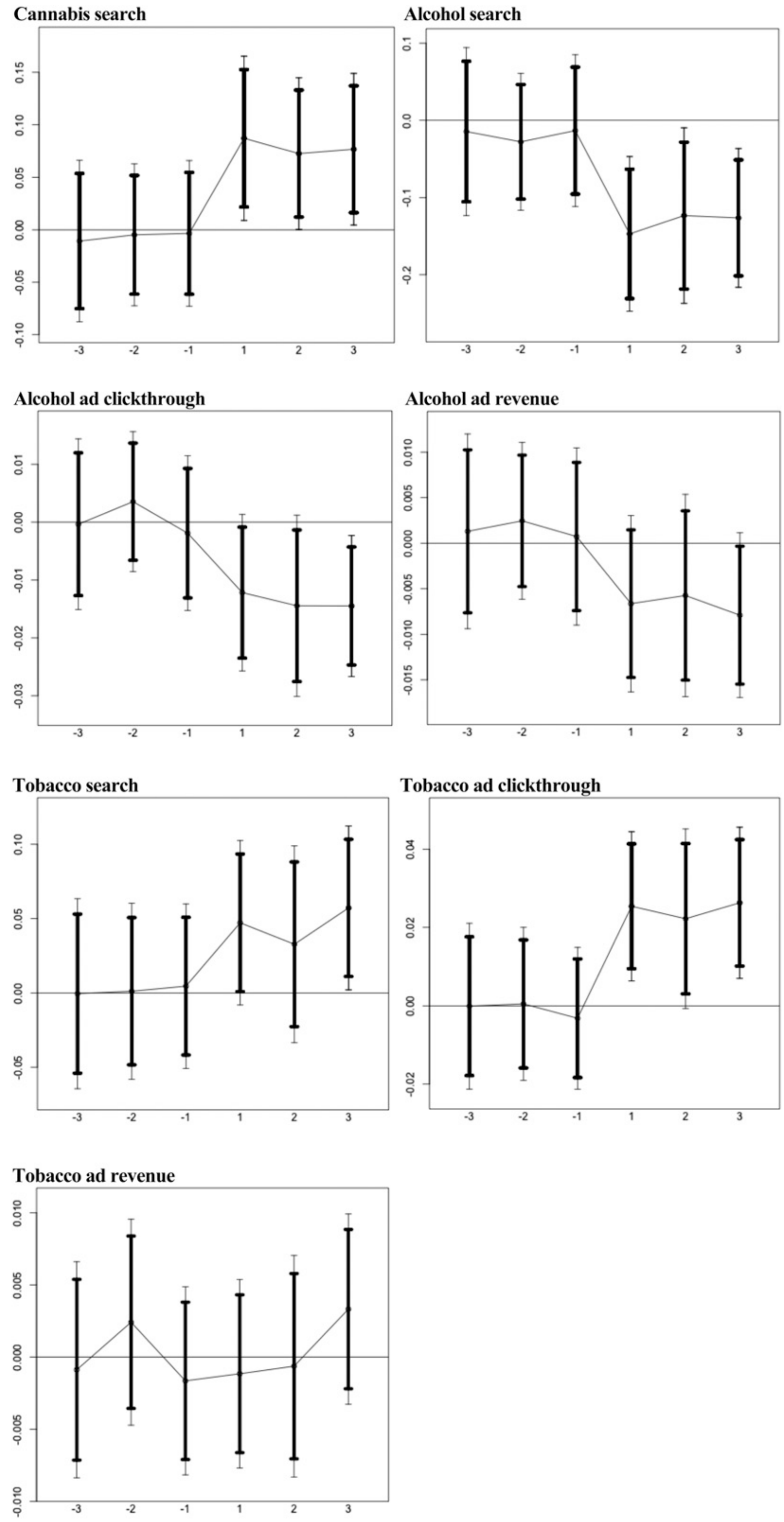
As acknowledged by prior research, the effect of cannabis legislations is an important public policy issue but typically difficult to estimate in empirical research, most of which analyzed survey data collected from the period after policy change and was unable to isolate the exact treatment effect (Zhao and Harris 2004). In this study, we employ a natural experiment approach to examine the treatment effect of RCL on cannabis searches and the spillover effects on other pleasure-inducing substances by analyzing big data with unobtrusive behavioral measures from periods before and after the policy change. Results reveal asymmetric effects of RCL on youth versus adults and on the alcohol versus tobacco industries.

Although the literature has not reached agreement on how cannabis policies affect youth, one major concern of the opponents against RCL is that a loosened policy would induce higher interest in cannabis among youth (Hopfer 2014). However, we find that the increase in online cannabis searches after RCL comes from adults only, not youth. If online searches serve as a reasonable proxy for consumer interest in our context, as suggested by prior research (e.g., Hu et al. 2014, Kim and Hanssens 2017), our results imply that RCL significantly increases adults' interest in cannabis, but not youth's,[8] which is in contrary to the widely held public concern over the effect of cannabis legalization on youth (Hopfer 2014, Loria 2017). One potential limitation of the present research is that the online search data come from one search engine alone. Hence, future researchers can further examine this phenomenon using alternative measures of consumer interest.

It can also be meaningful for future research to systematically investigate the theoretical mechanism behind our finding. Although alternative explanations may exist, one possible reason that could explain the attenuated treatment effect among youth is their rebellion/deviance tendency[9] (Aseltine 1995). The most common types of rebellion are nonconformity (against rules/laws/social standards) and noncompliance (against the authority of adults or parents), and rebellious adolescents feel proud or rewarded when they succeed in provoking societal or parental disapproval (Pickhardt 2011). Hence, youth tend to be curious about a substance when it is illegal (Agnew 2005); however, once legalized or widely accepted, the substance loses its "coolness" because it is less likely to engender disapproval (Loria 2017). Empirical evidence on such psychological tendency was also found in other related contexts. For instance, Sundh and Hagquist (2005) showed how a stricter tobacco policy actually encouraged youth curiosity about tobacco instead of discouraging it. For similar reasons, although RCL may make both youth and adults more aware of and receptive to the substance, a postlegalization increase in people's interest in cannabis would be mitigated or reversed among youth, as backed by our results. If the deviance tendency is indeed prevalent, policymakers may leverage it to reduce the attractiveness of cannabis and similar substances to youth.

Our findings on the effects of RCL on alcohol- and tobacco-related metrics shed new light on the cross-commodity relationships across these substances.

Figure 1. DID Assumption Tests



Notes. Each number on the horizontal axis is a time indicator for a 4-week period. Time indicators −1, −2, and −3 represent pretreatment periods, and 1, 2, and 3 represent posttreatment periods. In each graph, the plot depicts the coefficient of RCL effect at each point of time surrounding the treatment. The thin vertical bars represent 95% confidence intervals, and the thick vertical bars represent 90% confidence intervals.

There are two related streams of prior research, and mixed findings have been produced. The first stream examined cross-commodity price elasticity—that is, the effect of a price change for one substance on the consumption of/attitude toward other substances (e.g., Saffer and Chaloupka 1999, Cameron and Williams 2001). The second stream provided indirect evidence by analyzing data on hospital visits or traffic accidents (e.g., Model 1993, Chaloupka and Laixuthai 1997).[10] In comparison, we provide direct evidence about how cannabis policy change influences (1) people's searches for alcohol and tobacco and (2) advertising effectiveness of alcohol and tobacco sellers.

These findings on cross-commodity relationships help resolve the conflicting literature and provide distinct implications for practitioners. Historically, both alcohol and tobacco companies have been actively sponsoring/supporting campaigns against RCL (Cohen 2014, Williams 2016) because they are strongly concerned that legal marijuana may pose threats to them (*Bloomberg* 2016, Borchardt 2017). However, our results suggest that tobacco companies may need to reexamine their presumption and that anticannabis legalization is not in their best interest. This is because, although alcohol and cannabis appear to be substitutes, tobacco and cannabis are not (RCL in fact leads to increased interest in tobacco and enhanced effectiveness of tobacco ads). The alcohol industry, by contrast, has valid reasons to be concerned about legal cannabis and may need creative strategies to avoid market decline if RCL passes. The very recent partnership between alcohol giant Constellation and a Canadian cannabis company, Canopy, to develop cannabis-based beverages after cannabis legalization in Canada provides an exemplar.

Acknowledgments
The first two authors contributed equally to this work.

Endnotes

[1] Online Appendix II lists all the states where recreational cannabis is illegal, including both (a) the 10 control states where cannabis has remained illegal for all purposes and (b) states that have undergone some form of cannabis policy change other than RCL (decriminalization or medical cannabis legalization). As shown in Online Appendix V, the results remain consistent when we include the second group of states in the model as well while controlling for nonrecreational cannabis policy changes.

[2] In addition to search engines, the portal offers various services (e.g., email, blogs, and social groups) that require users to register their age information when creating the accounts. For users without registered accounts, the portal has an algorithm to estimate their ages based on cookies/online activities.

[3] In the cases of anonymous online searches (e.g., under incognito mode), although fresh cookies are created for such users, the portal may still link them with old cookies based on information such as Internet Protocol address, web-browser info, browsing patterns, and so on to infer about user information. The data points will only be dropped when the algorithm fails to find such linkages.

[4] Although tobacco ads are strictly banned on most traditional media platforms, the Federal Communications Commission does not currently regulate the internet. No other federal or state laws explicitly restrict online ads for tobacco products, and the state tobacco settlement agreements do not place additional restrictions on participating tobacco companies' internet marketing (Bach 2016).

[5] The federal Controlled Substances Act makes it unlawful to use a "communication facility" to advertise Schedule 1 drugs, including cannabis. Publishers also impose limits on cannabis advertising. For example, Bing and Twitter prohibit ads for "drugs and related paraphernalia"; Yahoo disallows ads for "drugs which may be legal or decriminalized in some regions, such as marijuana" (see https://www.cannabisbusinessexecutive.com/2017/08/legal-implications-advertising-cannabis-across-different-media/); and advertisers are not allowed to "promote the sale or use of illegal, prescription, or recreational drugs" on Facebook (see https://www.facebook.com/policies/ads/prohibited_content/drugs#).

[6] We include only the interaction term $Treat_k \times Post_{j|k}$ in the model but not $Treat_k$ (which indicates whether state k is a treated state or a control state) or $Post_{j|k}$ (which indicates whether week j occurs after RCL in state k) themselves. This is because (a) $Treat_k$ is a dummy classifier for the states, and adding it would cause collinearity because we have already included state-specific fixed-effect dummy variables $State_k^s$, and (b) $Post_{j|k}$ is conditional on each state k (i.e., its value is specific to each treated state and is always 0 for the control states), and thus $Post_{j|k} = Treat_k \times Post_{j|k}$ (when $Treat_k = 1$, obviously, $Post_{j|k} = Treat_k \times Post_{j|k}$; when $Treat_k = 0$, $Post_{j|k}$ is always 0 and still equals $Treat_k \times Post_{j|k}$).

[7] The numbers of alcohol and tobacco ads remain largely unchanged before and after RCL based on t-tests. However, because we do not have data on the contents of alcohol/tobacco ads (which might be different in the pre- versus post-RCL periods), we cannot completely rule out the potential endogeneity issue when using advertising metrics as outcome variables. Hence, we only consider the results on ad metrics as supplemental results that complement those on search volume. As an effort to account for potential endogeneity in policy change, we conduct robustness checks using synthetic controls and find consistent results: The estimated coefficients of $Treat \times Post$ and $Treat \times Post \times Youth$ are 0.0880 and –0.1686 ($p < 0.05$ for both) for cannabis searches, –0.1251 and 0.1772 ($p < 0.05$ for both) for alcohol searches, and 0.0277 ($p < 0.05$) and –0.0519 ($p < 0.1$) for tobacco searches.

[8] Some might speculate that youth do not actively search for cannabis online (before or after RCL), which might serve as an alternative explanation for the differential effect among youth. This explanation is unlikely because youth are in fact more active online searchers for cannabis-related information than adults on average (e.g., *Youth* has a significant positive coefficient, as shown in Table 2).

[9] Deviance can lead to experimentation with high-risk excitement and rejection of restraints. As young people move past the teen years, they gain more responsibility and are less inclined to deviance (Steinberg 2011). According to the reactance theory, youth's consumptions of cannabis and similar substances tend to be expressions of norm-breaking or rebellious behavior, a means for them to assert individuality or independence (Loria 2017).

[10] For example, Chaloupka and Laixuthai (1997) find that a cannabis price reduction leads to lower rates of motor vehicle accidents. Based on this finding, they conclude that a cannabis price reduction reduces alcohol consumption. The key assumption is that people under the influence of cannabis drive more carefully/slowly than those who are drinking and driving.

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