Online Appendix I
Summaries of Relevant Literatures

Does Cannabis Legalization Affect the Youth?

Prior research has *not* agreed on the impact of cannabis policy changes on the youth, although it is widely acknowledged as an important topic (Hopfer 2014). Some studies find that changes in cannabis policies significantly influence the youth. For example, based on Monitoring the Future (MTF) surveys, Chaloupka and Laixuthai (1997) found lower cannabis consumption among high school seniors following successful implementation of stricter legislative efforts in the "War on Drugs"; and Cerda et al (2016) find increased cannabis use among 8th and 10th graders in Washington. Estoup et al. (2016) studied 262 students and found significant increases in perceived risk and negative consequence among those enrolled in substance use intervention after cannabis legalization. In contrast, other studies suggest no or negligible impact of cannabis laws on the youth. Also analyzing MTF surveys, Johnson et al. (1981) reported no significant changes in the youth's attitude to and consumption of cannabis following cannabis decriminalization in seven states. Thies and Register (1993) and Pacula (1998) drew similar conclusions with data from the National Longitudinal Survey of Youth. A recent survey-based study suggests potentially differential effects of medical cannabis legalization (MCL) on adults' versus the youth's cannabis use, and calls for research on the impact of RCL (Mauro et al. 2017). Finally, Rusby et al. (2018) studied 444 adolescents in Oregon and observed no increase in cannabis use after cannabis legalization among those who never used cannabis before, but some increase among existing users. In sum, based on the mixed findings, it is inconclusive how cannabis policies affect the youth.

Besides academic research, government sponsored surveys which take place once every few years also provide some relevant statistics. The 2015 Healthy Kids Colorado Survey results indicate that, after recreational cannabis was legalized in the state, a decreased percentage of youths perceived

regular cannabis use as harmful; however, the proportion of them that ever tried cannabis or used it in the past month remained largely unchanged (Bent 2016). According to 2016 Washington State Healthy Youth Survey, the rates of cannabis use for 8th, 10th, and 12th graders appeared relatively steady in the past decade, despite the state's legalization of recreational cannabis in 2012 (Loria 2017). Although useful, these descriptive surveys by themselves do not proffer formal test of the treatment effect of cannabis legalization, nor do they compare the impact on the youth versus adults.

Is Alcohol a Complement or Substitute to Cannabis?

There have been debates about the cross-commodity relationship between cannabis and alcohol.

Some studies suggest that alcohol is a substitute to cannabis. Model (1993) documented that, in the states where cannabis is decriminalized, the number of emergency room episodes related to cannabis use increased while that related to alcohol use decreased. She thus concluded that cannabis decriminalization induced substitution away from alcohol to cannabis. Chaloupka and Laixuthai (1997) and DiNardo and Lemieux (2001) made similar conclusions based on MTF surveys of high school seniors. The former found that successful anti-cannabis efforts in the "War on Drugs" had an unintended consequence of raising young people's alcohol use. The latter showed that, after the Federal Uniform Drinking Age Act (which raised legal drinking age to 21), lower alcohol use among the youth was accompanied by a nearly one-for-one increase in cannabis use. In line with these findings based on U.S. data, there are two studies using Australian data from the National Drug Strategy Household Survey (NDSHS). Specifically, Cameron and Williams (2001) found significant positive effect of alcohol price on cannabis consumption, and Clements and Daryal (2005) documented substitutability between cannabis and three alcoholic drinks (beer, spirits, and wine).

Other studies hold opposing views and indicate that cannabis and alcohol are *not* substitutes. Pacula (1998) showed that increased tax on beer lead to reduced cannabis use, indicating

complementarity. Saffer and Chaloupka (1999) analyzed NHSDA (National Survey on Drug Use and Health) data and found strong evidence of complementary cross-price elasticity between alcohol and cannabis in their entire sample. However, such effects were insignificant for women and the youth, and cannabis decriminalization had no effect on alcohol use. Using the same data source, Farrelly et al. (1999) found significant negative effect of beer price on cannabis participation of the youth. Based on the College Alcohol Study (CAS) survey, Williams et al. (2004) showed that increased monetary cost of cannabis reduces both cannabis and alcohol use and that policies restricting access to alcohol (e.g., alcohol ban on campus) reduce both alcohol and cannabis use. Both of their findings suggest that cannabis and alcohol are economic complements. Zhao and Harris (2004) found mixed results regarding the relationship between cannabis and alcohol based on NDSHS data. Kerr et al. (2017) documented an increase in cannabis use after its legalization in Oregon among undergraduates who are also heavy users of alcohol. Based on a survey in Washington, Grant et al. (2018) find that pregnant and parenting women who were not abstinent from cannabis were also likely to consume alcohol.

In summary, previous findings on the cannabis-alcohol interrelationship are inconclusive and often limited to specific populations, calling for further research and implying potential existence of moderators (e.g., population groups). Based on these findings, it is unclear how loosened cannabis laws would affect the alcohol industry.

Is Tobacco a Complement or Substitute to Cannabis?

The literature on the interrelationship between cannabis and tobacco is relatively sparse. However, it has also provided mixed findings. For example, Chaloupka et al. (1999) found no significant effect of cannabis price on cigarette use, and no significant effect of cigarette price on cannabis participation. Farrelly et al. (1999) reported similar findings for adults but negative effect of cigarette price on cannabis use for the youth. Based on NDSHS survey data, Cameron and Williams (2001) found some

evidence on the complementary cross-price responses in the consumption levels of cannabis and cigarette, and Zhao and Harris (2004) documented the complementary relationship between cannabis and tobacco in terms of participation decisions. Tullis et al. (2003) surveyed 233 college students in the U.S. and concluded that tobacco-smoking initiation often coincides with or follows cannabis use. Based on a survey conducted in 2013, Wang et al. (2016) found higher rate of cannabis-tobacco co-use where medical marijuana is legal. However, a study on the Healthy Minds survey (Kerr et al. 2017) showed no significant change in cigarette use after cannabis legalization. In sum, given the limited literature with inconsistent findings, further research is necessary. Moreover, there has been no direct evidence about how cannabis legalization influences marketing performances (e.g., advertising effectiveness) of the tobacco industry.

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Online Appendix II
List of U.S. States Where Cannabis Is Illegal for Recreational Use

State		Status
Idaho	ID	Illegal for all purposes
Indiana	IN	Illegal for all purposes
Kansas	KS	Illegal for all purposes
Kentucky	KY	Illegal for all purposes
South Carolina	SC	Illegal for all purposes
South Dakota	SD	Illegal for all purposes
Utah	UT	Illegal for all purposes
Virginia	VA	Illegal for all purposes
West Virginia*	WV	Illegal for all purposes
Wyoming	WY	Illegal for all purposes
Missouri	MO	Illegal for all purposes; Decriminalized (first offense only)
Nebraska	NE	Illegal for all purposes; Decriminalized (first offense only)
North Carolina	NC	Illegal for all purposes; Decriminalized (civil infraction)
Alabama	AL	Legal for medical use only
Arizona	AZ	Legal for medical use only
Arkansas	AR	Legal for medical use only
Florida	FL	Legal for medical use only
Georgia	GA	Legal for medical use only
Hawaii	HI	Legal for medical use only
Iowa	IA	Legal for medical use only
Louisiana	LA	Legal for medical use only
Michigan	MI	Legal for medical use only
Montana	MT	Legal for medical use only
New Hampshire	NH	Legal for medical use only
New Jersey	NJ	Legal for medical use only
New Mexico	NM	Legal for medical use only
North Dakota	ND	Legal for medical use only
Oklahoma	OK	Legal for medical use only
Pennsylvania	PA	Legal for medical use only
Tennessee	TN	Legal for medical use only
Texas	TX	Legal for medical use only
Wisconsin	WI	Legal for medical use only
Connecticut	CT	Legal for medical use only; Decriminalized (first offense only)
Delaware	DE	Legal for medical use only; Decriminalized (civil infraction)
Illinois	IL	Legal for medical use only; Decriminalized (civil infraction)
Maryland	MD	Legal for medical use only; Decriminalized (civil infraction)
Minnesota	MN	Legal for medical use only; Decriminalized (petty misdemeanor)
Mississippi	MS	Legal for medical use only; Decriminalized (first offense only)
New York	NY	Legal for medical use only; Decriminalized (civil infraction)
Ohio	OH	Legal for medical use only; Decriminalized (civil infraction)
Rhode Island	RI	Legal for medical use only; Decriminalized (civil infraction)
Vermont	VT	Legal for medical use only; Decriminalized (civil infraction)

*West Virginia Medical Cannabis Act has been signed into law but will not take effect until July 2019. Hence, we consider West Virginia as a control state with no policy change.

Note: In states that have decriminalized the possession of cannabis, there is typically no arrest or prison time for possessing a small amount for personal consumption. Penalties may vary as marked in parentheses.

Online Appendix III
Procedure for Search Query Mining

Below, we illustrate the steps and algorithms employed in the mining of cannabis-, alcohol- and tobacco-related queries. In this appendix, we do not distinguish between 'words' and 'phrases'; and we use 'keywords' and 'queries' interchangeably.

The mining process of search queries follows three major steps:

Step (1): We manually compose a basic list of keywords related to cannabis, alcohol, and tobacco, respectively. For cannabis, we collect the keywords from online sources of cannabis lexicon on thecannabist.co and marijuanadictionary.com. This basic list of keywords serves as the 'seed-list' which we could further expand with steps (2) and (3). The seed-list for alcohol-related queries includes Wikipedia list of fermented (e.g., beer and wine) and distilled drinks (e.g., spirits and liqueurs) and their subcategories (wikipedia.org/wiki/list_of_alcoholic_drinks), cocktails (wikipedia.org/wiki/list_of_cocktails), and alcohol brands (wikipedia.org/wiki/category: alcoholic_drink_brands). The tobacco seed-list includes Wikipedia list of tobacco product types (wikipedia.org/wiki/tobacco_products) and the subcategories with each type, plus the list of tobacco brands including brands in each subcategory (wikipedia.org/wiki/category:tobacco_ brands).

Step (2): We mine the search logs and represent each search query with a vector of real numbers. This step is often known as 'word embedding', 'word2vec', or 'query2vec' in particular because the words are actually queries in our context. The technique leverages the key feature of distributed-language-models (Mikolov et al. 2013; Turian et al. 2010) which have demonstrated success in Natural-Language-Processing (NLP) applications, and is applied in various AI tasks such as Question&Answer system (Shen et al. 2017), text topic modeling (Li et al. 2017) and sentiment classification (Kim 2014).

Specifically, our query2vec procedure follows the structure as described in Grbovic et al. (2016), which is further based on the Skip-gram model in Mikolov et al. (2013). We provide a simplistic introduction of the Skip-gram and query2vec models below.

The basic idea of the Skip-gram model (Mikolov et al. 2013) is to represent each word with a vector of numbers so that the word representations are useful to predict the surrounding words in a word sequence (e.g., a sentence or a document). Formally, given a sequence of words $w_1, w_2, w_3, \dots, w_T$, the objective of the models is to maximize the following log probability:

$$\frac{1}{T}\sum_{t=-1}^{T}\sum_{-c\le j\le c, j\neq 0}\log p\left(w_{t+j}\middle|w_t\right) \qquad \text{(A3.1)},$$

where c defines the 'surrounding' window. If we represent each word w with a vector v, then the basic Skip-gram model defines $p\left(w_{t+j}\middle|w_t\right)$ with the corresponding vectors as

$$p\left(w_j\middle|w_i\right) = \frac{\exp\left(v'_{w_j}v_{w_i}\right)}{\sum_{k=1}^{K}\exp\left(v'_{w_k}v_{w_i}\right)} \qquad \text{(A3.2)},$$

where *K* is the number of unique words in the dataset. By maximizing the objective function, each word is represented by its corresponding vector.

In the context of online activities (e.g., online searches), instead of a sequence of words in a sentence, we observe a sequence of activities (e.g., search queries) in an online session. Hence, in line with the basic idea of the classic Skip-gram model, we can utilize an online activity to predict similar surrounding activities (Grbovic et al. 2016). Accordingly, we maximize the objective function and represent each query w by the corresponding vector v.

Step (3): In this step, we utilize the 'seed-list' of queries as in step (1), and the vector representation of queries as in step (2) to expand the query collection. Specifically, we define the distance between two queries to be the Euclidean distance between the corresponding vectors, i.e.,

$$d(w_j, w_i) = \left\| v_{w_j} - v_{w_2} \right\|_2 \qquad \text{(A3.3).}$$

For each query in the seed-list, we calculate its distances from the other queries, and find *K* 'nearest neighbor' queries with the smallest distances from the focal seed-list query[1]. We collect the neighbor queries of all the queries in the seed-list and perform manual data cleaning and deduplication. These neighbor queries, together with the queries in the seed-list, constitute the final query collection. Following the steps above, we obtain the query collections for cannabis, alcohol and tobacco, respectively.

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Table A3.1. Cannabis seed-list

420	Chocolate Thai	Herb and Al	Railroad weed
A-bomb	Christmas bud	Honey blunts	Rasta weed
Acapulco gold	Clickums	Indian hay	Red bud
Acapulco red	Cochornis	Indian hemp	Reefer
Afgani indica	Coliflor tostao	Indica	Reefers
African black	Columbus black	Indonesian bud	Righteous bush
African bush	Crack back	Instaga	Rompums
African woodbine	Crack bash	Instagu	Ruderalis
Assassin of Youth	Crazy weed	Jamaican gold	Sasfras
Astro turf	Cripple	Jamaican red hair	Sativa
Atom bomb	Crying weed	Jay smoke	Schwagg
Atshitshi	Cryppie	Jive stick	Sess
Baby bhang	Cryptonie	Jolly green	Sherman stick
Bad seed	Culican	Joy smoke	Sinsemilla
Bambalacha	Dagga	Ju-ju	Skunkweed
Basuco	Dawamesk	Kalakit	Smoke a bowl
BC bud	Diablito	killer green bud	Spliff
Beedies	Diambista	Khayf	Splim
Belyando spruce	Dimba	Kief	Sticky icky
Bhang	Dinkie dow	Killer green bud	Stink weed
Black bart	Dipped joints	Killer weed	Stoney weed

[1] We examined the expanded queries from various values of *K*, and selected *K*=30 to ensure the comprehensiveness of the collection. Using K>30 does not generate additional relevant and unduplicated queries. We also conducted robustness checks using queries identified with alternative *K* values (e.g., *K*=25) and found consistent conclusions.

Black ganga	Dirt grass	Kind bud	Sugar weed
Black gold	Ditch weed	King bud	Takkouri
Black gungi	Djamba	Krippy	Texas pot
Black gunion	Do a joint	Kush	Thai sticks
Black mo/black moat	Dody	Lakbay diva	Toke
Black mote	Don jem	Laughing grass	Toke up
Blaxing	Don Juan	Laughing weed	Trupence bag
Blowing smoke	Dona Juana (Spanish)	Lime Green	Unotque
Blue de hue	Dona Juanita (Spanish)	Liprimo	Up against the stem
Blue sky blond	Dope smoke	Loco Weed	Viper's weed
Bo-bo	Doradilla	Locoweed	Wacky weed
Bobo bush	Draf weed	Loose shank	Wake and Bake
Bogart a joint	Drag weed	Love leaf	Weed[2]
Bohd	Durong	Love weed	Weed tea
Boo boo bama	Duros	Maconha	Wet daddies
Boot the gong	Fallbrook redhair	Magic smoke	Wet sticks
Bullyon	Feed bag	Manhattan silver	Whackatabacky
Cam trip	Fuma D'Angola	Marijuana	Wicky stick
Cambodian red	Ganja	Maui wauie	Woo blunts
Cam red	Ganoobies	Maui-wowie	Woola blunt
Canappa	Gasper stick	Mexican green	Woolah
Cancelled stick	Gauge butt	Mexican locoweed	Woolie blunt
Candy blunt	Giggle smoke	Mexican red	Woolies
Cannabis	Giggle weed	Mighty mezz	Wooly blunts
Cannabis tea	Go loco	Mohasty	Yen pop
Carmabis	Goblet of jam	moocah	Yerhia
Cartucho	Gonj	Oolies	Yesca
Cavite all star	Good giggles	P-dogs	Zacatecas purple
Charas	Goof butt	Pack a bowl	
Cheeba	Green buds	Pakaloco	
Cheeo	Green goddess	Pakalolo	
Chemo	Grifa	Pakistani black	
Chiba chiba	Griffa	Panama red	
Chicago black	Gunja	Paper blunts	
Chicago green	Hanhich	Philly blunts	
Chiefing	Happy cigarette	Potten bush	
Chillum	Hawaiian Black	Pretendica	
Chira	Hawaiian homegrown hay	Ragweed	

Table A3.2. Alcohol seed-list

10 Cane	Carling	Jagertee	Planter's Punch
100 Pipers	Casa Dragones	James E. Pepper	Plum jerkum
2 Towns Ciderhouse	Casamigos	Jameson Irish	Poire Williams
4 Copas	Castel Group	Japanese Slipper	Poitín
7 & 7	Cement Mixer shot	Jim Beam	Popov

[2] The word "weed" is a homonym with two meanings: while it is most commonly used to refer to cannabis, it also means valueless wild grass. The fraction of searches for the other meaning of "weed" does not affect our results under the difference-in-difference framework for the following reason. Denote the searches for the word "weed" for cannabis-related information before and after RCL as $S\_cannabis^{before}$ and $S\_cannabis^{after}$, respectively; and the searches by people interested in its other meaning unrelated to cannabis as S_other^{before} and S_other^{after}. The difference in the total volume of searches for the word "weed" before and after RCL will be $(S\_cannabis^{after}+S\_other^{after}) - (S\_cannabis^{before}+S\_other^{before}) \approx S\_cannabis^{after} - S\_cannabis^{before}$ because $S\_other^{after} \approx S\_other^{before}$ (there is no theoretical reason to believe that people's interest in other meanings of the word "weed" that are unrelated to cannabis would change significantly after RCL).

Aberfeldy	Chalone Vineyard	Johnnie Walker	Porchcrawler
Aberlour distillery	Chambord	Jolly Shandy	Porto flip
Ableforth's	Champagne	Jose Cuervo	Prosecco
Absinthe	Chardonnay	Joseph Schlitz	Quentão
Absolut	Charles Shaw	Juan Collins	Rabo-de-galo
Ace Cider	Cheeky Vimto	Jungle Juice	Raki
Adonis	Chenin blanc	Jupiler	Rakia
Adrianna Vineyard	Chicha	Justerini & Brooks	Rebujito
Adult shake	Chivas Regal	Kahlúa	Red Bicyclette
Advocaat and soda lemonade	Cider	Kalimotxo	Red Russian
Agua de Sevilla	Cîroc	Kaoliang wine	Red wine
Agua de Valencia	Cockspur Rum	Karsk	Redbreast
Agua loca	Cocktail	Kentucky Vintage	Redheaded slut
Aguaymanto Sour	Cognac	Ketel One	Riesling
Agwa de Bolivia	Cojito	Kilju	Riunite
Akvavit	Alcopops	Killian's	Rohrbach
Alabama Slammer	Concha y Toro	Kingfisher beer	Rolling Rock
Albarino	Controy	Kir	Ron Zacapa Centenario
Alcohol	Coors	Kirsch	Rossini
Ale	Corona	Knockando	rotgut
Alizé	Corpse Reviver #2	Korbel	Rowan's Creek
Allied Domecq	Cragganmore	Kremlin Colonel	Royal Lochnagar
Amber Moon	Cremat	Kubuli	Royal Salute
AmberBock	Crème de menthe	Labatt	Rum
Amstel	Crested Ten	Lagavulin	Rumple Minze
Angel Face	Cristal	Lager	Ruskova
Angry Orchard	Crown Royal	Lagunitas	Rusty Nail
Anheuser-Busch	Cruzan	Lambrini	Sahti
Aperol Spritz	Cuauhtémoc Moctezuma	Le Tourment Vert	Sake
Applejack	Cuba Libre	Leblon Cachaça	Salmiakki Koskenkorva
Apple-Kneel	Cuban Sunset	Leffe	Salty Dog
Appletini	Curacao Punch	Leite de Onça	Samuel Adams
Arak	Daiquiri	Lemon Drop	Sangiovese
Arbor Mist	Dalmore	Leopard's Leap	Sangria
Arette	Dalwhinnie	Lillet	Sauvignon blanc
Armagnac	Damassine	Lime Rickey	Savoy Corpse Reviver
Armand de Brignac	Damn the Weather	Liqueur	Sazerac
Arrack	Dark 'N' Stormy	Liquor	Schwarzbier
Arsenal Cider House	Death in the Afternoon	Long Island Iced Tea	Scotch
Artois Bock	DeKuyper	Longmorn	Screaming Orgasm
Avión	Desi daru	Löwenbräu	Screwdriver
Awamori	Dewar's	Luksusowa	Scrumpy Jack
Baby Guinness	Diageo	Lunazul	Seagram
Babycham	Disaronno	Lynchburg Lemonade	Señor Río
Bacardi	Distillery	Ma La Sun	Seven and Seven
Backdraft	Dogfish Head	Macieira	Sex on the Beach
Baijiu	Dom Pérignon	Mackeson	Shandy
Baileys Irish Cream	Dommelsch	Macuá	Sheridan's
Ballantine's	Don Julio	Maerzen	Sherry
Barbera	dos equis	Maestro Dobel Tequila	Shiraz
Barleywine	Drambuie	Magic Hat	Shochu
Batida	drinks	Mai-Tai	Shock Top
Bay Breeze	Dubonnet	Malbec	Sierra Nevada
Beamish and Crawford	Duck Fart	Malesan	Singani
Beam's Eight Star	Early Times	malt	Singapore Sling

Beaulieu Vineyard	Ecco Domani	Mamajuana	Sirop de Picon
Becherovka	El Presidente	Mango Sour	Skittle Bomb
Beer	El Toro Loco Patron and Redbull	Manischewitz	SKYY
Bellini	Elijah Craig	ManX Spirit	Slammer Royale
Bénédictine	Elysian	Maotai	Slippery Nipple
Bernheim Original	Emperador	Margarita	Slivovitz
Bijou	Eristoff	Martell	Smirnoff
Birra Moretti	Espolon	Martini	Soju
Black and Tan	Evan Williams	Mateus	Sparkling wine
Black Nail	Fat Head's	Mauresque	Spirits
Black Russian	Ferrari Spumante	McDowell's No.1	Springbokkie
Black Velvet	Finlandia (vodka)	Mead	Spritzer
Black Warrior	fireball	Merlot	St. Ides
Blackthorn	firewater	Metaxa	Staropramen
Blenders Pride	Fish House Punch	Mezcal	Steel Reserve
Bloody Aztec	Fizzy apple	Michelada	Stella Artois
Bloody Margaret	Flaming Dr Pepper	Michelob	Stolichnaya
Bloody Mary	Flaming Sambuca	Midleton Very Rare	Stones Bitter
Blow my Skull Off	Flaming Volcano	Midori Sour	Stout
Blue Hawaii	Flirtini	Miller Lite	Strathisla
Blue Lagoon	Flor de Caña	Milwaukee's Best	Strongbow
Blue Moon	Four Peaks	Mimosa	Suze
Blue Nun	Franzia	Mint Julep	SweetWater
Bobby Burns	French 75	Moët & Chandon	Swish Beverages
Bock	Fuzzy Navel	Mojito	Sylvaner
Boddingtons Bitter	G. H. Mumm	Moloko Plus	Syrah
Bodega Catena Zapata	Gammel Dansk	Molson	Talisker
Boilermaker	Garnacha	Monkey Gland	Tamagozake
Bols	Genesee	Moonshine	Tanqueray
Bombay Sapphire	George Dickel	Moscato	Tavernello
Bombo	Get 27	Moscow Mule	Tempranillo
Booze	Gewurztraminer	Mousel	Tepache
Bonarda	Gimlet	Mouton Cadet	Tequila
Boschendal	Gin	Mudslide	The Glenlivet
Boulevardier	Ginza Mary	Mützig	Three Olives
Boundary Bay	Gireau	National Bohemian	Ti' Punch
Bourbon	Glen Elgin	Natural Ice	Tia Maria
Bourbon Lancer	Glen Ord	Natural Light	Tinto de Verano
Bramble	Glenkinchie	Nebbiolo	Tiswin
Brandy	Glögg	Negroni	Tom Collins
Brass Monkey	Glowtini	New Albanian	Trapiche
Brasserie Saint James	Golden Dream	New Midleton	Tschunk
Brewery	Goldschläger	Nihamanchi	Tubi 60
Brewing	Grain Belt	Noah's Mill	Ţuică
Brexitovka	Grand Old Parr	Noilly Prat	Vat 69
Brown-Forman	Green Vesper	Ogogoro	Vermouth
Buchanan's	Grenache	Old Bushmills	Vesper
Buck's Fizz	Grey Goose	Old Fitzgerald	Veuve Clicquot
Bud Extra	Grog	Old Forester	Vinsanto
Bud Ice	H. P. Bulmer	Old Grand-Dad	Viognier
Bud light	Hamlin's Wizard Oil	Old Milwaukee	Vladivar
Bud Silver	Hangman's Blood	Olde English 800	Vodka
Budweiser	Hanky-Panky	Olmeca	Ward 8
Bull Shot	Hardenberg-Wilthen	Orange Safari	West Coast Cooler
Bulleit	Harrogate Nights	Oranjeboom	Weyerbacher

Bulmers	Harvey Wallbanger	Ouzini	Wheat beer
Bumbo	Havana Club	Ouzo	Whiskey
Bumboo	Heaven Hill	Pabst Blue Ribbon	Whisky
Bundaberg	Heineken	Palinka	White Claw Hard Seltzer
Burgasko	Hennchata	Paloma	White Mountain Cooler
Busch	Hennessy	Palomino	White Russian
Bushwacker	Herbsaint Frappé	Pastis	White wine
Buttery Nipple	Himbeergeist	Paul John	Whyte & Mackay
Byejoe	hootch	Peeterman Artois	Williamine
Byrrh	Horilka	Pegu	Wine
Cabernet franc	Horse's Neck	Pernod Fils	Witbier
Cabernet sauvignon	Hpnotiq	Pernod Ricard	Wodka Gorbatschow
Cabin Still	Huangjiu	Perrier-Jouët	Woodford Reserve
Cachaça	Hudepohl	Peter Scot	Worthington's White Shield
Cacique Guaro	Ice Harbor	Phillips Union	Wyborowa
Caipirinha	InBev	Pilsener	Yanjing
Caipiroska	indian pale ale	Pils	Yellow Tail
Caipivodka	IPA	pilsner	Yorsh
Caju Amigo	Irish Car Bomb	Pimm's	Yuengling
California Cooler	Irish coffee	Piña Colada	Yukon Jack
Calvert Extra	J. P. Chenet	Pink Lady	Zagorka
Canadian Mist	J.P. Wiser's	Pinit grigio	Zhumir
Caol Ila	J.T.S. Brown	Pinot gris	Ziegenbock
Captain Morgan	Jack and Coke	Pinot noir	Zinfandel
Cardhu	Jack Daniel's	Pinotage	Zlaty Bazant
Caribou Lou	Jägerbomb	Pisco	Zurracapote

Table A3.3. Tobacco seed-list

Absolute Mild	Dipping tobacco	La Flor Dominicana	Richmond cigarette
Access Mild	Dissolvable tobacco	La Gloria Cubana	Rio Tabac Alpha Series
Akhtamar	Djarum Black	La Palina	Rocky Patel Premium
Alain Delon	Djarum Vanilla	Lambert & Butler	Röda Lacket
Alec Bradley	Dji Sam Soe 234	Lark cigarette	Roll-Your-Own
Amber Leaf	Dokha	LD cigarette	Romeo y Julieta
Anti-Semit	Domenico cigar	Legend cigarette	Rothmans cigarette
Apache	Dominant cigarette	Levi Garrett	Royal cigarette
Ararat	Don Pepin Garcia	Liggett Select	Saat cigarette
Aristoff	Doral cigarette	Longbeach cigarette	Saint Luis Rey
Arturo Fuente	Double happiness cigarette	Lucky Strike cigarette	Sakura cigarette
Ashford	Drum tobacco	Macanudo	Salem cigarette
Avolution	Du Maurier cigarette	Mahala Problem	Sampoerna Hijau
Bahman	Duke cigarette	Makla	San Cristobal de la Habana cigar
Bali Shag	Dunhill cigarette	Marlboro	Sancho Panza cigar
Basic cigarette	Dutch Masters	Marsh Wheeling	Sancti Spiritus cigar
Belomorkanal	Eclipse cigarette	Maverick cigarette	Scissors cigarette
Benson & Hedges	El Rey de los Habanos	Max cigarette	Senior Service cigarette
Bentoel	El Rey del Mundo	Maxus cigarette	Seven Stars cigarette
Berkeley cigarette	Elita cigarette	Mayfair cigarette	Shiazo
Bigger Hair	Embassy cigarette	Memphis cigarette	Signature 1932
Bintang Buana	Envio Mild	Merit cigarette	Signature Select
Black & Mild	EO Premium 601 Serie	Mevius	Silk Cut cigarette
Bolívar	Ernte 23	Mighty cigarette	Skoal
Bond Street cigarette	Esse cigarette	Minak Djinggo	Skruf Snus

Borkum Riff	Ettan snus	Misty cigarette	Snuff
Bow Tie Cigar Company	Eve cigarette	Mocne cigarette	Snus
Brick House cigar	Everest cigarette	Montecristo	Sobranie
Bristol cigarette	Extreme Mild cigarette	More cigarette	State Express 555
Bucanero cigar	f6 cigarette	MS cigarette	Sterling cigarette
Bugler tobacco	Fatima cigarette	Mu'assel	Stoker's
Bull Durham tobacco	Flair cigarette	Muratti	Superkings
Cabaiguán cigar	Fonseca cigar	Nacionales W	Surya Pro Mild
Camacho Cigars	Fortuna cigarette	Naswar	Sweet Afton cigarette
Cambridge cigarette	Four Square curlies	Nat Sherman	Swisher Sweets
Camel	Fuente Fuente OpusX	Natural American Spirit	Taj Chhap Deluxe
Canadian Classics	Fumadores	Navy Cut	Tali Jagat cigarette
Capri cigarette	Galan cigar	Neo Mild	Tareyton
Capstan cigarette	Garni cigarette	Neslite	Tatuaje
Captain Black cigar	Gauloises	Newport cigarette	Thang Long
Carroll's cigarette	Gawith Apricot	Next cigarette	Time cigarette
Caster cigarette	Gispert	Niemeyer tobacco	Tiparillo
Cavanders cigarette	Gitanes	Nil cigarette	Tipper cigarette
Champion cigarette	Gletscher Prise	Noblesse cigarette	Tobacco
Chancellor cigarette	Gold Flake cigarette	North Pole cigarette	Tobacco edibles
Charminar cigarette	Golden Bat cigarette	Old Henry cigar	Toscano cigar
Charms cigarette	Golden Virginia	Oliva Cigar	Trinidad cigar
Chesterfield cigarette	Göteborgs Rapé	Oliver Twist Tobacco	Troya cigar
Chewing tobacco	Grizzly tobacco	Padilla Habano	TRUE cigarette
Chunghwa cigarette	GT cigarette	Padilla Hybrid	U Mild
Cigarettes	Guantanamera cigar	Padilla Maduro	Vantage cigarette
Cigars	Gudang Garam	Padilla Miami	Vegas Cubanas
Clas Mild	Gutka	Pall Mall	Vegas Robaina
Classic Filter Kings	H. Upmann	Parisienne cigarette	Vegueros
Clavo cigarette	Habana Leon	Parliament cigarette	Viceroy cigarette
Cleopatra cigarette	Habanos	Partagás	Virginia Slims
Club cigarette	Hamlet cigar	Paul Garmirian	Vogue cigarette
Club Mild	Havana Soul cigar	Peace cigarette	West cigarette
Cohiba	Haus Bergmann	Perdomo	White Owl
Connoisseur Selection	Henry Clay cigar	Peter Stuyvesant cigarette	White Ox tobacco
Cool cigarette	Hestia Tobacco	Phillies cigar	Wills Navy Cut
Copenhagen snuff	Hirsh y Garcia	Piloto Cigars	Winfield cigarette
Cornell & Diehl	Hollywood cigarette	Pipe tobacco	Winston cigarette
Corojo Label	Hongtashan	Newport Platinum	Wismilak
Country cigarette	Hope cigarette	Por Larrañaga	Woodbine cigarette
Craven A	Hoyo de Monterrey	Prince cigarette	Ziganov
Creamy snuff	Insignia cigarette	Prince Albert tobacco	
Crossroads cigarette	Iqmik	Pueblo cigarette	
Crystal cigarette	Java cigarette	Punch cigar	
Cuaba	Jazy Mild	Pyramid cigarette	
Cuban Diplomat cigar	John Player & Sons	Quai d'Orsay cigar	
Cuesta-Rey	Joya de Nicaragua	Quintero cigar	
Cutters Choice	Juan López cigar	Rambler cigarette	
Dakota cigarette	Karo cigarette	Ramón Allones	
Dannemann	Kent cigarette	Red & White cigarette	
Davidoff	Kodiak tobacco	Red Man Chew	
Deluxe Tenor cigarette	Kool cigarette	Regal cigarette	
Derby cigarette	Krong Thip	Regent cigarette	
Diamond Crown	L&M	Rey Miguel cigar	
Diplomáticos	L.A. Lights cigarette	Reyes Family cigar	

Online Appendix IV
Summary Statistics

Substance search volume ratio (cannabis : alcohol : tobacco)	100 (baseline) : 255.2 : 83.4
Ad clickthrough rate ratio (alcohol : tobacco)	100 (baseline) : 86.0
Ad revenue per impression ratio (alcohol : tobacco)	100 (baseline) : 64.9
Percentage of youth	6.1%
Percentage of female	48.6%
Percentage of Device1 (tablet)	7.9%
Percentage of Device2 (mobile phone)	15.3%

Online Appendix V
Model Estimation with Expanded Control Group

In the main analysis, we use the states without any cannabis policy change as control states. As a robustness check, we re-estimate Equations (1) and (2) after including the data from all the other states listed in Online Appendix II. Because these additional states have undergone some sorts of cannabis policy changes (i.e., medical cannabis legalization or MCL, and/or decriminalization), we account for the effects of these policy changes by adding control variables in Equations (1) and (2) (a dummy indicator $MCL_k \times Post_{j|k}$ that becomes 1 for state k after medical cannabis is legalized in that state, and a dummy indicator $Decriminalized_k \times Post_{j|k}$ that becomes 1 after cannabis is decriminalized). As reported in Table A5 below, the estimated treatment effects of RCL (coefficients of *Treat*×*Post*) and the moderating effects of *Youth* (coefficients of *Treat*×*Post*×*Youth*) remain robust under this specification.

Table A5.

		Coefficient	
DV	IDV	Estimated from Equation 1	Estimated from Equation 2
Cannabis search	Treat×Post	.0745***	.0881***
		(.0067)	(.0140)
	Treat×Post×Youth		-.1424***
			(.0249)
	Decriminalized×Post	.0009	.0012
		(.0084)	(.0175)
	MCL×Post	.0134*	.0247*
		(.0069)	(.0144)
Alcohol search	Treat×Post	-.1037***	-.1149***
		(.0126)	(.0211)
	Treat×Post×Youth		.1585***
			(.0349)
	Decriminalized×Post	-.0113	-.0126
		(.0154)	(.0260)
	MCL×Post	-.0187	-.0218
		(.0127)	(.0214)
Alcohol ad clickthrough	Treat×Post	-.0094***	-.0111***
		(.0015)	(.0026)
	Treat×Post×Youth		.0196***
			(.0042)
	Decriminalized×Post	-.0005	-.0007

		(.0018)	(.0031)
	MCL×Post	-.0006	-.0009
		(.0015)	(.0026)
Publisher's revenue from alcohol ad	Treat×Post	-.0036***	-.0042**
		(.0011)	(.0019)
	Treat×Post×Youth		.0058*
			(.0031)
	Decriminalized×Post	-.0005	-.0009
		(.0014)	(.0023)
	MCL×Post	-.0013	-.0016
		(.0011)	(.0019)
Tobacco search	Treat×Post	.0238***	.0316***
		(.0041)	(.0063)
	Treat×Post×Youth		-.0474***
			(.0140)
	Decriminalized×Post	.0052	.0060
		(.0049)	(.0076)
	MCL×Post	.0074*	.0079
		(.0040)	(.0063)
Tobacco ad clickthrough	Treat×Post	.0121***	.0148***
		(.0030)	(.0039)
	Treat×Post×Youth		-.0364***
			(.0083)
	Decriminalized×Post	.0039	.0044
		(.0036)	(.0047)
	MCL×Post	.0016	.0017
		(.0029)	(.0039)
Publisher's revenue from tobacco ad	Treat×Post	.0023*	.0024
		(.0012)	(.0016)
	Treat×Post×Youth		-.0030
			(.0034)
	Decriminalized×Post	.0022	.0024
		(.0014)	(.0019)
	MCL×Post	.0020*	.0021
		(.0012)	(.0016)

Note: Other variables specified in Equations (1) and (2) are also included. Three, two, and one asterisks indicate 1%, 5%, and 10% statistical significance (two-tailed), respectively. We analyze aggregated data on population group level over time and the number of observations is 102,312.

Online Appendix VI
Alternative Model Specification - Estimating Treatment Effect for Each State Separately

Instead of estimating a staggered/pooled model, we also estimate the treatment effect for each RCL state separately. For each treated state, we specify the model below following the literature (e.g., Chen et al. 2017),

$$Y_{ijk} = \beta_0 + \beta_1 Treat_k + \beta_2 Post_j + \boldsymbol{\beta_3 Treat_k x Post_j} + \beta_4 Youth_i + \beta_5 Gender_i + \beta_6 Device1_i + \beta_7 Device2_i + \beta_8 Treat_k x Youth_i + \beta_9 Post_j x Youth_i + \boldsymbol{\beta_{10} Treat_k x Post_j x Youth_i} + \varepsilon_{ijk} \quad \text{(A6.1)}$$

where *Treat* is a dummy variable that equals one for the treated state, and zero for control states; *Post* is a dummy variable that equals one for the period after the policy change in the treated state, and zero for the period before policy change. All the other variables share the same meanings as those in Equation (2). We estimate Equation (A6.1) for one treated state at a time, using weekly population-group level panel data during a 24-week window (12 weeks before and 12 weeks after the policy change in the treated state) across the treated state and the control states (the ten states without any cannabis policy change). The coefficient $\boldsymbol{\beta_3}$ of the interaction term ***Treat*x*Post*** captures the effect of the policy change (i.e., RCL) on Y for adults (the baseline age group, when *Youth*=0); $\boldsymbol{\beta_{10}}$ of the three-way interaction term ***Treat*x*Post*x*Youth*** reflects the differential treatment effect for the youth versus adults. Tables A6.1 and A6.2 below summarize the results.

Table A6.1. Effect of RCL on Cannabis Search

Variables	**Coefficients (Standard Error)**						
	AK	CA	DC	ME	MA	NV	OR
Treat×Post	.0726***	.0845	.0484**	.0127	.4014**	.3740**	.1498**
	(.0237)	(.1688)	(.0217)	(.2407)	(.1899)	(.1642)	(.0759)
Treat×Post	-.1554***	-.2500	-.1903***	-1.2741	-.0996	-.4923	-.2552**
×Youth	(.0393)	(.2860)	(.0349)	(.7855)	(.3706)	(.3347)	(.1173)

Note: Other variables specified in Equation (A6.1) are also included. Three, two, and one asterisks indicate 1%, 5%, and 10% statistical significance (two-tailed), respectively. We analyze aggregated data on population group level over time and the number of observations is 3,168.

Table A6.2. Effect of RCL on Alcohol and Tobacco Industries

Outcome	Variables	Coefficients (Standard Error)						
		AK	CA	DC	ME	MA	NV	OR
Alcohol search volume	Treat×Post	-.0901**	-.1314	-.1329***	-.1273	-.0713	-.2906*	-.1934*
		(.0374)	(.2088)	(.0357)	(.1996)	(.1999)	(.1699)	(.1046)
	Treat×Post×Youth	.2281***	.1066	.0984*	.3751	.7207**	.2744	.0406
		(.0602)	(.3410)	(.0537)	(.5052)	(.3494)	(.3134)	(.1543)
Clickthrough-rate of alcohol ads	Treat×Post	-.0203***	-.0164**	-.0157**	-.0142	-.0124	-.0104	-.0154**
		(.0061)	(.0077)	(.0062)	(.0091)	(.0091)	(.0090)	(.0063)
	Treat×Post×Youth	.0275***	.0085	.0092	.0448**	.0007	-.0023	.0260***
		(.0098)	(.0123)	(.0093)	(.0195)	(.0151)	(.0160)	(.0092)
Publisher's revenue-per-impression from alcohol ads	Treat×Post	-.0047	-.0158	-.0122**	-.0016	.0055	-.0047	-.0165*
		(.0089)	(.0128)	(.0061)	(.0143)	(.0133)	(.0124)	(.0099)
	Treat×Post×Youth	.0075	.0339*	.0088	-.0061	-.0227	.0061	.0252*
		(.0143)	(.0204)	(.0091)	(.0308)	(.0221)	(.0222)	(.0146)
Tobacco search volume	Treat×Post	.0217	.0566**	.0459***	.0345	.0719	.0727	.0491**
		(.0152)	(.0286)	(.0141)	(.2859)	(.1309)	(.2715)	(.0214)
	Treat×Post×Youth	-.0612*	-.1394**	-.0769***	-1.2078	-.9230**	-1.3840	-.1088**
		(.0337)	(.0603)	(.0255)	(1.4042)	(.4172)	(1.0710)	(.0434)
Clickthrough-rate of tobacco ads	Treat×Post	.0373***	.0181*	.0246***	.0534***	.0302**	.0457***	.0128
		(.0078)	(.0095)	(.0075)	(.0136)	(.0125)	(.0143)	(.0090)
	Treat×Post×Youth	-.0765***	-.0292	-.0513***	-.0565	-.0125	-.0744**	-.0202
		(.0170)	(.0178)	(.0135)	(.0504)	(.0324)	(.0352)	(.0183)
Publisher's revenue-per-impression from tobacco ads	Treat×Post	.0148**	-.0113	.0084	.0186*	-.0035	.0023	.0035
		(.0063)	(.0114)	(.0062)	(.0104)	(.0085)	(.0102)	(.0062)
	Treat×Post×Youth	-.0439***	-.0015	-.0002	-.0202	.0169	-.0088	.0122
		(.0138)	(.0214)	(.0112)	(.0388)	(.0221)	(.0250)	(.0125)

Note: Other variables specified in Equation (A6.1) are also included in the model. Three, two, and one asterisks indicate 1%, 5%, and 10% statistical significance (two-tailed), respectively. We analyze aggregated data on population group level over time and the number of observations is 3,168.

Online Appendix VII
Robustness Check with Two-way Clustered Standard Errors

In this appendix, we check the robustness of the results by employing two-way clustered standard errors (SEs), which allows clustering both by state and by time (week), following Cameron et al. (2011).

Table A7. Estimation results with two-way robust clustered SEs

		Coefficient	
DV	IDV	Estimated from Equation 1	Estimated from Equation 2
Cannabis search	Treat×Post	.0721***	.0837***
		(.0094)	(.0188)
	Treat×Post×Youth		-.1613***
			(.0309)
Alcohol search	Treat×Post	-.1194***	-.1383***
		(.0154)	(.0268)
	Treat×Post×Youth		.1605***
			(.0383)
Alcohol ad clickthrough	Treat×Post	-.0098***	-.0112***
		(.0020)	(.0036)
	Treat×Post×Youth		.0169***
			(.0052)
Publisher's revenue from alcohol ad	Treat×Post	-.0050***	-.0055**
		(.0016)	(.0025)
	Treat×Post×Youth		.0063*
			(.0036)
Tobacco search	Treat×Post	.0285***	.0308***
		(.0077)	(.0111)
	Treat×Post×Youth		-.0712**
			(.0310)
Tobacco ad clickthrough	Treat×Post	.0131***	.0159***
		(.0047)	(.0058)
	Treat×Post×Youth		-.0333***
			(.0117)
Publisher's revenue from tobacco ad	Treat×Post	.0029*	.0031
		(.0017)	(.0024)
	Treat×Post×Youth		-.0038
			(.0044)

Note: Other variables specified in Equations 1 and 2 are also included. Three, two, and one asterisks indicate 1%, 5%, and 10% statistical significance (two-tailed), respectively. We analyze aggregated data on population group level over time and the number of observations is 35,496.

Additional Reference:

Cameron C, Gelbach J, Miller D (2011). Robust inference with multiway clustering. *J. Business & Economic Statistics*, 29(2), 238-49.

Online Appendix VIII
Robustness Check with Alternative Model Specification

We estimate an alternative model (Equation A8.1 below) following Israeli (2018, p.725) to ensure the robustness of the results:

$$Y_{ijk} = \alpha + \beta x Treat_k + \sum_w \gamma_w x Week_j^w + \delta x Treat_k x Post_{j|k} + \varphi X_k + f_i + \varepsilon_{ijk} \quad \text{(A8.1)}$$

The main difference between Equation (A8.1) and Equation (1) is that, instead of including a separate dummy indicator for each state as in Equation (1), Equation (A8.1) uses one single indicator $Treat_k$ to differentiate the group of treated states versus the group of control states (1 if RCL ever took effect in state k during the observational period, and 0 otherwise). The interaction term $Treat_k x Post_{j|k}$ then indicates whether week j occurred after RCL took effect in state k; and its coefficient captures the treatment effect of RCL. X_k represents a vector of state-level control variables, namely, political orientation (percentage of votes for the democrat candidate in the nearest presidential election; using percentage of votes in house election yields similar results) and demographics including income (median household income), education (the percentage of population with bachelor's degree or higher) and race (the percentage of non-Hispanic white). In addition, we include f_i to account for the fixed effect specific to each population group i (a unique combination of age group, gender and device as defined in section 2.3). Note that, because we control for the fixed effect of each unique population group, we have to omit the *Youth*, *Gender* and *Device* indicators in the model to avoid collinearity.

To examine the moderating effect of *Youth*, we modify Equation (A8.1) into:

$$Y_{ijk} = \alpha + \beta_1 Treat_k + \beta_2 Treat_k x Youth_i + \sum_w \gamma_{1w} x Week_j^w + \sum_w \gamma_{2w} Week_j^w x Youth_i + \delta_1 Treat_k x Post_{j|k} + \delta_2 Treat_k x Post_{j|k} x Youth_i + \varphi X_k + f_i + \varepsilon_{ijk} \quad \text{(A8.2)}$$

As shown in Tables A8 below, the treatment effects estimated from the alternative model are largely consistent with those from the main model specified in section 2.3.

Table A8. Estimation results of Equations A8.1 and A8.2

		Coefficient	
DV	IDV	Estimated from Equation A8.1	Estimated from Equation A8.2
Cannabis search	Treat×Post	.0682***	.0774***
		(.0096)	(.0137)
	Treat×Post×Youth		-.1266***
			(.0246)
Alcohol search	Treat×Post	-.1211***	-.1321***
		(.0110)	(.0177)
	Treat×Post×Youth		.1958***
			(.0296)
Alcohol ad clickthrough	Treat×Post	-.0108***	-.0132***
		(.0015)	(.0025)
	Treat×Post×Youth		.0177***
			(.0040)
Publisher's revenue from alcohol ad	Treat×Post	-.0051***	-.0056***
		(.0013)	(.0019)
	Treat×Post×Youth		.0062**
			(.0030)
Tobacco search	Treat×Post	.0183***	.0267***
		(.0064)	(.0089)
	Treat×Post×Youth		-.0617***
			(.0212)
Tobacco ad clickthrough	Treat×Post	.0136***	.0168***
		(.0036)	(.0042)
	Treat×Post×Youth		-.0345***
			(.0095)
Publisher's revenue from tobacco ad	Treat×Post	.0026**	.0032***
		(.0012)	(.0012)
	Treat×Post×Youth		-.0042
			(.0034)

Note: Other variables specified in Equations A8.1 and A8.2 are also included. Three, two, and one asterisks indicate 1%, 5%, and 10% statistical significance (two-tailed), respectively. We analyze aggregated data on population group level over time and the number of observations is 35,496.

Online Appendix IX
Estimating Treatment Effects for Adult Sub-dataset and Youth Sub-dataset Separately

To further understand the differential treatment effects of RCL on adults versus the youth, we estimate the following model for the adult sub-sample and the youth sub-sample separately:

$$Y_{ijk} = \beta_0 + \boldsymbol{\beta_1 Treat_k \cdot Post_{j|k}} + \beta_2 Gender_i + \beta_3 Device_{1i} + \beta_4 Device_{2i} + \sum_s \gamma_s State_k^s + \sum_w \delta_w Week_j^w + \varepsilon_{ijk} \quad \text{(A9.1)}$$

where the variables share the same meanings as specified in Section 2.3 and $\boldsymbol{\beta_1}$ captures the treatment effect. The estimated results are in the table below.

Table A9.

	Treatment effect	
DV	Adult subsample estimate	Youth subsample estimate
Cannabis search	.0848***	-.0809**
	(.0086)	(.0357)
Alcohol search	-.1379***	.0184
	(.0149)	(.0358)
Alcohol ad clickthrough	-.0110***	.0056
	(.0025)	(.0049)
Alcohol ad revenue	-.0054***	.0007
	(.0016)	(.0038)
Tobacco search	.0313***	-.0397*
	(.0095)	(.0240)
Tobacco ad clickthrough	.0157***	-.0184*
	(.0046)	(.0107)
Tobacco ad revenue	.0031*	-.0007
	(.0016)	(.0039)

Note: Coefficients are estimated for each subsample (adult vs youth) separately. All other variables specified in Equation (A9.1) are included. Three, two, and one asterisks indicate 1%, 5%, and 10% statistical significance (two-tailed), respectively. We analyze aggregated data on population group level over time and the number of observations is 17,748.

Online Appendix X:
Robustness check based on seed-list (without keyword expansion)

Table A10.1: Effects on cannabis search

	Equation 1	Equation 2
Treat×Post	.0705***	.0819***
	(.0083)	(.0158)
Treat×Post×Youth		-.1609***
		(.0281)
Youth	.1396***	.2018**
	(.0069)	(.0832)
Gender	-.0320***	-.0377***
	(.0041)	(.0060)
Device1	.0077	.0130
	(.0055)	(.0076)
Device2	.0101	.0120
	(.0067)	(.0095)

Table A10.2: Effects on alcohol search

	Equation 1	Equation 2
Treat×Post	-.1166***	-.1359***
	(.0126)	(.0208)
Treat×Post×Youth		.1582***
		(.0344)
Youth	.0914***	.2063**
	(.0098)	(.0951)
Gender	.0014	-.0036
	(.0061)	(.0074)
Device1	.0112	.0121
	(.0073)	(.0102)
Device2	.0160*	.0191
	(.0093)	(.0129)

Table A10.3: Effects on tobacco search

	Equation 1	Equation 2
Treat×Post	.0279***	.0297***
	(.0068)	(.0103)
Treat×Post×Youth		-.0675***
		(.0236)
Youth	.0661***	.2656***
	(.0043)	(.0558)
Gender	-.0024	-.0059
	(.0032)	(.0044)
Device1	.0078*	.0091*
	(.0044)	(.0056)
Device2	.0089*	.0095
	(.0051)	(.0070)