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Abstract

We use retail scanner data on purchases of high calorie food to study the link between recreational marijuana laws (RMLs) and consumption of high calorie food. To do this we exploit differences in the timing of introduction of marijuana laws among states and find that they are complements. Specifically, in counties located in RML states, monthly sales of high calorie food increased by 3.1 percent for ice cream, 4.1 for cookies, and 5.3 percent for chips. Results are robust to including placebo effective dates for RMLs in treated states as well as when using synthetic control methods as an alternative methodology.

Keywords: Border Analysis, Difference-in-Difference, Junk Food, Recreational Marijuana Laws, Synthetic Control Method, U.S. Counties, Obesity

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Introduction

In the United States, more than one third of the population is currently considered obese. No state has an obesity prevalence of less than 20 percent, ranging from around 20 percent in California and Massachusetts to around 35 percent or higher in Mississippi and West Virginia. It has been widely reported that the South has the highest prevalence of obese individuals with almost 35 percent, and the West has the lowest with around 25 percent.[1] The American Medical Association and the National Institutes of Health currently describe obesity as a national health epidemic.[2] Given the burden that obesity causes to the health system—currently estimated at around $200 billion per year—both researchers and policymakers have grown very concerned about the origins of this epidemic.

For instance, Blouin et al. (2009), Offer, Pecher, et al. (2010), Ritzer and Malone (2000) and Courtemanche and Carden (2011), among others, argue that a major factor in promoting poorer quality foods that lead to changes in tastes and obesity is the rapid growth of fast food chains and big retailers. Along these same lines, Courtemanche et al. (2016) provide some evidence that relates obesity rates to local economic conditions in the United States. They find that after controlling for demographic characteristics and state and year fixed effects, changes in several economic variables collectively explain 43 percent of the rise in obesity and 59 percent of the rise in Class II/III obesity. Their analysis points to large effects among the heaviest individuals, with half the rise in the 90th percentile of the body mass index explained by economic factors.

[1] www.endocrineweb.com/conditions/obesity/obesity-america-growing-concern

[2] The standard definition of obesity is given by the *body mass index (BMI),* and it is calculated by dividing the weight by the square of the height of the individual. A BMI of 30 kg/m^2 or more indicates that a person is obese.

With the recent push to legalize recreational marijuana, there has been growing interest in understanding the direct and indirect effects of cannabis consumption and, in particular, any undesired impacts of recent marijuana laws.[3] Recent research focuses on traffic fatalities (Anderson et al., 2013), workplace fatalities (Anderson et al., 2018), alcohol consumption (Baggio et al., 2019), increased sexual intercourse (e.g., Grossman et al., 2004), risky sex (e.g., George and Koob, 2010), fertility (Baggio et al., 2018) and several others. Interestingly, however, there is extremely limited research available on the potential role of marijuana consumption and food consumption. This, in spite of the fact that the most widespread urban myth among consumers is that marijuana consumption is associated with the so-called 'munchies,' namely an irresistible urge to consume large amounts of snacks or junk food, such as ice cream, cookies, candies, and the like, which may likely contribute to a further increase in obesity rates. In fact, while there is some neuroscience-based hypothesis that may help support this idea (e.g., Patel and Cone, 2015) there is no formal causal evidence that may help support any actual behavioral change. The existing evidence is mostly correlational and indirect (e.g., Sabia et al., 2017).

In this research we study the impact of recreational marijuana laws (RMLs) in the United States on changes in high calorie food consumption by using micro data in the form of retail scanner data on monthly purchases of products in grocery, convenience, drug, or mass distribution stores in over two thousand U.S. counties over the period 2006–16. We find that marijuana consumption measured by the introduction of recreational laws causally impacts the consumption of junk food and likely leads to a further increase in obesity rates in the population, which may be cause for further alarm to policymakers.

In order to conduct our research, we rely on differences in the timing of the legalization of recreational marijuana across states. We also compare retail food purchases for the subsample of contiguous counties across RML and non-RML shared borders only. In addition, we test the robustness of our findings by applying placebo tests and, in particular, applying a synthetic control method, that appears to confirm our findings. Our paper is organized as follows. The next section describes the data and our empirical methodology. The third section provides robustness checks. Finally, in the last section we provide a brief summary and conclusions.

Empirical Analysis

Data

Our identification strategy is based on the availability of data on purchases of groceries observed in the Nielsen Retail Scanner database in medical marijuana law (MML) and non-MML states before and after RMLs became effective. The database contains purchases of products in all categories from convenience, drug, or mass distribution stores across the United States over the period between 2006–16. The key outcome variables are retail purchases for three categories of high calorie foods namely, ice cream, cookies, and chips, which come from the Nielsen Retail Scanner database in RML states and non-RML states before and after RMLs became effective. The data offer coverage for 52 designated market areas located in the 48 contiguous U.S. states, which allows us to accurately measure the extensive margin of junk food consumed as sales do

[3] In fact, with Canada and Uruguay already having legalized recreational marijuana consumption and with several states in the U.S. having done so, it is rather important to understand not only the direct impact of cannabis use, but also any unintended behavioral spillover effects (Baggio et al., 2018).

not suffer from the underreporting issues, which is typical of self-reported data. Overall, we have sales data for more than two thousand U.S. counties.

We assign treatment based on when RML became effective. We use a dichotomous variable that takes a value equal to one for each month from the effective date of the legalization, and a value of zero otherwise. RML states are defined as treated states. The control states also include the states that legalized medical marijuana before 2006, our first year of data, and those that did not have policy change by the end of 2016.[4] In addition, we also control for states that decriminalized or legalized medical marijuana within our sample period. Information on approved and effective dates of medical marijuana laws come from previous literature (for a summary, see Baggio et al., 2018), as well as annual state-level data on beer and cigarette tax rates to control for other policy changes during the study period that may be correlated with RMLs (and MMLs) implementation.[5]

We control for a set of time-varying covariates that may potentially influence food consumption and may be correlated with RMLs. Specifically, we include annual county-level variables to capture variation in county economic conditions over time such as the unemployment rate and median household income. We also add a set of demographic characteristics for the county, including total population, percentage of male and Hispanic population, and the share of population by age groups. Information on economic characteristics comes from Local Area Unemployment Statistics and Small Area Income and Poverty Estimates. Information on demographic variables was gathered from the

[4] Dates of enactment and implementation of RMLs (and MMLs) come from the Marijuana Policy Project www.mpp.org Treatment is assigned according to enactment dates: Alaska, February 2015; California, November 2016; Colorado, December 2012; District of Columbia, February 2015; Oregon, July 2015; Washington, December 2012.

[5] State cigarette and beer tax information is based on several sources: American Petroleum Institute, state revenue departments, Distilled Spirits Council of the U.S., Commerce Clearing House, and Tax Foundation.

Census Bureau.[6] Summary statistics for economic and demographic variables are presented in Table 1.

Empirical Methodology

We employ a difference-in-difference (DID) design by estimating a reduced-form specification, conditioning on county and year-month fixed effects while exploiting the spatial discontinuity offered by state borders. In fact, in order to improve identification, we restrict our analysis to a sample consisting of all the contiguous county pairs sharing a state border where one of the counties belongs to a treated state (RML state) and the other to a control state (non-RML state). This approach has been shown to provide better identification than a traditional DID strategy in the context of marijuana laws (Baggio et al., 2019). The identification relies on cross time variation in counties in the legalization of recreational marijuana to identify the effect of RMLs on high calorie food sales. In other words, we compare change in RMLs over time to the change in sales across state boundaries. Conditional on observable characteristics and using individual fixed effects to eliminate the influence of unobservable county-specific characteristics, counties located in different states will be similar in unobservable characteristics, but different in the purchases of high calorie products given the timing in the enactment of marijuana laws.

Indeed, bordering counties provide a better control group than other control county in the United States because they can be expected to be relatively similar to adjacent treated counties (e.g., Dube et al., 2010). Starting from a full set of set of 2,191 counties, which yields 322 distinct county-pairs, restricting the data for counties bordering

[6] Specifically from the Census U.S. Intercensal County Population Data and Intercensal Estimates of the Resident Population

RML states, we are left with 88 county pairs. Formally, we estimate the following specification:

$$(1) \qquad y_{cpt} = \alpha + \beta RML_{st} + \mathbf{X}_{ct}\boldsymbol{\gamma} + \theta_c + \delta_t + \sigma_p t + \eta_{cpt},$$

where y_{cpt} denotes the log of high calorie food sales for either ice cream, cookies, or chips for county-pair p. RML_{st} is an indicator for whether in state *s* recreational marijuana law is effective in time period *t*. The term θ_c represents a county fixed effect, and δ_t represents the time period, year-month fixed effect that is constant across counties. $\mathbf{X}_{ct}$ is a full vectors of county-level covariates. $\sigma_p t$ is either a state- or county-pair-specific time trend that controls for systematic trend differences between treated and control states/pairs (Dhar and Ross, 2012). This also controls for unobservable state-level factors evolving over time at a constant rate. The key coefficient of interest β represents the estimated effect of the legalization of recreational marijuana on sales of junk food. The identification of β relies on the assumption that trends in the outcome variable in counties in the control group are a reasonable counterfactual, i.e., sales trends in the states that did not implement RMLs would have been the same in the absence of the treatment.

The identification strategy for the DID approach is based on the assumption that trends in sales in counties located in RML and non-RML states are parallel in the period preceding the policy change and thus provide a valid counterfactual. While we control for state-specific trends we also test for the existence of pre-existing trend differences between treatment and control states as follows:

$$y_{cpt} = \alpha + \sum_{i=-6}^{4} \beta_i 1(\tau_{ct} = i) + \mathbf{X}_{ct}\boldsymbol{\gamma} + \theta_c + \delta_t + \sigma_p t + \eta_{cpt}. \quad (2)$$

where τ_{ct} indicates the event month-year, which takes value equal to one when an observation is i semesters away from the semester the legalization of recreational marijuana became effective. We use semesters to reduce noise. The case $(\tau = 0)$ denotes the semester of the policy change. For $(\tau \leq -1)$ RML states were untreated. The coefficients β_is are estimated relative to semester preceding the policy change $(\tau = -1)$, the omitted coefficient. Note that i equal to -6 or 4 denotes more than five semesters before or more than three after RMLs became effective, respectively. The event study is also useful to investigate dynamic responses to the treatment. For instance, the progressive rollout of the law itself, e.g., a delayed establishment of dispensaries, may generate different effects over time. In addition, since there are multiple observations for counties sharing borders with more than one other county, we cluster standard errors for both regressions at the county-pair level. This also allows for within state serial correlation in the error terms while assuming independence across pairs because unobserved factors within county pairs may be correlated over time (Bertrand et al., 2004). Regressions were weighted using county-year population.[7]

Results

We find a substitution effect between recreational use of marijuana for each category of high calorie food considered. In particular, we find that legalizing recreational marijuana leads to an increase in sales of junk food as monthly sales in RML states increase by 5 percent for ice cream, 6 percent for cookies, and 6.6 percent for chips, respectively. Interestingly, even in the most taxing case, namely when including state- and

[7] Unweighted regressions yielded similar results.

pair-specific time trends, we still find that our overall results hold. In particular, while we find a slight reduction in the magnitude of the effect and a slight decrease the precision of the estimate, our estimates indicate that sales of cookies increase by 4.1 percent and sales chips increase by 5.3 percent. We also find that sales of ice cream increase by 3.1 percent, although this last estimate is statistically insignificant at conventional level. Results are shown in Table 2.

Figure 1 shows no pre-existing trend differences in junk food sales as estimated β_is are, both in magnitude and statistically, not different from zero in the years before RML implementation. The event study captures differences in the short-term and long-term effects, which we expect to exist due to time variation in the implementation of the policy as well as the availability and access to recreational marijuana. The increase in sales starts at the time the legislation becomes effective. The effect slightly decreases in the semesters thereafter for ice cream and chips, but not for cookies. The evidence provided by the event studies provides validity to the identification strategy based on discontinuity at the state border.

Robustness

We examine the sensitivity of our results and preferred specification using a placebo regression for a falsification and Synthetic Control Method. First, we check that the effects we find are not spurious by estimating the regression, equation (1), using placebo RMLs dates. Specifically, we test for the potential impact of placebo dates for RMLs in the treated states. For each RML state, we draw randomly 1,000 dates in the time period that goes from June 2006 to the month before the actual effective RML date using a uniform distribution. The data observed for treated states from the actual effective date until the end of the sample period are dropped from the sample. The treatment indicator is defined according to the placebo dates. That is, it takes value equal to one starting from the placebo date for state *s*, zero otherwise. Then, we estimate the same specification as for equation (1) for each of the 1,000 placebo dates. This gives us a distribution of the treatment effects for the placebo treatment. Table 3 shows estimates for the date placebo test. As expected, across junk food categories, we find no effects of the placebo treatment, which provides support that the main results are not spurious correlations, but rather treatment effects. Indeed, the estimated effects are close to zero and are statistically insignificant at any conventional level.

Second, following Abadie et al. (2010), Cavallo et al. (2013), and Galiani and Quistorff (2017), we employ a synthetic control method (SCM) that can be used to relax the common trend assumption and still provide a valid counterfactual to the treated units. Specifically, it creates a control group by choosing weights for states that have not legalized marijuana in order to create a counterfactual state that can resemble both the trends of treated units experiencing a discrete change in RML. We restrict our sample to aggregate sales for a balanced panel of states with at least 18 months before/after RMLs were implemented and for states for all months within the observed period, 2006–16.[8] We use the dependent variable, log of total population, share of population below 19 years old, and the share or high school dropouts for each year in the pre-treatment period. In Figures 2-4, left columns, we show trends in junk food sales and estimated effects by categories for the three legalizing states: Colorado, Oregon, and Washington. We confirm the more

[8] We create a synthetic control after excluding all states changing medical and recreational marijuana laws from the donor pool. California is excluded because in this case there are no more than 18 months of data. Alaska is excluded because sales data are available only for contiguous U.S. states. The total number of states in the donor pool is 31.

general findings above that recreational marijuana consumption appears to increase sales of high calorie food. In Figures 2 to 4, right columns, the black line shows the estimated effect for legalizing states, calculated as the difference between the actual sales and the synthetic control predictions for the treated state. The light blue lines denote the estimated effects associated with each placebo states, i.e., every other state in the donor pool. Comparing the actual to placebo effect is useful to assess the significance of the SCM estimates. As the figures indicate, the estimated effect for the treated state is large relative to the distribution of the effects for the donor state. This suggests that the SCM results are not likely to be driven entirely by chance and confirms that high calorie food and marijuana are complements.

Conclusion

In this research we apply a difference-in-difference approach by exploiting differences in the timing of the legalization of recreational marijuana across the United States and compare junk food retail sales at the county level for those counties located across borders in states that legalized and those did not legalize recreational use, before and after the change in RMLs. We find that in counties located in RML states, monthly sales of high calorie food increased by 3.1 percent for ice cream, 4.1 for cookies, and 5.3 percent for chips. Results are robust to including placebo effective dates for RMLs in treated states as well as when using synthetic control methods as an alternative methodology. Whereas our research appears to be the first that causally links cannabis consumption to junk food consumption, our findings may be particularly relevant from a policymaking perspective, at a time when more states are considering legalizing marijuana consumption while battling an obesity epidemic and when different countries have already fully legalized or are considering legalizing consumption.

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Table 1 – Descriptive Statistics for Bordering Counties

	Mean	SD
Medical marijuana laws (MML)	0.105	0.306
Recreational marijuana laws (RML)	0.073	0.260
Marijuana decriminalized	0.28	0.45
Unemployment rate	8.024	3.714
Median income (thousands)	61.632	15.810
Total population (thousands)	1,119.004	830.630
% Male	0.50	0.01
% Hispanic	0.161	0.165
% Black	0.136	0.172
% Asian	0.069	0.042
% Population 0-19 years old	0.274	0.038
% Population 20-39 years old	0.24	0.04
% Population 40-64 years old	0.317	0.026
% High school dropouts	0.116	0.029
% High school	0.255	0.040
% Some college	0.295	0.054
% Bachelor	0.334	0.090
Ice cream sales ($ thousands)	721.287	547.280
Cookies sales ($ thousands)	761.920	587.194
Chips sales ($ thousands)	1,217.678	957.963

Notes: Calculated for US counties (2006–16) and weighted by total population by county-year. All the monetary data are in 2016 dollars.

Table 2 – Border Analysis, Overall Effects of RMLs on Junk Food Sales

	(1)	(2)	(3)
Cookies			
RML = 1	0.0581***	0.0303***	0.0402**
	(0.0200)	(0.0113)	(0.0184)
Number of observations	21,794	21,794	21,794
R-squared (within)	0.6823	0.7236	0.7173
Mean	12.981		
Chips			
RML = 1	0.0640***	0.0524***	0.0518***
	(0.0202)	(0.0121)	(0.0187)
Number of observations	21,808	21,808	21,808
R-squared (within)	0.7080	0.7540	0.7454
Mean	13.482		
Ice-cream			
RML = 1	0.0491**	0.0285**	0.0306
	(0.0215)	(0.0131)	(0.0228)
Number of observations	20,625	20,625	20,625
R-squared (within)	0.6949	0.7305	0.7128
Mean	12.948		
Covariates	YES	YES	YES
State-specific trends	NO	YES	NO
Pair-specific trends	NO	NO	YES

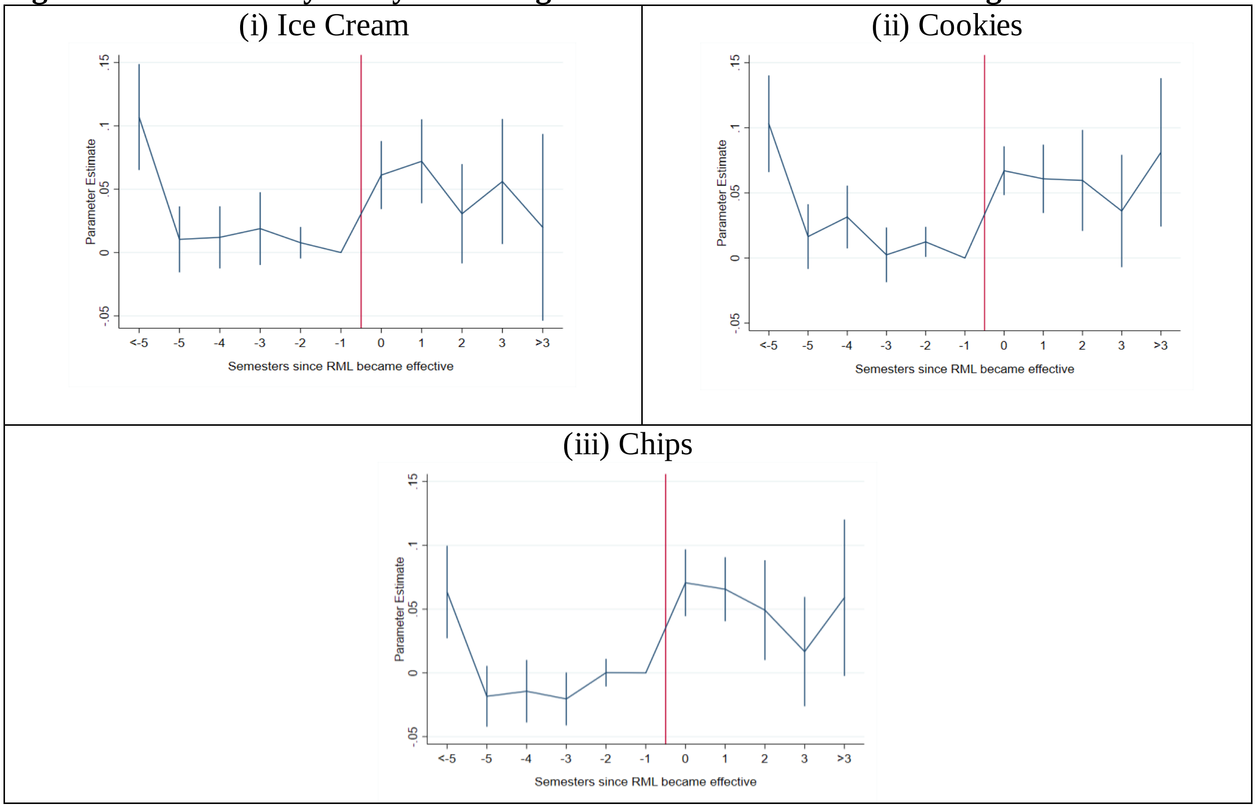
Notes: *** p<0.01, ** p<0.05, * p<0.1. The outcome variable is the log of junk food sales (ice cream, cookies, and chips). Controls include share of Black, Asian, Hispanic, and other races, share of population for the 0–19, 40–64, and over 65 age group, unemployment rate and median household income, share of high school dropouts, share of population with high school degree, and share of population with some college, as well as indicators for decriminalized or legalized use of medical marijuana. Regressions also include county and year-month fixed effects and are weighted by population in county-year. Standard errors are clustered by county pair (100 clusters).

Table 3 – Robustness Test: Placebo Dates

	Cookies	Chips	Ice Cream
RML=1	-0.0197	-0.0160	-0.0081
	(0.0118)	(0.0114)	(0.0111)
Placebo coefficient > 0	126	150	350
Placebo coefficient > 0 and significant at 5% level	10	8	45
Placebo coefficient > 0 and significant at 10% level	18	12	78
Number of observations	11,381	11,381	9,446

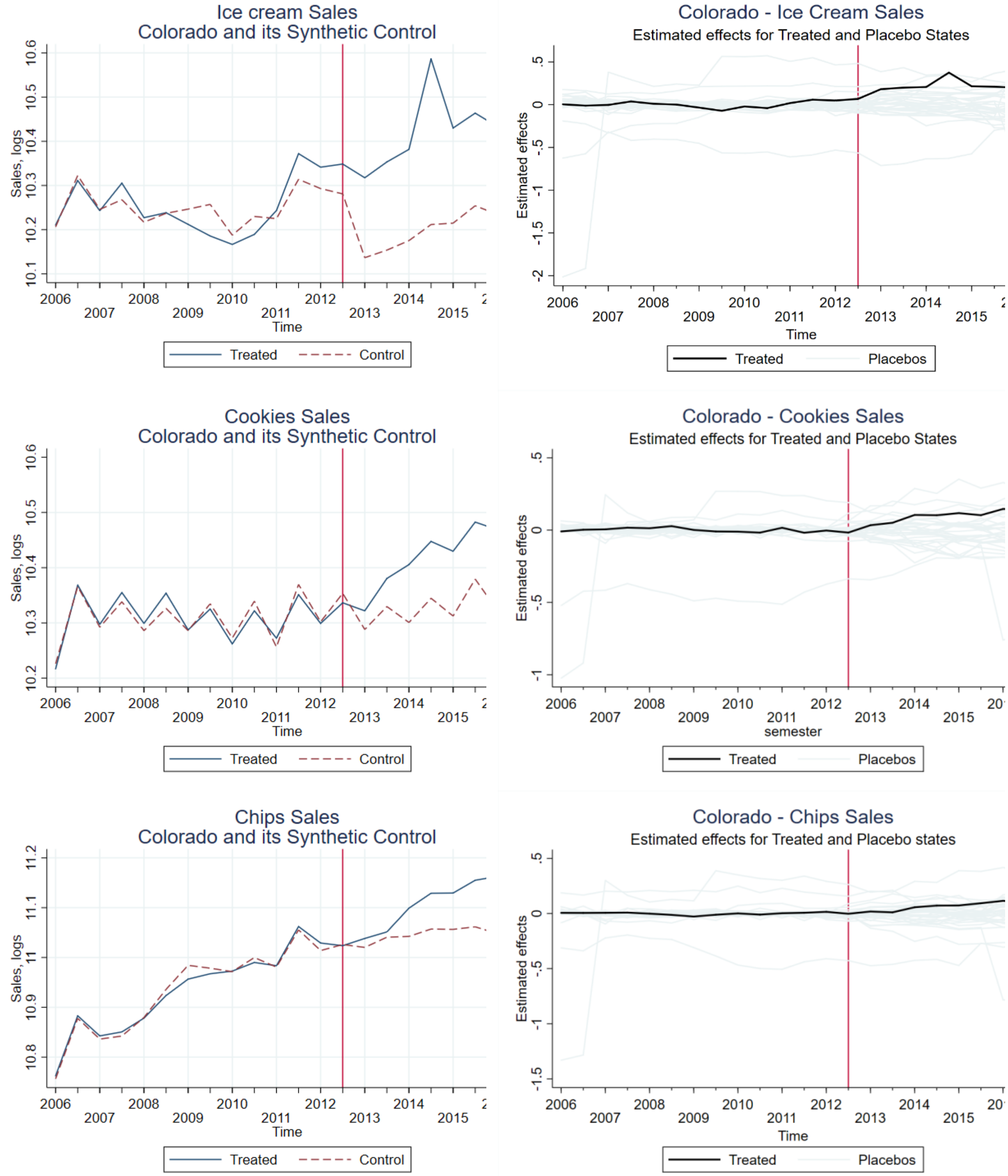
Notes: The outcome variable is the log of junk food sales (ice cream, cookies, and chips). Controls include share of Black, Asian, Hispanic, and other races, share of population for the 0–19, 40–64, and over 65 age group, unemployment rate and median household income, share of high school dropouts, share of population with high school degree, and share of population with some college, as well as indicators for decriminalized or legalized use of medical marijuana. Regressions also include county and year-month fixed effects, pair-specific trends and are weighted by population in county-year. Standard errors are clustered by county pairs (100 clusters).

Figure 1 – Event Study Analysis for Log Sales of Junk Food in Bordering Counties



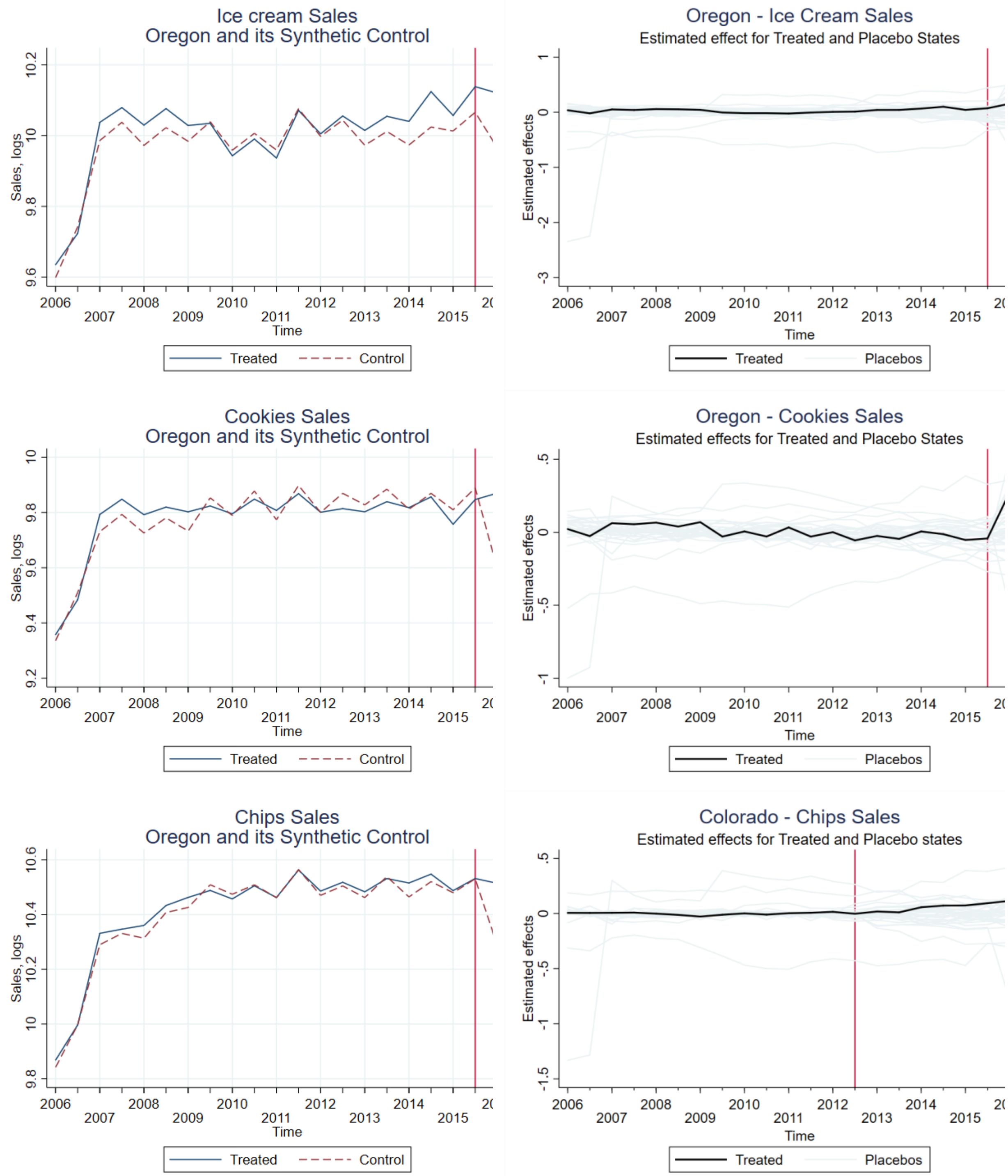
Notes: *** p<0.01, ** p<0.05, * p<0.1. Estimates obtained from regressions controlling for covariates, state-by-month, county and year-month fixed effects, and pair-specific time trends. Regressions are weighted by population in county-year. Standard errors are clustered by county pair (100 clusters).

Figure 2 – Synthetic Control Method: Log Sales of Junk Food for Colorado State and Its Synthetic Control (left), Estimated Effects for Colorado and Placebo States (right)



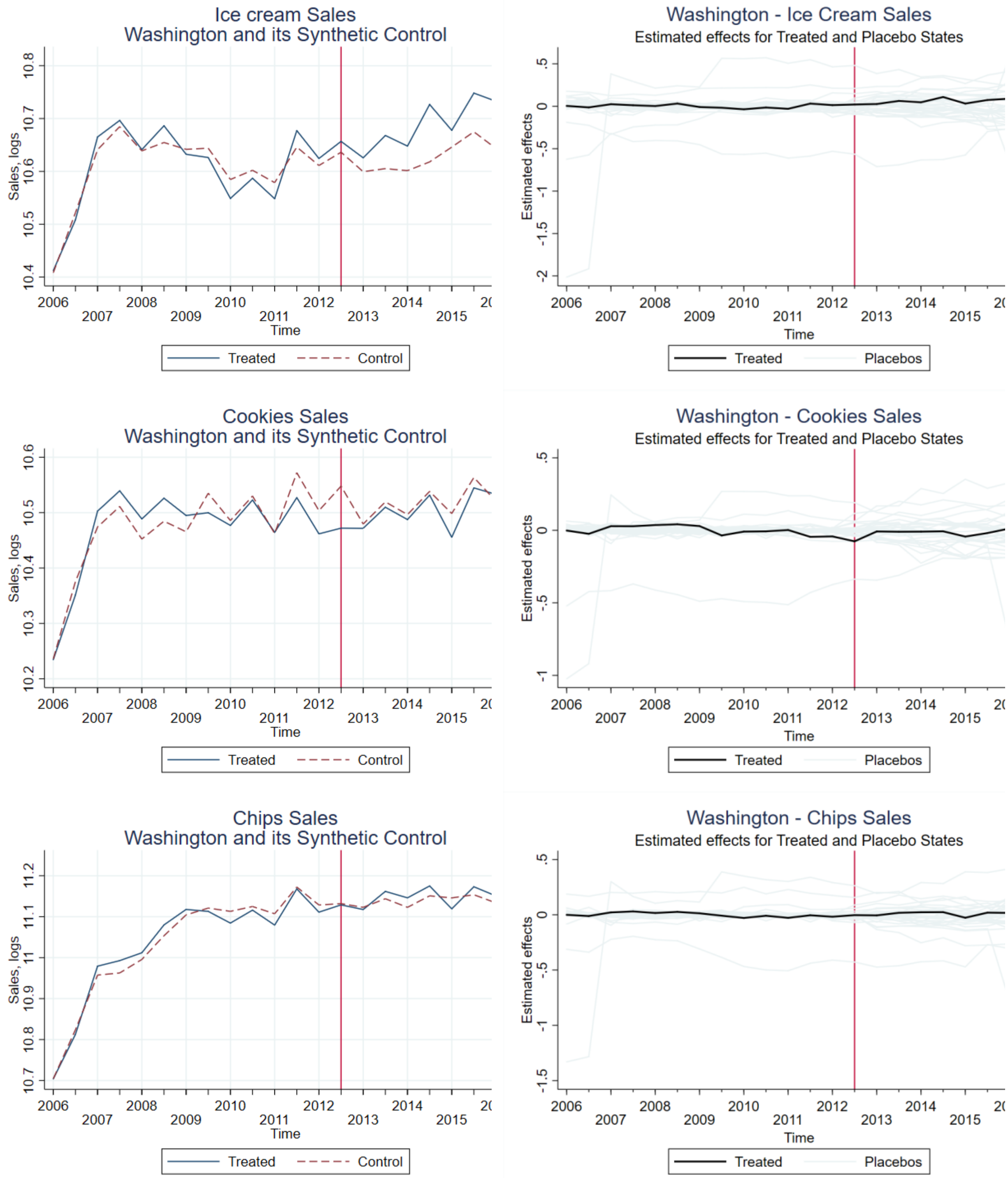
Notes: Graph obtained from Synthetic Control Analysis for Colorado State after excluding all states changing medical and recreational marijuana laws in 2006–16 from the donor pool. To fit the SCM we use the dependent variable, log of total population, share of population below 19 years old, and the share or high school dropouts for each year in the pre-treatment period. California is excluded because for them there are not more than 18 months of data. Alaska is excluded because of lack of sales data.

Figure 3 – Synthetic Control Method: Log Sales of Junk Food for Oregon State and Its Synthetic Control (left), Estimated Effects for Oregon and Placebo States (right)



Notes: Graph obtained from Synthetic Control Analysis for Oregon State after excluding all states changing medical and recreational marijuana laws in 2006–16 from the donor pool. To fit the SCM we use the dependent variable, log of total population, share of population below 19 years old, and the share or high school dropouts for each year in the pre-treatment period. California is excluded because for them there are not more than 18 months of data. Alaska is excluded because of lack of sales data.

Figure 4 – Synthetic Control Method: Log Sales of Junk Food for Washington State and Its Synthetic Control (left), Estimated Effects for Washington and Placebo States (right)



Notes: Graph obtained from Synthetic Control Analysis for Washington State after excluding all states medical and recreational marijuana laws in 2006–16 from the donor pool. To fit the SCM we use the dependent variable, log of total population, share of population below 19 years old, and the share or high school dropouts for each year in the pre-treatment period. California is excluded because for them there are not more than 18 months of data. Alaska is excluded because of lack of sales data