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ABSTRACT

How Do Parents Respond to Regulation of Sugary Drinks in Child Care? Evidence from California*

To reduce sugar intake in children, California regulates the provision of sugar-sweetened beverages and juice by child care facilities. The regulation may reduce children's consumption of sugary beverages in the short run and weaken their preferences for sugary drinks in the long run. Whether these objectives are achieved depends on how parents respond to the regulation by providing sugary drinks at home. Using detailed scanner data of grocery purchases, we find that affected California households increased their juice purchases right after the regulation became effective. However, this increase disappears after one year. Moreover, we find no increase in the purchases of sugary substitutes. Our findings suggest that parents provide more juice for their children after child cares limit their juice provision, but such offsetting behavior disappears after one year. Regulating the consumption of sugary drinks in child cares may be an effective policy to lower children's preferences for sugary drinks.

JEL Classification: O15, O18, P16, H54

Keywords: obesity, health, sugary beverage, children, child care regulation

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1 Introduction

The social and economic consequences of obesity have generated concern among academics, policymakers, and decision makers due to the high prevalence it has among developed countries and especially in the U.S. In particular, the prevalence of obesity has more than doubled in the U.S. in the past 30 years (Cawley, 2015). Obesity imposes a large economic burden on individuals and their families that could take the form of lost productivity and foregone economic growth as a result of lost working days, lower productivity at work, mortality and permanent disability. Also, obesity is found to be associated with lower wages, lower probability of being employed and higher medical care costs (Cawley, 2015). The standard American diet is generally characterized by an excessive consumption of calories from high-fat products and high-sugar drinks, and it has long been criticized for contributing to obesity and other related health issues, such as type-2 diabetes (Grotto and Zied, 2010).

Various policies and interventions were implemented to promote a healthy and balanced diet and prevent obesity, including a tax on sugar-sweetened beverages, informational campaigns, labeling laws and child nutrition programs (Fletcher et al., 2010; Bollinger et al., 2011; Taber et al., 2011). The main challenge in evaluating these interventions is that offsetting behavior is difficult to observe (Cawley, 2015). For example, at school, children might consume healthy food due to a school-mandated sugar-sweetened food restriction. Nevertheless, these students might purchase unhealthy foods outside of school hours, which will eventually lead to a higher consumption of unhealthy foods at home (Cawley, 2015).

In this paper, we study the effects of a California regulation that prohibits child care facilities from providing sugar-sweetened beverages to children and limits their daily provision of juice to no more than one serving per day. The regulation was enacted by the California Healthy Beverages in Child Care Act (AB 2084) and became effective on January 1, 2012. Using detailed home-scan consumption data, we investigate the potential offsetting responses and behaviors in pre-school children's overall consumption of sugar-sweetened beverages.

The rationale behind the Californian regulation, as reported in the legislation, is that almost 20 percent of children between two and five years of age in California are over-weight or obese, a pattern which is difficult to reverse in adolescence or adulthood.[1] The legislation requires California child care facilities, which include "all licensed child care homes and centers," to comply with the stricter standard of beverage serving.[2] Since 2012, California has become the first and only state in the U.S. that restrict the provision of juice and sugar-sweetened beverage in child care facilities. Juice provision is restricted to no more than one serving per day of 100% juice and other sugar-sweetened beverage such as soda are banned. Before the regulation, juice in day care facilities in California was typically served up to three or four times per day with each meal, including breakfast, lunch, dinner, and snack time.[3] One advantage to studying the consumption behavior of preschool children is that the places where they consume food and beverages are relatively limited to child care facilities and home, compared to those of adults. Therefore, household purchase of beverage and provision in child care constitute most beverage consumption by children.

We then construct appropriate counterfactuals to compare with the households whose children were affected by the sugar-sweetened regulation. To do so, we target households from the Nielsen homescan panel between the years 2004-2016 that are in unaffected states and have at least one preschool child and two working parents. We do this because we believe that children who have working parents are more likely to attend child care facilities. We adopt an exact matching algorithm to identify the matched unaffected/control households. After we identify those appropriate unaffected households, we use a difference-in-differences methodology which compares the annual juice purchase of affected households with that of matched unaffected households. We later demonstrate that we satisfy the crucial assumption for the validity of our identification strategy, which is that the trends in affected versus unaffected households were the same prior to the regulation in the sugar-sweetened beverages consumption. The results we present in this paper show a significant increase in juice purchased in the year the regu-

[1]The legislation can be found here: `http://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=200920100AB2084`.

[2]The regulation applies regardless whether the child care facility participates in the federal Child and Adult Care Food Program (CACFP) or not. The CACFP is a federal program that provides reimbursements for nutritious meals and snacks to children and adults who are enrolled for nutritional meals at specific child care centers, day care homes, and adult day care centers. The CACFP also provides reimbursements for meals served to children and youth participating in after-school care programs, children residing in emergency shelters, and older adults or chronically impaired persons with disabilities in their care. Details about the Child and Adult Care Food Program could be found here: https://www.fns.usda.gov/cacfp/meals-and-snacks

[3]Details about the Healthy Beverages in Child Care Act (AB 2084) could be found at http://www.healthybeveragesinchildcare.org/.

lation was activated for treated households compared to households with pre-school children and other similar characteristics in control states, while we control for state-specific unobserved heterogeneity. Since juice consumption is limited to one serving per day at the day care facility, this pattern indicates that affected children consume more juice at home. However, this offsetting behavior disappears the following year, in 2013, and since then it follows the same pattern of that in the unaffected households. This indicates that the overall juice consumption for pre-school children in California dropped after the regulation was enacted. What is striking is that, a few years later, in 2016, home consumption of juice in affected households decreased compared to that of unaffected households. We later provide evidence that our identification assumptions and main results are highly robust to an extensive battery of robustness exercises.

We also study whether there is any switching behavior from juice to other sugary products for affected compared to unaffected households. We do not find significant substitution effects in affected households' expenditures towards other sugary products, such as soda, ice-cream, candy and cookies; or ingredients of home-made juice, such as raw sugar and fruits, as a result of the juice ban compared to unaffected households. We then look at different subgroups of the sample. First, we find that households in areas with high child care availability are those that drive the increase in home-consumption of sugary beverages one year after the act was in effect. This indicates that these pre-school children are likely to have stronger preference towards sweetened beverages and it might be harder for them to adjust their preferences and habits. Second, we report heterogeneous treatment effects of juice consumption by household income levels. We find that households with incomes above the median are those that exhibit stronger offsetting behavior and slower adjustment of their preferences. Households in which parents work long hours or have more high-paying occupations are likely to rely more on child care facilities. Thus, these pre-school children are likely to find it harder to adjust to the sugar-sweetened beverages consumption restriction at the child care facility.

The implications of sugar consumption for children's diet and health are serious and the importance of identifying which interventions best predict behavioral changes is of paramount importance when policy makers design policies. The existing literature that evaluates the effectiveness of the various interventions on sugary drinks shows conflicting findings. In particular, the most commonly analyzed policy in this literature is a tax on unhealthy food products, such as a "fat tax" or a "sugar tax." Besides the mixed empirical results about those interventions' effectiveness and the consequences on consumer welfare loss, the main concern is that food taxes are "regressive" (e.g. Cawley, 2015; Muller et al., 2017). That is, taxes that take a larger percentage of income from low-income earners rather than from high-income earners. In a recent study, using experimental data, Muller et al. (2017) find that not only unhealthy food taxes are regressive, but also thin subsidies on healthy food favor the high-income households over the low-income ones. In this case, subsidies on healthy food are technically not regressive, but are still highly ineffective, since there is extensive evidence that high-income earners eat healthier than low-income earners (Guenther et al., 2008; Drewnowski, 2009). Additionally, high-income households exhibit a more elastic demand and are responsive to changes in the price of sugar-sweetened beverages (Zhen et al., 2011). We believe that our paper makes a substantial contribution in this literature. The evidence we provide in this paper suggest that interventions that target and reduce the early stage consumption of sugary drinks can be highly effective for pre-school children. These interventions are budget-neutral and have the potential to lead to a substantial reduction of sugar consumption in adults in the future.

Our paper also contributes to the literature on early childhood intervention. Unlike the existing literature that finds that primary or secondary schooling has little impact on obesity prevention (e.g. Brunello et al., 2013; Clark and Royer, 2013), both Frisvold and Lumeng (2011) and Carneiro and Ginja (2014) provide evidence that early childhood education could help pre-school children formulate good health habits and prevent obesity. These two papers evaluate the impact of the Head Start Program in the U.S., which provides comprehensive involvement services in education, health, and nutrition behaviors of low-income children who are below 5 years old and their families. Children are eligible to participate in this program if they are of pre-school or kindergarten age and if they live in poverty. The authors provide evidence for the effectiveness of the program, which nevertheless consists of multiple treatments in terms of education, health, and nutrition on a very particular subgroup (i.e., low-income families). Our paper complements their design and findings, showing evidence of a state-wide intervention that targeted pre-school children from the whole distribution of income and socioeconomic backgrounds. Additionally, we demonstrate that the type of food that is served at the child care facilities plays an important role in the development of children's health and diet preferences.

2 Background

Sugar-sweetened beverages contain a high added sugar content and little nutritional value, and are considered to be highly associated with poor health outcomes, including obesity, diabetes, fractures and tooth decay (Malik et al., 2006). In fact, sugar supplementation increase one's preferences for sweet foods and this has been found to be the case even for those who initially dislike sucrose (Sartor et al., 2011). Sugar-sweetened beverages could lead to obesity in preschool children because there is imprecise and incomplete compensation for energy consumed in liquid form (Ludwig et al., 2001). Juice is traditionally considered to be healthy. However, it has many potential detrimental effects, such as obesity, energy imbalances, diarrhea, over-nutrition or under-nutrition, and development of dental issues (Baker et al., 2001). Moreover, preschool children are still at the stage in which they develop their food preferences and a preference towards sweet foods could be easily attained if juice is served frequently (Birch, 1999).

California is a step ahead of all other states and in 2012 it passed legislation to establish nutrition standards for beverages served in licensed child care centers and home facilities. The legislation's goal was to improve the nutritional environment in child care, because millions of children in California enter school with unhealthy taste preferences and dietary habits that developed in early childhood environments, including child care facilities.[4]

Starting on January 1, 2012, California passed the Healthy Beverages in Child Care Act, which requires all child care facilities to limit juice to no more than one serving per day. At the same time, it promotes water consumption and prohibits all sugar-sweetened beverages. Under the law, no beverages with added sweeteners, either natural or artificial, can be served to children in child care facilities. Additionally, after January 2012, all child care facilities in California have to ensure that water is available all the time and only fat-free or low-fat milk (1%) can be served to children over the age of two. These requirements are more stringent compared to that of the federal Child and Adult Care Food Program that is in place in all states. For example, CACFP imposes no restriction on the provision of sugar-sweetened beverages. Only starting in 2016, the CACFP dietary guidelines suggest that sugar-sweetened beverages contribute to the over-consumption of sugar among children. These dietary guide-

[4]More details about the goals of the legislation can be found here: `http://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=200920100AB2084`.

lines recommend that program participants should avoid providing sugar-sweetened products to eligible children, but state that it is beyond their responsibilities to prohibit consumption of sugar-sweetened beverages. Thus, although juice has been considered less healthy, it is still included in the standard list of reimbursable beverages, meals, and snacks under the CACFP.

However, the Healthy Beverages in Child Care Act (AB 2084), in California, strictly prohibited all licensed child child care facilities to serve sugar-sweetened beverages and restricted consumption of juice to no more than one serving per day.[5] Households with a pre-school child in other states are unaffected by this intervention. This provides us with a group of affected and unaffected households that we will compare to evaluate the effectiveness of this intervention.

3 Data and Empirical Approach

3.1 Data Description

Our primary dataset is the Nielsen Consumer Panel Data from the Kilts Center for Marketing at the University of Chicago. The Consumer Panel Data is a panel dataset of household purchases. It includes about 40,000 to 60,000 households each year from year 2004 to 2016. Nielsen, the marketing company, provided bar-code scanners to participating households to record their purchases. The dataset includes information on the date, retailer location, and quantity of products each household purchased.

The purchases are identified at the bar-code level. We know a plethora of characteristics for each recorded purchase: price, quantity, and product attributes. Nielsen categorizes products according to different hierarchies. There are about 1,400 product modules, which are then grouped into 122 product groups. For example, grape juice is categorized to the product module of "Fruit Juice - Grape," which in turn belongs to the module group of "Juice, Drinks - Canned, Bottled." For the purpose of this study, we include all purchases of products that fall into group "Juice, Drinks - Canned, Bottled" as juice purchases.

Households were recruited across the U.S. and remained in the Consumer Panel for one to several years. Nielsen only retained households whose purchase data satisfy minimum quality

[5]The only exception to the policy is when the own parent or the legal guardian of the child provides the sugar-sweetened beverages to the child care facility for their own child.

criteria in the Consumer Panel Data. We therefore have an unbalanced panel of households from the 48 continental states and Washington, D.C. We have demographic information for households such as age, household composition, income, labor force participation, residential county, etc. Since California's regulation on health beverage became effective on January 1st, 2012, we aggregate household purchases by year so that our analysis is conducted at the household-year level.

We also obtained information on child care availability across the U.S. from the Census. The data for the availability of child care facilities per county are available for the years of 2002, 2007, and 2012. Using the estimated number of children below 5, we measure the child care availability in each county by the number of child care facilities per 10,000 children.[6]

3.2 Empirical Approach

3.2.1 Exact Matching Process

The legislation regulates which beverages child care facilities in the state of California can provide to pre-school children. Households that send at least one child to child care facilities in California are potentially affected by the law. If pre-school children's preferences for sugary drinks are weakened by the law, we may see a reduction in the purchase of juice and soda in these households. On the other hand, parents may purchase more juice for their children so that they could bring it to the child care facility for consumption. If such a compensating behavior exists, we may see that juice purchases increase after the enactment of the regulation. Ideally, we focus on these households as our treatment group.

Unfortunately, the Consumer Panel data does not include information on the utilization of child care facilities by the households. However, households report the number of children under the age of 6 and parents' work hours.

The average school starting age is 6 in California and 6.12 in other states.[7] Accordingly, we consider children under the age of 6 to be pre-school children who are most likely to be in child care. In total, 44,592 households in the data have at least one pre-school aged (under six

[6]Since the Consumer Panel Data only provides the number of children below 6, ideally, we could also have population estimates for children under age 6. But the Census uses kids at the age of 5 years old as the cut-off for the population grouping of different ages.

[7]*https://nces.ed.gov/programs/statereform/tab5_1.asp*

years old) child in the family at the time of the survey.

Working parents are more likely to utilize child care services. Therefore, we focus on households in which both parents work at least 30 hours a week and, in the case of single parent household, the single parent works at least 30 hours per week.

In the absence of information of actual child care usage, we define our *target group* as California's households that have at least one pre-school child and all parents work at least 30 hours per week. In total, 15,681 household-year observations satisfy the criteria of working parents with at least one pre-school aged child. Among these observations, 1,485 observations are Californian residents and 14,196 observations live outside of California.

These out-of-California households may potentially serve as our control group. However, such a control group could be quite different from the treated group due to location-related characteristics. California is more urban than the rest of the states in the U.S. and the average household income and expenditure are higher in California than elsewhere. Moreover, states differ in child care availability. The counties' average number of child care facilities per 100 children under the age of 5 is 4.3 in California and 3.5 elsewhere.[8] Kids attending child care more regularly may have different dietary preferences compared to those who do not. The general awareness of healthy diet practices may differ across states as well. Indeed, we find that the trend of household juice purchases in California is different from other states in the country.

In order to have a comparable control group, we perform an exact matching exercise. This technique matches each treated household to all possible control households with the same values on all covariates, forming subclasses such that within each subclass all units (treatment and control) have the same covariates' values. We match households from other states to households in California that have the same demographic and consumption characteristics. Our exact matching variables are the following: presence and age of children, parents' working hours per week, total expenditure[9] excluding drinks and coupons, child care availability[10] of the county where households live and whether households purchase any tobacco. One of the

[8]The number of child care facilities per 100 children for each county is calculated from the data we collected from Economic Census and Intercensal Population Estimates.

[9]In particular, we match based on the decile of total expenditure.

[10]In particular, we match based on the tertile of child care availability.

covariates is the presence and age of children. The presence and age of children are characterized by 8 categories in the Consumer Panel Data. These categories are under 6 only, 6-12 only, 13-17 only, under 6 & 6-12, under 6 & 13-17, 6-12 & 13-17, under 6 & 6-12 & 13-17 and no children under 18. Four of these categories include at least one child under 6. The composition of children of different ages may affect beverage consumption and how they change due to factors such as sibling influences. We match exactly on this categorical variable to ensure that kids under 6 have similar sibling influence for the both treated and control groups.

Five categories characterized the working hours per week for male/female head. These categories include the following groups for working hours per week: under 30 hours, 30-34 hours, 35+ hours, not employed for pay and no male/female head. Since we focus our attention to parents who work 30 hours or more, since these are more likely to send their children to child care, we exclude those parents who work less than 30 hours per week, or are not employed for pay. We match out-of-California parents or single parent to California ones with the same working hour categories. Exact matching on this variable allows us to compare households whose children spend similar time at day care.

Consumption in general and juice consumption is likely to be correlated with income. People with higher income tend to have a healthier dietary habit and are more responsive to price changes (Finkelstein et al., 2010 and Muller et al., 2017). In the Consumer Panel Data, household income is recorded two years before the panel year that records the purchase. Moreover, the income variable's values are integers that present the ranges of income, and the top range of income level is not consistent across the panel years. Since there has been literature using the household's overall expenditure as a better measurement for their income level compared to self-reported income level, we instead use households' overall expenditure to be one of the matching criteria.[11] To avoid the confound from expenditure on drinks and coupons, we use a household's total expenditure excluding drinks and coupons. We divide households in each panel year into deciles and match households within an expenditure decile in each year.

Since our focus is preferences on healthy diet, we want to compare households with similar

[11] It is quite standard to use consumption to measure the material well-being than the income for the developing countries (Banerjee and Duflo, 2007 and Deaton, 1997). In terms of U.S., Meyer and Sullivan (2003) find evidence that consumption is a better measurement than income for the poor in U.S. and Gottschalk and Moffitt (2009) find the measurement error of reported income from U.S. survey is "mean reverting," which means that the rich tends to report lower income than their actual earnings and the poor behave the opposite.

awareness of healthy lifestyle. We create a binary variable that indicates whether the household purchases any tobacco or not. We include this variable in our matching criteria.

Child care use depends on the availability of child care facilities in the local area. To measure child care availability, we obtain county-level numbers of child care facilities per 100 children using the most recent data from the Census. To compare households living in areas with similar child care accessibility, we sort households into three groups based on this measure of child care availability.

We drop 258 observations for which there were not exactly matched controls, which left us with 1,227 observations in the treated group. Table 1 reports the descriptive statistics (means and standard deviations) for the key variables that we use in our analysis. As shown in Table 1, there are 1,227 matched treated households and 4,972 matched control households. The average quantity of juice purchases in treated households is 2,858 ounces, while the average quantity of juice purchases in control households is 2,836 ounces. The juice expenditure, overall expenditure and expenditure per capita (in dollars) between matched treated and control households are very similar. The household size in treated households is 4.1, while in control households it is 3.9. Moreover, the average number of child care facilities per 100 children under the age of 5 in the control group is 4.2, which is very close to the corresponding number for treated counties which is 4.3.

	Matched Treated Group	Matched Control Group
	Households	
Juice purchased (OZ)	2858.4	2835.6
	(2742.4)	(2802.8)
Expenditure on juice ($)	104.91	101.54
	(93.23)	(98.16)
Overall expenditure ($)	4624.99	4656.70
	(2636.32)	(2492.65)
Expenditure per capita ($)	1200.46	1243.42
	(723.33)	(684.58)
Household size	4.1	3.9
	(1.2)	(1.0)
Male age	40.8	39.5
	(7.8)	(7.5)
Female age	39.1	37.8
	(7.7)	(7.4)
Single parent portion (%)	9.4	4.3
Number of households	1227	4972
	Counties	
Child care availability	4.3	4.2
	(1.0)	(1.8)

Table 1: Summary Statistics

Notes: This table reports the means and standard deviations (in parentheses) of the key variables in our paper. Upper-panel statistics are at the household level, and the lower panel includes county-level child care availability, which is approximated by the number of childcare facilities available per 100 children under the age of 5 in the county.

3.2.2 Difference-in-Differences Design

Our main empirical strategy relies on the difference-in-differences matching estimator (Heckman et al., 1998; Smith and Todd, 2005. Let C_{it} be California household i's total juice purchases in year t. Let $\mathbf{M}_{it}$ be the set of non-California households matched to household i in year t. Suppose $n_{it} = |\mathbf{M}_{it}|$, namely there are n_{it} matched non-California households for household i in year t. Also let C_{jt} be the non-California household j's total juice purchases in year t. Then, we construct ΔQ_{it} as the treatment-control difference in juice consumption:

$$\Delta Q_{it} = C_{it} - \frac{1}{n_{it}} \sum_{j \in \mathbf{M}_{it}} C_{jt}. \quad (1)$$

In our preferred specification, we regress the treatment-control difference ΔQ_{it} on a set of year indicators:

$$\Delta Q_{it} = \sum_{t=2004}^{2016} \delta_t Y_t + \epsilon_{it} \tag{2}$$

where Y_t is a set of binary indicator variables that indicate years 2004 to 2016; δ_t are the parameters of interest; and ϵ_{it} are error terms. In this specification, the observations include the set of California households for which at least one non-California household match was found.

Alternatively, we could include pair fixed effects instead of calculating the treatment-control difference first. Here, a pair is a match of a treated California household i and its non-California control household j.[12] In particular, we estimate the following specification:

$$C_{it} = \sum_{t \neq 2011} \delta_t D_{it} Y_t + d_{it} + X_{it}\beta + \epsilon_{it} \tag{3}$$

where C_{it} is the total juice consumption in year t for household i, D_{it} is an indicator variable indicating whether household i lives in California, Y_t is a year indicator, d_{it} is the pair fixed effect, ϵ_{it} is the error term, and δ_t and β are coefficients to be estimated. X_{it} is a vector of demographic variables of households i in year t. This vector includes controls for the age and presence of children in the households, the log of total expenditure excluding drinks, child care availability, binary variables that indicate whether the male head of the household is employed and whether the female head of the household is employed, tobacco usage, household composition, age of the male head, age of the female head, education level of the male head, education level of the female head, marital status, race, alcohol usage, household size, type of residence, and binary variables that indicate the presence of household member of Hispanic origin, kitchen appliances, and household internet connection. Since we conduct a year-by-year matching, year fixed effects are subsumed in the pair fixed effects. Standard errors are clustered at the pair level. In this specification, the observations include the set of Californian households and matched households outside of California. We chose year 2011 as the base year, namely the year before the legislation was enacted in California, and thus we will compare juice consumption in any other year to 2011.

For comparison, we also run a regression similar to equation (3) but instead use the full sam-

[12]See, e.g., Dube et al. (2010) for using pair fixed effects to implement a difference-in-differences strategy.

ple of households. In the full sample, the treated and untreated households are not matched. Therefore, when we use the full sample, no pair fixed effects are included in the regression. Instead, we include county fixed effects to control for time-invariant location-related heterogeneity:

$$C_{it} = \sum_{t \neq 2011} \delta_t D_{it} Y_t + \mu_c + X_{it}\beta + \epsilon_{it} \tag{4}$$

where C_{it} is the total juice purchased in year t for household i, D_{it} is an indicator variable indicating whether household i live in California, Y_t is a year indicator, μ_c is a county fixed effect, and ϵ_{it} is an error term. The coefficient of interest is δ_t, which captures the treatment-control difference before and after the enactment of California's regulation related to the base year (2011). Standard errors are clustered at the county level.

4 Results

4.1 Main Results

To see whether the parallel trend assumption that underlays our difference-in-differences approach is valid, we plot the average annual juice purchases of California households as well as the average of their matched non-California households in Figure 1.

Recall that equation (3) specifies the treatment-control difference for household i in California:

$$\Delta Q_{it} = C_{it} - \frac{1}{n_{it}} \sum_{j \in \mathbf{M}_{it}} C_{jt}.$$

Suppose in year t, N_t California households get at least one matched non-California household. The solid line in Figure 1 plots the average juice purchase in ounces by these California households between 2004 and 2016:

$$\overline{C}_t^* = \frac{1}{N_t} \sum_{i=1}^{N_t} C_{it}.$$

Similarly, the dashed line in Figure 1 plots the average annual juice purchases in ounces by the matched non-California households:

$$\overline{C}_t^o = \frac{1}{N_t} \sum_{i=1}^{N_t} \left[\frac{1}{n_{it}} \sum_{j \in \mathbf{M}_{it}} C_{jt} \right].$$

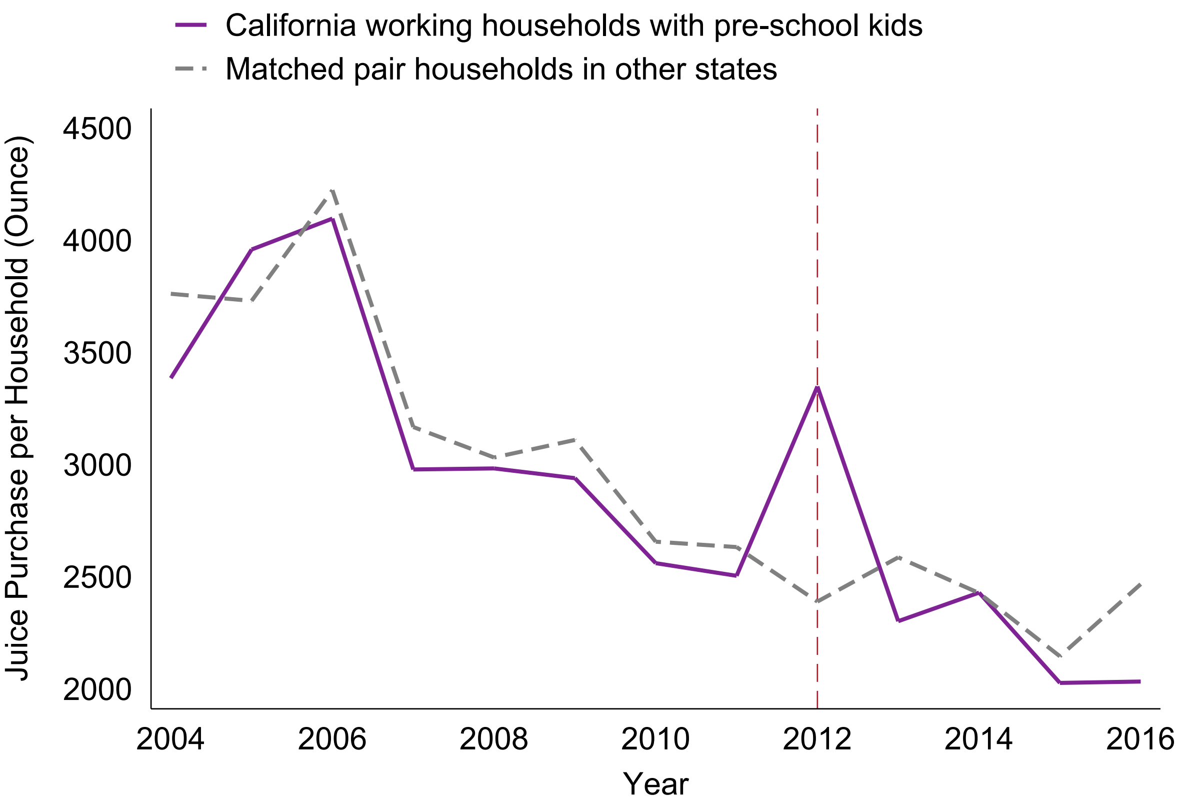

Figure 1: Juice Purchasing California Households and Matched Non-California Households

Notes: The figure plots the trends for the average annual fruit juice purchase by households where there is at least one pre-school child and all parents are working. The solid purple line represents California households. The gray dashed line matched households that share the exact demographic and other matching characteristics but reside outside of California. The red vertical dashed line indicates the first year that the California regulation on beverages in child care is enacted, i.e., Year 2012.

As shown in Figure 1, there are clean parallel trends for California households and their matches before 2012. Matched California households and their controls share a downward trend in juice consumption. However, there was a sharp increase in juice consumption in California related to the control in 2012. This juice purchase gap decreased after one year. Figure 1 suggests that in the short run, parents provided more juice at home or from home when the child care facilities regulated juice consumption in 2012.

Table 2 presents the main OLS estimates for the year indicators (δ_t) from the specification based on equations (2) to (4). The dependent variable in columns (1) and (2) is ΔC_{it}, i.e., the treatment-control difference in the quantity of juice purchases. These estimates come from estimation model (2). The specification in column (1) does not include a constant and reports the coefficient estimates for all year indicators.

The estimate in column (1) shows that, for most years before 2012, the year when the juice regulation started, the household juice purchase in California was slightly smaller compared to the matched control states. In 2012, there was a significant increase in juice purchased for the treated households, while the juice purchase difference changes from negative to positive and increases to a difference equal to 958.8 ounces at the 5% level of significance. Given that the sugar-sweetened beverages consumption was regulated at day cares after 2011, this result suggests that preschool children in California might have demanded more home purchasing juice in 2012 to substitute their reduced consumption at day care. Alternatively, this could mean that preschool children in affected households demand their parents to buy them juice and bring it to the childcare. For the following years until year 2016, estimates become statistically insignificant, with most of the signs becoming negative and small in magnitude. In 2016, the difference is decreased by 434.2 ounces at the 10% level of significance.

Column (2) is based on a similar specification to column (1), but now a constant is included in the regression model and year 2011 is the omitted baseline year. Column (2) reports the coefficient estimates for all year indicators except 2011. The pattern that we observe is the same as the one in column (1), that is, the difference in juice consumption between affected and unaffected households is statistically insignificant in all years, except 2012. In 2012, the year the juice regulation was implemented, there was a statistically significant increase in juice purchased.

Dependent Variable:	Matched Samples				Full Samples
	Juice Purchase Difference		Juice Purchase		Juice Purchase
	(1)	(2)	(3)	(4)	(5)
Year 2004	-375.978	-247.989	-259.563	-246.143	58.117
	(364.137)	(474.944)	(488.579)	(482.925)	(463.343)
Year 2005	228.939	356.928	222.664	148.000	300.957
	(411.401)	(512.081)	(404.738)	(375.343)	(315.197)
Year 2006	-126.652	1.337	34.196	-262.938	579.347
	(472.902)	(562.683)	(534.030)	(511.466)	(363.441)
Year 2007	-189.159	-61.170	-20.008	-5.342	38.179
	(276.645)	(411.714)	(307.477)	(300.716)	(283.976)
Year 2008	-48.847	79.142	117.899	174.739	176.111
	(286.945)	(418.704)	(277.253)	(273.388)	(284.526)
Year 2009	-170.236	-42.247	-24.693	58.554	-107.409
	(308.923)	(434.062)	(288.206)	(257.262)	(277.811)
Year 2010	-95.623	32.366	-46.156	-29.120	-238.294
	(264.923)	(403.931)	(283.239)	(281.429)	(160.451)
Year 2011	-127.989				
	(304.920)				
Year 2012	958.801**	1086.791**	856.397**	723.020*	629.364*
	(414.475)	(514.554)	(392.400)	(373.522)	(365.100)
Year 2013	-284.545	-156.555	-62.790	-98.768	178.635
	(432.472)	(529.158)	(576.066)	(548.701)	(363.423)
Year 2014	1.875	129.864	83.609	91.775	457.450
	(343.619)	(459.402)	(426.600)	(375.935)	(367.121)
Year 2015	-118.617	9.373	-112.532	-60.203	-61.754
	(278.380)	(412.882)	(337.604)	(302.182)	(325.479)
Year 2016	-434.163*	-306.174	-388.800	-376.491	-119.188
	(257.869)	(399.340)	(454.777)	(410.069)	(257.220)
R^2	0.011	0.010	0.313	0.363	0.333
Observations	1227	1227	6199	6199	15681
Demographic controls	No	No	No	Yes	Yes
Pair Fixed Effects	No	No	Yes	Yes	N/A
County Fixed Effects	No	No	No	No	Yes

Table 2: Juice Regulation and Household Purchase of Juice

Notes: The dependent variable in the first two columns is the weighted quantity difference of juice purchase between the matched treated and control group. Both report coefficients from equation 2. The first column reports the coefficients of all the year dummies with no constant included into the regression model. Column (2) reports the coefficients of the year dummies except for year 2011, treating it as base year to be compared with. The dependent variable in columns (3), (4) and (5) is juice purchase within a year for a household. The three columns report the coefficients for year dummy interacted with the treatment dummy, using year 2011 as the base year. Estimation in columns (3) and (4) uses the matched samples, with pair fixed effect included into the models. Households demographic controls are included in the estimation for column (4). Estimation in column (5) uses the full target samples, including county fixed effects and households demographic controls. Standard errors in parentheses are clustered by matched pair in columns (1) and (2) and by county in columns (3) and (4). N/A means not applicable.
$* \, p < 0.10$; $** \, p < 0.05$; $* * * \, p < 0.01$.

In Table 2 columns (3), (4) and (5) the outcome variable is the household's juice purchase. These three columns report the estimated effects for all year indicators interacted with the treatment indicator, 2011 is baseline year and is thus omitted. The estimation in columns (3) and (4) come from equation (4) and use the matched samples, while pair fixed effect is included in the models. Household demographic controls are included in the regressions used in column (4). The juice consumption in 2012 in affected compared to unaffected households increased by 856.4 ounces compared 2011, the baseline year, when we only include pair fixed effects in column (3). This increase is statistically significant at a 5% level of significance. When we include demographic controls in column (4), the magnitude slightly drops to 723.02 ounces and is only statistically significant at the 10% level. However, the two sets of estimates point to the same conclusion as the estimates in columns (1) and (2).

The estimated effects in column (5) correspond to equation (5) and use the full targeted sample, including county fixed effect and household demographic controls. As we would expect, when the matching process is not implemented, but we use the full sample instead, the estimate and standard error decrease for the interaction term in 2012, leading to a loss in precision. However, as we can notice the juice ban policy still induces a large increase in juice consumption in affected compared to unaffected households by 629.4 ounces.

Notice that, while the Californian regulation limits juice provision by child care, it does not prohibit parents from providing their children with juice prepared at home. One reason that parents buy more juice in 2012 is so that their children could still consume juice at child care at the amount similar to prior years. Such offsetting behaviours may be due to the demand of their own children or peer pressure if from other parents. Another reason that parent buy more juice in 2012 is that their children now consume more juice at home. While we are not able to separate or apportion the two channels, our findings suggest that there was some short-term persistence in children's juice consumption. But such persistence was short-lived.

In the years following 2012, children seem to adjust their preferences and stop demanding more juice or their parents stop prepare juice for their children to consume in child care. In the meantime, their consumption of juice at day care dropped as a result of the regulation, which means that the overall juice intake for the treated kids in California decreased. In 2016, the kids' juice consumption significantly decreased. It increased the household juice purchase difference by 1086.8 ounces on average compared to year 2011. The effect on juice consumption in year 2016, compared to year 2011, is not statistically significant but is still negative with a large magnitude. Therefore, although the coefficients are insignificant, there is suggestive evidence that the juice regulation leads to a gradual decrease in the overall juice intake for the California children affected by the policy.

Table 3 presents the main results while we vary the base year, from 2011 to any other available year in the sample. Results seem to follow the same pattern irrespective of which year is used as the baseline year. The only exception is when we use 2005 as the base year, when all year indicators estimates are insignificant– even for 2012. In all other cases, we notice an increase in juice consumption the year after the reform took place, in 2012, while in all other years the juice consumption does not differ significantly compared to 2011.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year 2004	-375.978		-604.917	-249.326	-186.819	-327.131	-205.742	-280.355	-247.989
	(364.137)		(549.405)	(596.852)	(457.305)	(463.608)	(477.524)	(450.311)	(474.944)
Year 2005	228.939	604.917		355.591	418.098	277.787	399.175	324.562	356.928
	(411.401)	(549.405)		(626.807)	(495.765)	(501.585)	(514.475)	(489.321)	(512.081)
Year 2006	-126.652	249.326	-355.591		62.507	-77.805	43.584	-31.029	1.337
	(472.902)	(596.852)	(626.807)		(547.877)	(553.149)	(564.863)	(542.052)	(562.683)
Year 2007	-189.159	186.819	-418.098	-62.507		-140.311	-18.923	-93.536	-61.170
	(276.645)	(457.305)	(495.765)	(547.877)		(398.585)	(414.688)	(383.036)	(411.714)
Year 2008	-48.847	327.131	-277.787	77.805	140.311		121.389	46.776	79.142
	(286.945)	(463.608)	(501.585)	(553.149)	(398.585)		(421.629)	(390.540)	(418.704)
Year 2009	-170.236	205.742	-399.175	-43.584	18.923	-121.389		-74.613	-42.247
	(308.923)	(477.524)	(514.475)	(564.863)	(414.688)	(421.629)		(406.962)	(434.062)
Year 2010	-95.623	280.355	-324.562	31.029	93.536	-46.776	74.613		32.366
	(264.923)	(450.311)	(489.321)	(542.052)	(383.036)	(390.540)	(406.962)		(403.931)
Year 2011	-127.989	247.989	-356.928	-1.337	61.170	-79.142	42.247	-32.366	
	(304.920)	(474.944)	(512.081)	(562.683)	(411.714)	(418.704)	(434.062)	(403.931)	
Year 2012	958.801**	1334.780**	729.862	1085.454*	1147.960**	1007.649**	1129.038**	1054.425**	1086.791**
	(414.475)	(551.711)	(583.987)	(628.829)	(498.319)	(504.110)	(516.937)	(491.908)	(514.554)
Year 2013	-284.545	91.433	-513.484	-157.892	-95.386	-235.697	-114.308	-188.921	-156.555
	(432.472)	(565.356)	(596.894)	(640.834)	(513.385)	(519.008)	(531.475)	(507.165)	(529.158)
Year 2014	1.875	377.853	-227.064	128.527	191.034	50.722	172.111	97.498	129.864
	(343.619)	(500.669)	(536.026)	(584.560)	(441.142)	(447.673)	(462.069)	(433.887)	(459.402)
Year 2015	-118.617	257.362	-347.556	8.036	70.542	-69.769	51.620	-22.993	9.373
	(278.380)	(458.357)	(496.735)	(548.755)	(392.464)	(399.791)	(415.847)	(384.291)	(412.882)
Year 2016	-434.163*	-58.185	-663.102	-307.511	-245.004	-385.315	-263.927	-338.540	-306.174
	(257.869)	(446.197)	(485.538)	(538.639)	(378.191)	(385.789)	(402.405)	(369.703)	(399.340)
R^2	0.011	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
Observations	1227	1227	1227	1227	1227	1227	1227	1227	1227

Table 3: Robustness to Different Base Year

Notes: The dependent variable in all the columns is the weighted quantity difference of juice purchase between treated households and matched control households. All columns report coefficients from equation 2. The first column reports coefficients for all year dummies with no constant included into the regression model. Columns (2) to (9) report the coefficients for the year dummies except for the year that is treated as base year. Standard errors in parentheses are clustered by matched pair.

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

Figure 2 shows the coefficient estimates for all years in the sample that arise from the regression where the treatment-control difference is the dependent variable. This figure reassures us that there are no significant differences in juice purchase between affected/treated and unaffected/control households in any year prior to the policy change. In 2012, there was a spike, which indicates that affected households react and purchase significantly more juice compared to the unaffected households. In the years following the policy change, the juice purchase pattern converges back to the pre-policy years and shows similar juice consumption patterns between affected and unaffected households. In 2016, we observe a decrease in juice purchases for affected households. These patterns are compatible with the regressions estimates that we find in Tables 2 and 3.

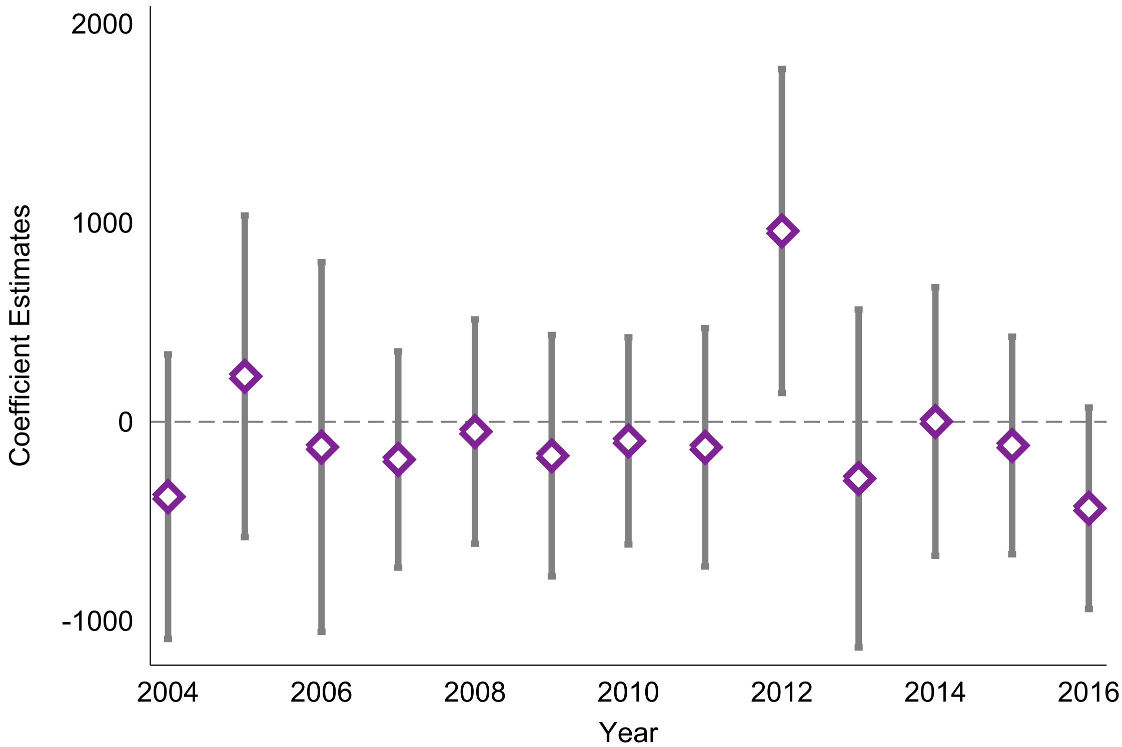

Figure 2: Coefficient Estimates from Weighted Differencing Regression

Notes: The figure plots the coefficient estimates from Equation (2). The dependent variable is the weighted difference of juice purchase between each treated households and their matched households. The coefficients represent year impact on the weighted difference.

4.2 Impact on Consumption of Substitutes

4.2.1 Defining Different Types of Substitutes

To examine whether treated children switch their preferences to other types of drinks or sugary food, we examine the impact of the policy on the consumption of goods that are substitutes to juice. We define three types of substitutes. The first type of substitutes is soda, which is also a main contributor to sugar sweetened beverages. The second and boarder type of substitutes include soda as well as the ingredients of home-made juice. Home-made juice may be healthier but still is sugary and may also include added raw sugar. Thus, we define the second type of substitutes as "Alternative Drinks," which include soda, raw sugar, and fruits. Our third type of substitutes is any other solid sugary food such as ice cream, candies, and cookies, and we call them "Sugary Foods." Unlike the unit of the quantity of juice consumed which is all "OZ (Ounce)," the unit of quantity of these types of substitutes purchased from households are not consistent. Thus, instead of the quantity of juice consumed (in ounces), we use expenditures to measure the purchase of these substitutes. Accordingly, the dependent variables in dollar term are the weighted difference of purchases, similarly to that in equation (2).

Table 4 presents the annual difference between affected and unaffected households in expenditures on soda, alternative drinks, and sugary foods in columns (2), (3), and (4) respectively. For comparison, we also regress expenditure differences spent on fruit juice on annual indicators in column (1). We find that there is no significant change of the expenditure differences on substitute goods between paired households during the sample period. These results are robust to the different compositions of sugary foods.

4.2.2 Weighted Annual Trends on Expenditure on Juice and Other Substitutes

In Figure 3, we plot the annual weighted average expenditure per household for the matched treated and control samples for all years between 2004 and 2016. From the top left to the right bottom figures, the vertical axis represents the expenditure on fruit juice, soda, alternative drinks and sugary food in dollars, respectively. The pink solid line represents the working households in California with at least one pre-school child, namely the affected group. The grey dashed line represents the matched control pairs in the other states that is the unaffected

Dependent Variable:	Weighted Difference in Expenditure			
	Fruit Juice (1)	Soda (2)	Alternative Drinks (3)	Sugary Foods (4)
Year 2004	-6.322	-13.878	-16.193	-15.266
	(11.639)	(13.642)	(17.152)	(16.698)
Year 2005	17.276	14.098	-17.816	-9.299
	(12.437)	(12.480)	(20.124)	(20.765)
Year 2006	12.059	0.770	-18.354	-9.963
	(15.322)	(13.669)	(20.071)	(24.694)
Year 2007	-1.190	-8.186	8.268	3.644
	(9.110)	(7.500)	(12.706)	(14.685)
Year 2008	3.412	-4.339	18.326	-13.611
	(9.487)	(9.627)	(12.957)	(21.999)
Year 2009	-3.885	3.816	13.440	-0.544
	(9.954)	(8.703)	(11.369)	(16.082)
Year 2010	-3.854	-8.445	2.322	-31.737
	(8.206)	(7.784)	(14.984)	(19.886)
Year 2011	-5.426	0.280	11.132	-6.155
	(9.562)	(8.513)	(13.960)	(17.092)
Year 2012	32.435**	11.387	-11.206	1.336
	(13.743)	(11.567)	(30.005)	(40.820)
Year 2013	-4.674	-5.570	-16.203	-19.202
	(15.190)	(8.063)	(18.784)	(29.045)
Year 2014	2.503	8.203	17.003	2.479
	(12.403)	(10.342)	(17.236)	(23.833)
Year 2015	9.528	-3.138	10.446	-48.789
	(10.682)	(8.607)	(21.337)	(38.702)
Year 2016	-9.225	6.849	-2.228	-12.872
	(8.217)	(10.402)	(18.712)	(27.088)
R^2	0.011	0.007	0.007	0.007
Observations	1227	1227	1227	1227

Table 4: Juice Regulation's Impact on Potential Substitute Goods

Notes: Columns (1) to (4) reports the coefficients of the yearly impact on the average expenditure differences between paired households on fruit juice, soda, alternative drinks, and sugary foods. Apart from soda, we include the potential home made juice into alternative drinks category. For sugary foods, we also include some potential solid sugary foods such as candies and cookies. Standard errors are clustered by pair.
$* \, p < 0.10$; $** \, p < 0.05$; $*** \, p < 0.01$.

group.

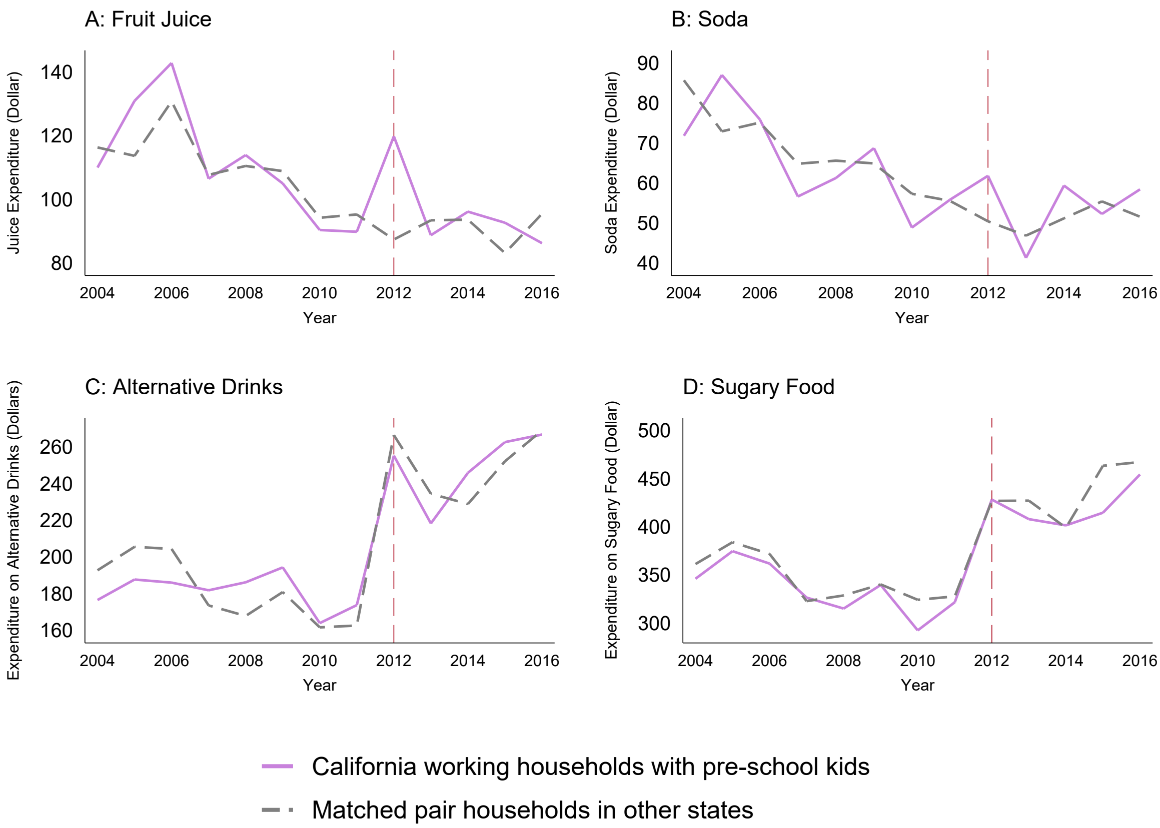

Figure 3: Weighted Trends of Expenditure on Juice and its Potential Substitutes

Notes: These figures plot the weighted average annual expenditure trends on fruit juice, soda, alternative drinks and sugary food for matched pairs from the left top subplot to the right bottom one. The vertical axes are all in dollar amount. The pink solid line represents the working households in California with at least one pre-school kids and the grey dashed line represents the matched pairs in other states.

Figure 3 panel A shows the average expenditure in fruit juice for treated and matched control households. We notice that the annual trends on expenditure in fruit juice follow a different pattern, especially in the year of the regulation. As discussed earlier, there is a significant increase in juice consumption in 2012, the year the juice ban policy was first implemented. In the other three figures, the time trends in expenditure (in dollars) for the potential substitutes of fruit juice follow a very similar trend, showing no evidence of substitution behavior. In Figure 3 panel B, we notice that the expenditure difference (in dollars) between affected and unaffected households in soda, which is a substitute for fruit juice, follows parallel trends over the sample period. The same applies to panel C, in which the expenditure trends for "Alternative Drinks" follow similar time trends in the sample period. The Alternative Drinks group combines soda, raw sugar, and fruits. The same applies to case D, in which we observe the annual trends in expenditure for “Sugary Food” to follow common time trends. Sugary food includes any solid sugary food such as ice cream, candy, and cookies.

Summarizing the patterns we observe in terms of the three types of substitutes, their figures follow parallel trends in expenditure along the sample period, we provide further evidence that it is unlikely that the kids substitute fruit juice in favor of other sugary foods and drinks.

4.3 Heterogeneous Treatment Effects by Child Care Availability and Income

4.3.1 By Child Care Availability

In order to gain further insight into the effects of child care juice banning on children's behavior and preferences we explore heterogeneous effects across different dimensions. The juice regulation applies to all child care facilities in California. It is worthwhile to examine whether the regulation had a differential impact on household juice purchase across regions with different levels of child care availability and income.

In Table 5 column (1), we report the baseline estimates that are shown in Table 2 as a point of comparison, using all matched observations. In columns (2)-(5) we present the estimated effects of the regulation on juice consumption and expenditure for different levels of child care availability, based on different stratifications of the sample. In particular, in columns (2) and (3) we group households based on the three quantiles of child care availability in the county in which the household lives. The upper quantile is defined as households in counties with the highest level of child care availability, while the lower quantile is defined as households in counties with the lowest level of child care availability. The middle quantile consists of households in counties with a middle level of child care availability. Since the state of California in general has a high level of child care availability, the number of observations that are categorized as being in the upper quantile in the matched sample is 760, accounting for more than 60% of the total number of matched observations. We also use a complementary way to divide the regions as above and below the median based on child care availability in the county in which the household lives and the estimated effects are reported in columns (4) and (5), respectively.

Dependent Variable:	Juice Purchase Difference						
		Level of Child Care Availability				Level of Expenditure	
	Baseline (1)	High Level (2)	Middle&Low Level (3)	Above Median (4)	Below Median (5)	Above Median (6)	Below Median (7)
Year 2004	-375.978	-204.665	-730.419	-331.005	-431.070	-567.791	-219.396
	(364.137)	(436.831)	(680.106)	(451.784)	(637.488)	(794.883)	(232.722)
Year 2005	228.939	494.717	-555.105	588.143	-178.805	308.907	111.486
	(411.401)	(450.459)	(920.637)	(561.928)	(572.658)	(648.667)	(392.205)
Year 2006	-126.652	103.950	-1363.521	128.586	-615.859	-321.358	3.152
	(472.902)	(483.372)	(1546.220)	(603.824)	(747.672)	(851.411)	(493.966)
Year 2007	-189.159	118.200	-766.993*	123.402	-501.720	-310.578	-92.023
	(276.645)	(332.917)	(451.376)	(384.994)	(356.627)	(444.312)	(343.583)
Year 2008	-48.847	189.961	-486.662	159.409	-276.328	95.450	-193.145
	(286.945)	(366.015)	(432.270)	(370.719)	(358.771)	(526.215)	(202.086)
Year 2009	-170.236	-239.151	-48.815	-110.308	-241.472	-617.072	192.818
	(308.923)	(422.661)	(431.180)	(482.024)	(355.702)	(508.247)	(335.999)
Year 2010	-95.623	-38.966	-203.626	115.557	-375.437	-315.337	119.416
	(264.923)	(319.032)	(470.565)	(288.625)	(458.961)	(439.250)	(271.496)
Year 2011	-127.989	-158.807	-56.973	-48.029	-257.579	-177.955	-75.322
	(304.920)	(381.853)	(502.444)	(429.567)	(414.071)	(477.049)	(386.066)
Year 2012	958.801**	1488.683**	143.599	1269.134*	666.723	1827.445***	-83.571
	(414.475)	(586.280)	(474.233)	(705.906)	(502.646)	(638.028)	(421.026)
Year 2013	-284.545	169.457	-616.741	-800.259	-37.431	-617.194	98.506
	(432.472)	(873.475)	(387.645)	(693.132)	(548.493)	(768.699)	(286.542)
Year 2014	1.875	374.655	-397.533	167.669	-120.813	-232.537	230.959
	(343.619)	(550.273)	(375.408)	(488.844)	(427.840)	(574.176)	(397.585)
Year 2015	-118.617	38.122	-246.567	-475.119	101.767	-35.612	-235.272
	(278.380)	(492.462)	(310.078)	(444.917)	(364.743)	(439.231)	(232.232)
Year 2016	-434.163*	31.257	-925.440**	-331.303	-504.295	-420.776	-450.495*
	(257.869)	(340.942)	(374.175)	(351.539)	(372.558)	(431.322)	(233.967)
R^2	0.011	0.017	0.043	0.020	0.015	0.025	0.009
Observations	1227	760	467	614	613	614	613

Table 5: Heterogeneous Effect

Notes: The dependent variable is the weighted quantity difference of juice purchase between the matched treated and control group. In column (1), we report baseline estimates from Table 2 in column (1) for comparison, using all matched observations. Columns (2) and (3) report the effect on households from regions with high level of child care availability and middle&low level of child care availability respectively. The criteria for segment are consistent with the matching process. Columns (4) and (5) report the effect for households in counties with the upper median child care availability and counties with below median child care availability, respectively. Columns (6) and (7) report the effect for households with upper median overall expenditure level and those with below median overall expenditure level, respectively. Standard errors in parentheses are clustered by matched pair.

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

The estimates in columns (2) to (5) indicate that the increase in juice consumption in 2012 was driven by households in counties with high level of child care availability. In particular, the estimate in column (2) suggests that households in counties with high level of child care availability in California purchased 1488.7 ounces more juice in 2012 relative to their matched pairs who live in the same level of child care availability in other states. Interestingly, the juice consumption pattern for households in areas with high child care availability is different compared to that in the baseline model in column (1). The estimated effects in column (2) are all positive and the magnitudes decrease over time, which means that the juice purchase level for the treated households living in counties with high level of child care availability are still higher compared to their matched unaffected households, even after 2012.

This could imply that kids on average in counties with high child care availability attend child care more regularly, which means that those kids are more likely to have more persistent juice preference and it might be harder for them to switch tastes when the juice regulation is enacted. On the other hand, column (3) suggests that there is not a significant substitution effect in 2012 for treated kids who live in counties with middle or low level of child care availability. In the following years, the estimated effects become negative but insignificant. However, in 2016 the juice purchase for treated households in counties with middle or low level of child care availability is significantly lower than that their matched control pairs by 925.4 ounce, at a 10% level of significance. This reinforces the argument that kids that attend child care more regularly have a strong preferences for juice, while kids who attend child care less regularly would more easily switch their preferences.

However, the number of observations in column (3) is smaller than those in column (2). As a robustness check, we run the regressions separately for households above (column 4) and below (column 5) the median child care availability and the number of observations is similar in those two groups. The pattern is similar to that in columns (2) and (3). Comparing the estimates in columns (4) and (5), we notice that the increase in juice consumption in 2012 was driven by households in counties with above the median child care availability. Persistent to the previous results, the increase in juice consumption in 2012 was driven by kids who are likely to attend child care more regularly.

4.3.2 By Income

In columns (6) and (7) of Table 5, we report separate estimates for kids in households with income above and below the median, respectively. To deal with inconsistencies in the way the income variable is categorized,[13] we use the overall expenditure in non-drinks to approximate the household income level and report the heterogeneous effect by income.

The estimates in column (6) suggest that treated households with income above the median in California consume on average 1827.4 ounces more juice relative to their matched pair households in other states in 2012. On the other hand, the estimated effect in 2012 for households in counties with income below the median is negative and insignificant.

Overall, the increase in juice in 2012 seems to be driven by households that live in counties with high child care availability and that have above-median income. This may be due to two reasons. First, the effects might be driven by kids in urban areas. Households in urban areas may earn relatively more and urban areas tend to have higher child care availability. Second, households in which the parent(s) work longer hours tend to earn more and they are likely to put their kids in child care due to the long working hours.

Therefore, preschool kids from households with higher income level might attend child care more regularly and find it harder to adjust to the new juice policy at child care. Households with lower income levels might send their preschool kids less regularly to child care due to the limited child care availability or due to not working may keep their kids home rather than putting them in care. These households did not seem to experience an increase in their juice consumption in 2012. Instead, they decreased their juice purchases in 2016. As a result, kids that attend child care less regularly are more likely to adjust to the new child care policy more quickly and might consume less juice at home at the end of the sample period.

4.4 Robustness of the Estimates

In this section, we present a set of robustness checks and alternative specifications that support the causal interpretation of our main findings.

The baseline definition of juice that we use so far is that juice includes only fruit juice.

[13]The income variable is a categorical variable and the values for the top range of household income changes over time.

However, there are also other types of juice, including fruit punch, syrups, cider, clam juice, and vegetable juice. In Table 6, we present our main estimates while we change the definition of juice and we re-run the main specification. In column (1) we report the main specification using the baseline definition. In column (2) we also include fruit punch and syrups into the juice category, re-run the main specification and report the estimates for each year indicator. In column (3), we further include cider and clam juice to the juice definition and re-estimate the year indicators on the juice purchase differences between affected and unaffected households. The pattern in Table 6 is very similar to that in Table 2 and it does not depend on the adopted definition of juice. In particular, there was a statistically significant increase in juice consumption in 2012. The estimates based on all three definitions of juice are very similar and insensitive to the different definitions for juice; 958.801, 958.117 and 941.966 in columns (1), (2) and (3), respectively. All three estimates are significant at a 5 % level of significance. In the following years, juice consumption drops substantially. In 2016, this drop in juice consumption of affected compared to unaffected households becomes statistically significant and it does not depend on which definition of juice we adopt.

In columns (4) to (6), we examine the impact of the regulation on juice expenditure rather than juice consumption. We report the estimates for all year indicators that represent annual changes in juice expenditures between affected and unaffected households. In column (4) we restrict juice to fruit juice, in column (5) we also include fruit punch and syrups, while in column (6) we further include cider and clam juice to the juice definition. As we notice in Table 6, whether we include the extra juice types does not really affect the estimates between columns (1) and (3), or columns (4) and (6). While in columns (4) to (6) we use the juice expenditure as the dependent variable, the substitution effect in year 2012 is still large and significant. Juice regulation increased the difference in expenditure between affected and unaffected households by more than 30 dollars per household on average in 2012. This difference is significant at a 5% level of significance. In the following years, juice expenditure dropped substantially. In 2016, we observe a negative effect on juice consumption between affected and unaffected households, which is statistically significant. The difference in juice expenditure is also negative in the following years, but statistically insignificant. These patterns remain unchanged no matter which definition of juice we adopt.

Dependent Variable:	Juice Purchase Difference			Juice Expenditure Difference			Juice Purchase Difference		
							Truncated samples		
	Baseline (1)	Include punch (2)	All juice (3)	Fruit juice (4)	Include punch (5)	All juice (6)	Fruit juice (7)	Include punch (8)	All juice (9)
Year 2004	-375.978	-375.793	-383.061	-6.322	-6.746	-6.360	-104.461	-108.107	-105.905
	(364.137)	(365.570)	(364.765)	(11.639)	(11.707)	(11.647)	(254.999)	(255.275)	(256.264)
Year 2005	228.939	225.610	225.044	17.276	16.880	17.070	327.937	323.510	348.788
	(411.401)	(411.754)	(408.604)	(12.437)	(12.494)	(12.422)	(341.152)	(341.418)	(331.871)
Year 2006	-126.652	-125.873	-167.706	12.059	11.972	11.454	-26.893	-26.010	-65.149
	(472.902)	(472.901)	(474.307)	(15.322)	(15.311)	(15.333)	(357.191)	(357.142)	(357.946)
Year 2007	-189.159	-189.852	-202.746	-1.190	-1.494	-1.502	77.414	77.559	88.375
	(276.645)	(277.033)	(279.934)	(9.110)	(9.137)	(9.189)	(240.205)	(240.259)	(241.175)
Year 2008	-48.847	-47.696	-62.638	3.412	3.337	2.955	198.047	180.732	185.998
	(286.945)	(286.580)	(286.803)	(9.487)	(9.447)	(9.474)	(227.244)	(225.960)	(227.109)
Year 2009	-170.236	-170.567	-192.012	-3.885	-4.116	-4.587	-35.843	-36.187	-66.384
	(308.923)	(309.149)	(310.089)	(9.954)	(9.982)	(9.973)	(304.110)	(304.425)	(302.496)
Year 2010	-95.623	-97.755	-120.470	-3.854	-4.144	-4.538	-15.463	-16.721	-40.313
	(264.923)	(265.178)	(266.083)	(8.206)	(8.219)	(8.247)	(243.078)	(242.947)	(243.323)
Year 2011	-127.989	-128.678	-144.932	-5.426	-5.337	-5.319	-116.203	-161.572	-131.955
	(304.920)	(304.950)	(304.930)	(9.562)	(9.524)	(9.677)	(261.129)	(261.128)	(260.515)
Year 2012	958.801**	958.117**	941.966**	32.435**	31.994**	31.994**	740.344*	739.716*	724.287*
	(414.475)	(414.400)	(413.840)	(13.743)	(13.594)	(13.693)	(384.719)	(384.496)	(384.135)
Year 2013	-284.545	-284.524	-291.338	-4.674	-3.682	-5.012	-333.377	-334.694	-274.360
	(432.472)	(433.191)	(433.009)	(15.190)	(16.560)	(15.262)	(254.099)	(253.986)	(271.073)
Year 2014	1.875	0.364	-23.537	2.503	2.451	1.846	-25.359	-19.997	-51.203
	(343.619)	(343.691)	(344.709)	(12.403)	(12.456)	(12.386)	(310.341)	(311.174)	(311.773)
Year 2015	-118.617	-119.767	-135.427	9.528	8.692	8.968	-210.845	-209.739	-228.148
	(278.380)	(277.504)	(277.245)	(10.682)	(10.496)	(10.611)	(254.020)	(254.082)	(252.283)
Year 2016	-434.163*	-434.754*	-460.891*	-9.225	-9.968	-10.232	-177.555	-178.175	-288.907
	(257.869)	(257.502)	(257.438)	(8.217)	(8.204)	(8.194)	(204.457)	(203.971)	(196.012)
R^2	0.011	0.011	0.011	0.011	0.011	0.011	0.009	0.009	0.010
Observations	1227	1227	1227	1227	1227	1227	1188	1190	1187

Table 6: Robustness Exercises for the Main Estimates

Notes: The dependent variable is the weighted difference of juice purchase between the matched treated and control group. In column (1), we report baseline estimates from column (1) of Table 2 for comparison. The baseline estimates use all matched observations. Columns (2) and (3) report the effects on households from regions with high level of child care availability and middle&low level of child care availability respectively. The criteria for segment is consistent with matching. Columns (4) and (5) report respectively the effects on households from counties with above-median child care availability and counties with below-median child care availability. Standard errors in parentheses are clustered by pair.

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

To make sure that outliers are not driving our estimates, we perform an exercise that truncates the sample and we re-estimate the main specification while the outcome variable is the difference in juice purchase between affected and unaffected households. In particular, we exclude households that purchase excessive quantities of juice and are at the upper 99% percentile level of juice consumption, as well as those households that do not purchase juice at all (more than lower 1% percentile) according to the distribution of juice purchase from the full sample. The Nielsen Company which constructed the consumer panel dataset targeted households that are demographically diversified and geographically dispersed to cover a large range of socioeconomic backgrounds and geographic accessibility to services and facilities. In our paper, we only target a specific group of households. That is, those households in which both parents are working and have at least one pre-school kid; we consider them to be our targeted households. The full sample includes those targeted households, but also households that are not in our targeted group. The mean quantity of juice purchased between targeted households and non-targeted households is quite different. On average, targeted households purchase more juice compared to non-targeted households. Thus, the idea behind this is that by truncating the sample of matched households, the sample becomes more similar to the full sample.

After we drop those households, we re-run our main specification which is equivalent to the one in columns (1), (2), and (3) and we report the estimates for the year indicators in columns (7), (8), and (9). In column (7) we consider the baseline definition of juice; in column (8) we also include fruit punch juices and syrups; in column (9) we include all other types of juice. The juice regulation affected the juice purchased between affected and unaffected households in 2012, which is the same pattern we observed in columns (1), (2) and (3). The difference in juice consumption is significant at the 10% level of significance, while the magnitude of the estimate is slightly smaller. However, the impact on juice purchase in year 2016 is not significant anymore and the magnitude drops, implying that by truncating the sample, we lose efficiency.

We notice that the most augmented definition of juice used in columns (3), (6), and (9) does not include vegetable juice. The reason is that vegetable juice is considered to be a healthy option and usually it is not preferred by kids. But even if we include the vegetable juice into the fully augmented juice definition and we re-run our main specifications, the estimates remain nearly unchanged.

5 Conclusions

In this paper, we exploit a reform that took place in 2012 in California which regulated the provision of sugar-sweetened beverages for pre-school children in child care facilities. In particular, child care facilities only in California, had to restrict the quantity of juice from 4 to 1 servings per day and encourage water consumption instead. This regulation aimed at reducing the sugar-sweetened beverages consumption and changing children's preferences for sugary drinks from an early age.

The rationale behind this regulation is to promote a healthy and balanced diet and prevent obesity. The prevalence of obesity is a major issue in developed countries and is also associated with elevated mortality and other serious health problems, such as type-2 diabetes, hypertension, and asthma (Must et al., 1999). A fundamental issue with obesity is that people have time-inconsistent preferences. That is, eating is immediately enjoyable while losing weight is not and the benefits of losing weight are not immediate, but they are in the distant future (Cawley, 2015). Ruhm (2012) models two decision systems, the rational and the impulsive, to explain the propensity to overeat energy-dense food.

The combination of economic and biological factors is likely to result in overeating readily available food (Ruhm, 2012). Ruhm (2012) models two decision systems, and argues that food consumption reflects the interaction between two parts of the brain: a deliberative system that makes decisions as traditional models in economics and an impulsive system that responds rapidly to stimuli, but does not account for long-term consequences. Extensive literature focused on the optimal incentives to help consumers overcome the impulsive decision system (e.g. Cawley and Price, 2013; Just and Price, 2013; Charness and Gneezy, 2009). The basic assumption underlining both decision models is that consumers prefer energy-dense food over healthy food and the food preferences, partially those decided by one's genes, also depend on the eating environment and child-feeding practices (Birch, 1999).

Our paper provides empirical evidence that pre-school children's preferences for sugar sweetened beverages could be reversed if they are provided with alternative, healthier options. As a consequence of the regulation, in affected households, there was a sudden offsetting behavior to compensate for the quantity of juice that they could not consume at day care anymore. This is the case especially for those children who are found to attend day care very regularly and are likely to get used to the original unhealthy serving pattern. In particular, there was a significant increase in the juice consumption at home for the year following the reform as compared to the unaffected households. However, we find that a couple of years after the regulation was enacted, pre-school children in affected households quickly stopped demanding more juice at home, and they even reduced their juice consumption, suggesting that their preferences are not time persistent yet. This might be a budget-neutral and effective policy tool to limit the well-known obesity problem, which starts in the early stages of a child's life. Along with the increasing female labor force participation, it is important to note that children's preferences can change due to policies implemented at the child care facility. This contributes to the argument that child care services become more and more important for a child's development.

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