Association Between Seattle's Sweetened Beverage Tax and Change in BMI Among a Patient Population of Youth

THE EVALUATION OF SEATTLE'S SWEETENED BEVERAGE TAX

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Jones-Smith JC, Chakrabarti S, Knox M, Mooney S, Walkinshaw LP, Arterburn D, Eavey J, Godwin J, Chan NL, Saelens BE.

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CONTACT INFORMATION

Jessica C. Jones-Smith, PhD
jjoness@uw.edu
415-613-6047

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CONTENTS

ASSOCIATION BETWEEN SEATTLE'S SWEETENED BEVERAGE TAX AND CHANGE IN BMI AMONG A PATIENT POPULATION OF YOUTH

EXECUTIVE SUMMARY

Objective

This study used a quasi-experimental design to evaluate the association between Seattle's Sweetened Beverage Tax (SBT) and changes in body mass index (BMI), a measure of obesity, among a patient population of children and youth in Seattle and surrounding areas.

Methods

We used data from electronic medical records for visits anytime from 2014 to 2019 to Kaiser Permanente Washington Health System (KP) centers and Seattle Children's Odessa Brown Children's Clinic (abbreviated OBCC) among children aged 2-18 years to compare changes in children's weight status (based on a BMI metric that accounts for age and sex) from before to after tax implementation for those living in Seattle versus those living in three nearby Washington counties outside Seattle (King County (excluding Seattle), Pierce County, and Snohomish County). The BMI metric is currently recommended by the Centers for Disease Control and Prevention (CDC) when the goal is to evaluate the impact of an intervention on children's weight status. It takes a child's BMI as a percentage of the BMI value at the 95th percentile of BMI in an age- and sex- matched U.S. Reference population. For short, this is referred to as "BMI%95th."

We used two types of statistical weighting in our analyses to account for measurable differences between people living in Seattle and in the surrounding areas that might also influence BMI%95th change over time (such as neighborhood characteristics or age). Our initial weighting created more balance on confounders (such as age and neighborhood characteristics) between people living in Seattle and those living in the comparison areas allowing us to better isolate BMI%95th changes that were uniquely due to the tax. However, in our preferred models, we pursued additional weighting to balance differential trends before the tax in BMI%95th.

Our primary statistical models used to evaluate the associate between the tax and BMI%95th were two different types of difference-in-difference models—first difference models and a synthetic control difference-in-difference model.

Results

The final sample for the first difference models consisted of 24,097 unique patients each observed twice. Of these, 7,078 patients lived in Seattle and 17,019 live outside of Seattle but within one of the three surrounding counties (King County (excluding Seattle), Pierce County and Snohomish County). The synthetic control difference-in-difference models had to be restricted to a subsample of patients who had at least 1 BMI measurement per year for all six years and thus included 4,170 patients.

Overall, the results from both the first difference models and the synthetic control difference-in-difference models indicate that the tax was associated with less increase in BMI%95th as evidenced by lower increases from before to after the tax among children living in Seattle versus the comparison area. Our preferred, more conservative model, the synthetic control difference-in-difference, suggested the tax was associated with a 0.99 percentage point decrease in BMI%95th, which would be a 1.2% reduction from baseline levels of BMI%95th in Seattle (which was approximately 84%). This is a small, but reasonable, beneficial effect associated with the timing of Seattle's Sweetened Beverage Tax.

INTRODUCTION

Seven cities in the U.S., including Seattle, have implemented Sweetened Beverage Taxes. These taxes were pursued with the goal of improving population health by disincentivizing intake of sugar-sweetened beverages, the single largest contributor to added sugar intake in the U.S. As described in the accompanying report on the impact of these taxes on BMI among adults in Seattle, only two previous studies have examined the potential impact of sweetened beverage intake on BMI. Both of these studies are among children and adolescents. One study evaluates Mexico's sweetened beverage tax and finds it is associated with a reduction in obesity prevalence among adolescent girls.[1] The second study examines sweetened beverage taxes in Philadelphia, San Francisco, and Oakland and finds evidence for a reduction in average BMI among youth associated with these taxes (as compared to youth in comparison areas).[2]

In this report, we evaluate the association between Seattle's Sweetened Beverage Tax and BMI among children and youth, which accompanies our evaluation of the same associations among adults. Any impacts of such a tax could be different for children and youth versus adults for a number of reasons. First, adults with children may change the beverages they feed their children in response to the health signaling effects of "sin taxes" more readily than they change their own intake. Second, children may respond differently to a change in price of these products than do adults. Third, adolescents in the U.S. on average are high consumers of sweetened beverages, and therefore may be more impacted by price changes of the tax and have more room to make behavioral changes to their diet. Additionally, the prevention of increases in BMI among children and youth through population-level policies such as a sweetened beverage tax might be more physiologically tenable compared to incurring weight loss among adults. Finally, it is expected that children will gain weight and height through childhood, so we need to account for this in the metric used to evaluate the impact of taxes on proxies for adipose (fat) tissue in children and youth.

METHODS AND RESULTS

Many of the methods for the analyses of the association between Seattle's Sweetened Beverage Tax and children's body mass index using data from electronic health records are the same as described in the accompanying report on the tax and adult body mass index. For the sake of brevity, we will not repeat details here. Elements that differ from the methods outlined in the accompanying report are described below.

Study Sample

The study sample was limited to children and youth residing in three counties: King, Pierce, and Snohomish who were between the ages of 2-18 years at any point during the period from January 1, 2014, to December 31, 2019, and who received primary care at the Kaiser Permanente Washington Health System or the Seattle Children's Odessa Brown Children's Clinic (OBCC). Additional exclusion criteria were the same as described in the report on adult BMI outcomes (excluding those individuals with bariatric surgery or cancer and observations surrounding a pregnancy). For excluding extreme BMI values, we removed those individuals whose BMI z-score was <-5 or >+8, which has been identified by the Centers for Disease Control and Prevention as likely to be implausible or erroneous. Additionally, for our "first difference" analyses (described further below), we removed individuals with a very large change in BMI corresponding to the 1st and 99th percentile of the distribution (<-81 and >95 percentage point change).

Outcome

Our outcome of interest was a measure of body mass index (BMI, weight in kilograms/height in meters squared) currently recommended for evaluating the impact of interventions on BMI among children—the BMI expressed as a percentage of the BMI value of the 95th percentile of BMI for an age- and sex-matched reference population. BMI expressed as a percentage of the BMI value at the 95th percentile for an age and sex matched reference population (henceforth abbreviated BMI%95th) is a newly recommended measure[3] of BMI that is better at capturing change in BMI among populations in which overweight and obesity are prevalent, such as among U.S. children. Extreme obesity in children has previously been defined at having a BMI that is 120% of the BMI at the 95th percentile of the distribution of

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[1] Gračner T, Marquez-Padilla F, Hernandez-Cortes D. Changes in Weight-Related Outcomes Among Adolescents Following Consumer Price Increases of Taxed Sugar-Sweetened Beverages. JAMA Pediatr. 2022;176(2):150-158.

[2] Flynn J. Do sugar-sweetened beverage taxes improve public health for high school aged adolescents? Health Econ. 2022;(October 2021):47-64.

[3] Hales CM, Freedman DS, Akinbami L, Wei R, Ogden CL. Evaluation of alternative body mass index (BMI) metrics to monitor weight status in children and adolescents with extremely high BMI using CDC BMI-for-age growth charts. National Center for Health Statistics. Vital Health Stat 2(197). 2022.

the age- and sex-matched CDC reference population. When comparing change in the BMI%95th, lower numbers imply a lower weight status and negative values suggest a reduction in child weight status. For example, suppose a child had a BMI of 18 and the BMI at the 95th percentile for age and sex was 17 at their first visit. Their BMI%95th would be (18/17)X100= 105.9% of the BMI value at that 95th percentile of the distribution. If at their second visit, their BMI was 17.5 and the referent BMI for their age was now 18, then their BMI%95th would be 17.5/18 = 97.2%. Change over time would be second visit BMI%95th (97.2) – first visit BMI%95th (105.9) = -8.7 percentage point (pp) change.

Weight and height were obtained from electronic health records for visits made within Kaiser Permanente Washington Health System and OBCC, the latter being the only primary care clinic of Seattle Children's. When weight was measured at a clinic visit, but height was not measured on the same day, we imputed height based on a random effects model of height growth over time.

Exposure

The exposure of interest is Seattle's Sweetened Beverage Tax. Addresses linked to each clinic visit were geocoded to determine whether the address was inside or outside of Seattle. We classified children and youth as exposed to the tax if their geocoded address was either inside the Seattle city limits (for OBCC) or in a census tract that was inside or touching the Seattle boundary (KP) (due to different geocoding protocols for data from each of the health systems).

Brief statistical methods

We used a version of propensity score weighting as one method of balancing potential confounders of the relationship between exposure to the tax and BMI outcomes. The process used was fine stratification average treatment effect (FSATE) weighting and is described in the **Appendix**.

To identify the effect of the tax on child and youth BMI%95th, we initially planned to use three models, as described in the accompanying report on adult BMI (the first difference, comparative interrupted time-series, and event study models). However, two of those models—the comparative interrupted time-series and the event study models suggested that our models were not adequately controlling for differential trends in BMI%95th before the tax was implemented. This indicated that our models may be overstating the impact of the tax. For this reason, we pursued a different model in attempt to better control for differential pre-tax trends between Seattle and the comparison area. This model is a synthetic control difference-in-difference model. It involves weighting the comparison sample such that the average pre-tax trend is as similar as possible to Seattle and then evaluating whether the trends differ after the tax. We therefore present the first difference models and the synthetic control models in the main report. We show the comparative interrupted time-series models and the event study models in the **Appendix**.

Model 1: First Difference Model

The first model to test whether the BMI metric changed differently among children living in Seattle versus the comparison area was a simple "first difference" model. Specifically, for each child we took their BMI%95th value from the visit closest to but not after December 31, 2017 (last day before the tax went into effect) for the pre-period BMI%95th and subtracted this from their BMI%95th measurement closest to but not after January 1, 2020 (the day after the last day in the post-tax period for this study). This allows for the evaluation of the most time after the tax went into effect compared to the child's weight status as close as possible to when the tax was implemented. We then divided this by the number of days between the measurement dates and multiplied by 365.25 days in a year to create our annualized BMI%95th change measure. This value is used as the outcome in this first difference model. We then modeled annualized BMI change as a function of Seattle residence or non-residence. The result from this model can be interpreted as the difference in the BMI metric (BMI%95th) change from before to after the tax in Seattle, beyond the change seen in the comparison area. In addition, this model includes time-varying insurance type (e.g., to account for whether an individual changed type of insurance from commercial to public insurance from one point to the next, as a proxy for socioeconomic status) and an indicator for age group (to capture the general change in rate of BMI growth between 2-5 and 6-18).

Population-specific effects

To explore the degree to which the association between the tax and BMI%95th change is stronger in any population group, we ran the weighted model above separately for different population groups. Specifically, we ran models separately by age, sex, racial and ethnic identity, by medical center (KP or OBCC), insurance type, and by pediatric medical complexity algorithm (a score to summarize the medical complexity of each patient, which is based on the number and severity of underlying health conditions).[4]

Model 2: Synthetic Control Difference-in-Differences

Since both the CITS and the Event Study models suggested that the FSATE weighting was not balancing confounders adequately to equalize trends in child weight status in the pre-tax period (see Appendix for details), we fitted a type of statistical model that explicitly works to balance pre-policy trends in the outcome by weighting observations in the comparison area sample such that those with similar trends in the outcome in the pre-tax period are weighted more heavily. This creates a comparison area sample that has closer-to-parallel trends before the tax to the Seattle sample and therefore we can be more confident that any divergence in the trends in the post-tax period is due to the tax. To run this model, it is required that we create a "balanced panel" which means that all children are measured the same number of times over the course of the study period at the same time (which in our case we considered in the same year). To create such a subsample from our original sample, we limited this analysis to children who had at least one BMI measurement in all six years of our observation period (four in the four years before the tax and two in the two years after the tax). For those who had more than one BMI measurement in a year, we considered the mean of their BMI measurements in each calendar year to represent the BMI for that year.

Results

The final sample consisted of 24,097 unique patients each observed twice in the first difference models. Of these, 7,078 patients lived in Seattle and 17,019 lived outside of Seattle but within one of the three surrounding counties (King County (excluding Seattle), Pierce County, and Snohomish County). There were 2,909 children visiting OBCC and 21,188 were from KP. The subsample of patients who had at least one BMI measurement per year for all six years was 4,170 patients who were included in the synthetic difference-in-difference models.

Table 1 displays unweighted and weighted (explained further below) sample characteristics of patients living in Seattle and the comparison area. The unweighted populations were modestly different between Seattle and the comparison area on some individual-level (e.g., age) demographic characteristics and substantially different on some area-level characteristics (census tract-level racial/ethnic composition). Specifically, modest differences were seen in individual-level age composition, with patients living in Seattle versus the comparison area more likely to be in the youngest age categories and less likely to be in 10–14-year-old age category. Additionally, the Seattle sample as compared to the comparison area sample had a lower proportion of the population who reported as American Indian/Alaskan Native, Asian, more than one race, Native Hawaiian or other Pacific Islander; and a higher percent who reported as Black/African American.

The pediatric medical complexity score indicated that patients in Seattle had modestly lower levels of non-complex chronic conditions and complex chronic conditions. There were large differences in patient insurance type with patients living in Seattle substantially less likely to have commercial insurance.

Census tract racial composition indicators (which are based on Census data linked to patient addresses and not our patient sample characteristics) were modestly different between Seattle and the comparison area for most categories of racial and ethnic population composition at the tract level (**Table 1**). Census tract proportion of Hispanic, American Indian/Alaskan Native, Native Hawaiian/Other Pacific Islander, and White populations were lower and proportions of Asian and Black populations were higher in Seattle versus the comparison area. Census tract proportion of two or more races and other racial identity were similar between the two areas. There were also modest differences in the average tract-level percent of the population who moved in that last year and in the average tract-level percent of the

[4] Tamara D. Simon, Mary Lawrence Cawthon, Susan Stanford, Jean Popalisky, Dorothy Lyons, Peter Woodcox, Margaret Hood, Alex Y. Chen, Rita Mangione-Smith; for the Center of Excellence on Quality of Care Measures for Children with Complex Needs (COE4CCN) Medical Complexity Working Group, Pediatric Medical Complexity Algorithm: A New Method to Stratify Children by Medical Complexity. *Pediatrics* June 2014; 133 (6): e1647–e1654. 10.1542/peds.2013-3875

population living in poverty, both of which were higher in Seattle versus the comparison area. There were substantial differences between Seattle versus the comparison area in the average tract-level percent of the population with a college degree or higher and in the tract-level population density, both of which were higher in Seattle.

The Seattle and comparison area sample characteristics after FSATE-weighting are shown in the last two columns of **Table 1**. The weighting balanced the large differences in insurance type, pediatric medical complexity algorithm score, and census tract level population density and proportion of the tract with a college education or above. Some of the modest differences in age and patient and census tract racial composition remained even after the statistical weighting process.

TABLE 1: SAMPLE CHARACTERISTICS, UNWEIGHTED AND WEIGHTED USING FINE STRATIFICATION AVERAGE TREATMENT EFFECT WEIGHTS (FSATE)

	SEATTLE UNWEIGHTED	COMPARISON UNWEIGHTED	SEATTLE FSATE-WEIGHTED	COMPARISON FSATE-WEIGHTED
	N=7,088	N=17,060	N=7,088	N=17,060
	% OR MEAN (SE)			
SEX				
FEMALE	49.1 (0.6)	48.6 (0.4)	49.8 (1.5)	48.1 (1.1)
AGE AT FIRST VISIT				
2-5 YEARS OLD	47.2 (0.6)	42.2 (0.4)	48.1 (1.5)	43.4 (1.1)
6-9 YEARS OLD	24.7 (0.5)	25.6 (0.3)	22.01 (1.2)	25.3 (1.0)
10-13 YEARS OLD	23.6 (0. 5)	27.5 (0.3)	25.6 (1.3)	26.7 (1.0)
14-18 YEARS OLD	4.5 (0.2)	4.7 (0.2)	4.4 (0.6)	4.6 (0.5)
RACIAL AND ETHNIC IDENTITY				
HISPANIC	10.1 (0.4)	10.9 (0.2)	10.5 (0.9)	11.2 (0.7)
NON-HISPANIC, AMERICAN INDIAN/ALASKAN NATIVE	0.3 (0.1)	0.4 (0.045)	0.4 (0.2)	0.3 (0.04)
NON-HISPANIC, ASIAN	10.6 (0.4)	13.6 (0.3)	13.3 (1.01)	14.4 (0.9)
NON-HISPANIC, BLACK OR AFRICAN AMERICAN	17.0 (0.4)	9.6 (0.2)	14.7 (1.02)	11.8 (0.9)
NON-HISPANIC, MORE THAN ONE RACE	8.1 (0.3)	11.2 (0.2)	9.5 (0.9)	11.0 (0.7)
NON-HISPANIC, NATIVE HAWAIIAN, OR OTHER PACIFIC ISLANDER	0.8 (0.1)	1.3 (0.1)	1.2 (0.3)	1.05 (0.08)
NON-HISPANIC, OTHER RACE	7.1 (0.3)	5.7 (0.2)	6.1 (0.7)	6.9 (0.7)
NON-HISPANIC, WHITE	46.0 (0.6)	47.4 (0.4)	44.3 (1.5)	43.3 (1.06)
PEDIATRIC MEDICAL COMPLEXITY ALGORITHM (PMCA), MAXIMUM VALUE				
PMCA 1 NON-CHRONIC	62 (0.6)	62 (0.4)	64 (1.0)	64 (1.0)
PMCA 2 NON-COMPLEX CHRONIC	21 (0.5)	26 (0.3)	23 (1.0)	25 (1.0)

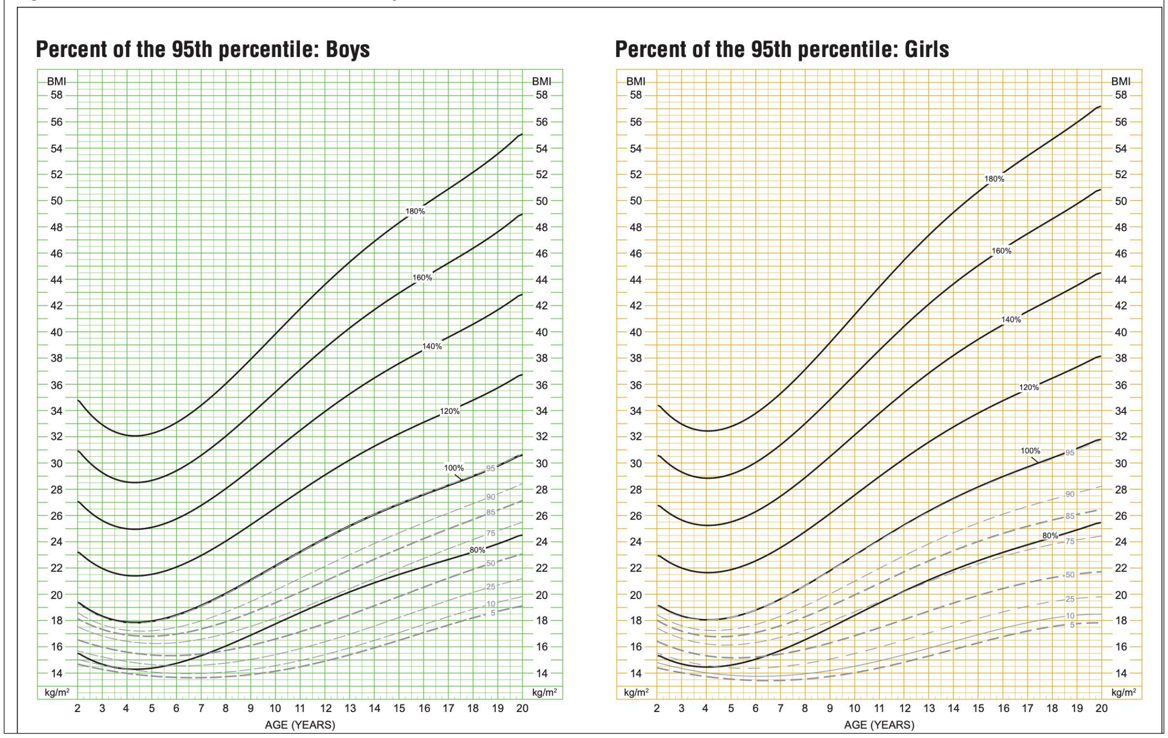
PMCA 3 COMPLEX CHRONIC	7.7 (0.3)	10 (0.2)	8.3 (0.8)	9.3 (0.5)
MISSING	9.4 (0.3)	1.6 (1.0)	4.6 (0.5)	2.0 (0.3)
INSURANCE TYPE				
COMMERCIAL	55.6 (0.6)	73.2 (0.3)	63.9 (1.4)	66.3 (1.2)
CENSUS TRACT RACE/ETHNICITY				
TRACT % HISPANIC	7.8 (0.1)	10.2 (0.05)	13.0 (0.3)	9.6 (0.1)
TRACT % AMERICAN INDIAN/ALASKAN NATIVE	0.5 (0.01)	0.7 (0.01)	0.7 (0.02)	0.6 (0.02)
TRACT % ASIAN	16.7 (0.2)	13.1 (0.07)	16.1 (0.2)	16.5 (0.4)
TRACT % BLACK	10.9 (0.1)	5.6 (0.04)	8.1 (0.2)	6.8 (0.2)
TRACT % TWO OR MORE RACIAL GROUPS	5.4 (0.03)	5.4 (0.02)	6.03 (0.1)	5.3 (0.05)
TRACT % NATIVE HAWAIIAN/OTHER PACIFIC ISLANDER	0.7 (0.02)	1.0 (0.01)	1.3 (0.06)	0.9 (0.03)
TRACT % OTHER RACIAL GROUP	0.2 (0.005)	0.2 (0.003)	0.1 (0.008)	0.2 (0.008)
TRACT % WHITE	57.9 (0.3)	63.9 (0.1)	54. 7 (0.5)	60.2 (0.4)
CENSUS TRACT CHARACTERISTICS				
TRACT DENSITY, PEOPLE PER SQUARE MILE	9,043.4 (56.7)	3,916.2 (17.2)	5,863.6 (92.8)	5,633.5 (183.9)
TRACT % LIVING IN POVERTY	14.0 (0.1)	10.6 (0.06)	13.8 (0.3)	11.6 (0.2)
TRACT % OF PEOPLE WHO MOVED IN LAST YEAR	18.4 (0.1)	16.5 (0.05)	18.1 (0.1)	18.7 (0.3)
TRACT % OF PEOPLE WITH COLLEGE EDUCATION OR MORE	52.1 (0.2)	34.8 (0.1)	39.8 (0.6)	40.0 (0.6)

Table 2 displays a variety of BMI metrics for Seattle and the comparison area, overall and stratified by pre- and post-tax. This table uses all the observations from children in the sample, rather than just reflecting their characteristics at the first visit. Unweighted estimates in Seattle show that the mean BMI%95th is 83.8%, meaning that on average children's BMIs were 83.8% of the BMI values at the 95th percentile using the CDC reference population.[5] The average untransformed BMI was 18.3 kg/m^2 and BMI z-score is 0.25. Obesity prevalence is 10%.

In the comparison area, all BMI metrics are higher, particularly BMI z-score (0.43 in the comparison area) and obesity prevalence (15% in the comparison area). The average BMI%95th goes down in the comparison area by half as much as in Seattle (-1.33 percentage points), while BMI z-score increases (0.43 z-scores). Untransformed BMI increases slightly more in the comparison area compared to Seattle.

The FSATE weighting brings the pre-tax BMI metrics for Seattle and the comparison closer together.

Figure 7. Alternative metric 2: Percent of the 95th percentile



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[5] For reference, for readers more familiar with BMI growth curves, **Figure 7** from the CDC (2022) show the BMI%95th values overlayed onto the CDC BMI for age and sex growth curves. A value of 85% is above the median, but below the 95th percentile. Citation: Hales CM, Freedman DS, Akinbami L, Wei R, Ogden CL. Evaluation of alternative body mass index (BMI) metrics to monitor weight status in children and adolescents with extremely high BMI using CDC BMI-for-age growth charts. Figure 7. National Center for Health Statistics. Vital Health Stat 2(197). 2022. DOI: https://dx.doi.org/10.15620/cdc:121711.

TABLE 2: BMI METRICS FOR SEATTLE AND COMPARISON AREA, OVERALL AND PRE- AND POST-TAX, WEIGHTED AND UNWEIGHTED				
	SEATTLE	COMPARISON	FSATE-WEIGHTED SEATTLE	FSATE-WEIGHTED COMPARISON
	MEAN (SE)			
	OVERALL			
OBSERVATIONS	**62,390**	**157,954**	**62,390**	**157,954**
BMI%95TH	83.8 (0.06)	86.1 (0.04)	84.9 (0.2)	85.9 (0.1)
BMI	18.3 (0.02)	19.2 (0.01)	18.7 (0.05)	19.1 (0.03)
BMI Z-SCORE	0.25 (0.004)	0.43 (0.003)	0.35 (0.01)	0.42 (0.008)
AVERAGE WITHIN INDIVIDUAL CHANGE IN BMI%95TH	-2.66 (0.06)	-1.33 (0.04)	-1.98 (0.1)	-0.11 (0.1)
AVERAGE WITHIN INDIVIDUAL CHANGE IN BMI Z-SCORE	-0.019 (0.005)	0.043 (0.003)	0.015 (0.01)	0.15 (0.010)
AVERAGE WITHIN INDIVIDUAL CHANGE IN BMI	1.47 (0.02)	1.85 (0.01)	1.42 (0.03)	2.20 (0.04)
OBESITY PREVALENCE	0.10 (0.001)	0.15 (0.0009)	0.12 (0.003)	0.15 (0.002)
PRE-TAX				
OBSERVATIONS	**39,685**	**100,948**	**22,705**	**57,006**
BMI%95TH	84.2 (0.07)	86.2 (0.05)	83.1 (0.1)	85.9 (0.07)
BMI	18.0 (0.02)	18.7 (0.01)	19.0 (0.03)	20.0 (0.02)
BMI Z-SCORE	0.24 (0.006)	0.40 (0.004)	0.29 (0.007)	0.49 (0.005)
OBESITY PREVALENCE	0.098 (0.001)	0.14 (0.001)	0.11 (0.002)	0.16 (0.002)
POST-TAX				
OBSERVATIONS	**39,685**	**100,948**	**22,705**	**57,006**
BMI%95TH	85.6 (0.2)	85.8 (0.1)	83.8 (0.3)	86.2 (0.2)
BMI	18.4 (0.06)	18.6 (0.03)	19.3 (0.08)	19.9 (0.06)
BMI Z-SCORE	0.36 (0.01)	0.38 (0.009)	0.35 (0.02)	0.49 (0.01)
OBESITY PREVALENCE	0.12 (0.004)	0.14 (0.003)	0.12 (0.006)	0.16 (0.005)

**This table uses all the observations available during the study period from the 24,097 children included in the first difference models.*

Model 1: First Difference Model

Table 3 displays the results from the first difference models using the FSATE weights. The difference-in-difference estimate--or the degree to which annualized change in BMI%95th changed for Seattle beyond changes seen in the comparison area—indicates the tax was associated with a decrease in BMI%95th of 1.47 percentage points (pp) beyond the change seen in the comparison area (FSATE$_{Seattle}$: -1.47 (SE: 0.45); p-value 0.001).

The average BMI%95th was approximately 84% in Seattle at baseline, so a -1.5 pp change in BMI%95th percentile would represent a 1.9% change.

TABLE 3. ASSOCIATION BETWEEN SEATTLE'S SWEETENED BEVERAGE TAX AND BMI%95TH: DIFFERENCE-IN-DIFFERENCE ESTIMATES FROM THE FIRST DIFFERENCE MODELS, FSATE WEIGHTED, OVERALL AND STRATIFIED BY POPULATION GROUPS.

	DIFFERENCE-IN-DIFFERENCE ESTIMATE		OBSERVATIONS
	COEFFICIENT (SE)	P-VALUE	
OVERALL	**-1.474*** (0.453)**	**(0.001)**	**24,097**
SEX			
MALE	-1.413*** (0.483)	(0.003)	15,177
FEMALE	-1.569* (0.871)	(0.072)	8,920
AGE			
2-5 YEARS	-1.830*** (0.60)	(0.002)	12,367
6-18 YEARS	-1.207* (0.685)	(0.079)	11,730
INSTITUTION			
KP ONLY	-1.246*** (0.465)	(0.007)	21,188
OBCC ONLY	-3.862*** (1.216)	(0.002)	2,909
RACIAL AND ETHNIC IDENTITY			
HISPANIC	0.396 (1.471)	(0.788)	2,564
NON-HISPANIC, AMERICAN INDIAN/ALASKAN NATIVE	8.054** (3.385)	(0.020)	88
NON-HISPANIC, ASIAN	-1.081 (1.052)	(0.304)	3,065
NON-HISPANIC, BLACK	-0.922 (1.668)	(0.581)	2,852
NON-HISPANIC, MULTI-RACE	-1.339 (1.537)	(0.384)	2,481
NON-HISPANIC, NATIVE HAWAIIN/OTHER PACIFIC ISLANDER	0.191 (1.826)	(0.917)	275
NON-HISPANIC, (AN)OTHER RACE	-0.588 (1.154)	(0.611)	1,490
NON-HISPANIC, WHITE	-2.204*** (0.587)	(0.0002)	11,282
INSURANCE TYPE			
COMMERCIAL	-1.98 (0.94)**	0.035	7,734

PUBLIC	-1.2 (0.49)**	0.013	16,363
PEDIATRIC MEDICAL COMPLEXITY			
PMCA 1	-1.429** (0.585)	(0.015)	15,025
PMCA 2	-1.507* (0.896)	(0.093)	5,840
PMCA 3	-0.938 (1.557)	(0.547)	2,298

**p<0.10; **p<0.05; ***p<0.01*

Also shown in **Table 3** are the results stratified by population demographic and other characteristics. The stratified models suggest that for many demographic groups, the direction of the estimate of the association of the tax with BMI was negative such that those in Seattle gained less BMI than those in the comparison area from before to after the tax (Seattle column). The relationship was stronger for children aged 2-5 years. The estimate was also negative and statistically significant for both health systems; however, the magnitude of the effect was twice as large for patients from OBCC compared to KP. The estimated impact of the tax was stronger for males compared to females. By racial and ethnic identity, the effect is larger and stronger for non-Hispanic, White youth compared to children of most other racial or ethnic identities. However, while not reaching statistical significance and of lower magnitude, the point estimates are negative (consistent with a lowering of BMI) for many racial/ethnic groups. An exception was for American Indian/Alaskan Native children where the estimate was large and positive indicating an increase in BMI%95th in association with the tax however, the sample size is very small, and this deserves further investigation. The impacts were negative and statistically significant for both patients with commercial and public insurance, which we use as a proxy for socioeconomic resources. Finally, the estimate of the tax impact was larger for youth with lower pediatric medical care acuity scores (i.e. those with fewer medical conditions.

Model 2: Synthetic Control Difference-in-Difference Model

This model was successful at creating parallel trends in child BMI%95th during the pre-tax period between Seattle and the comparison area samples (**Figure 1**). The results of this model suggest that the tax was associated with lower gains in BMI%95th for Seattle youth as compared to the comparison area (difference-in-difference: -0.999 percentage points (95%CI: -1.23, -0.76) after the tax was implemented, after achieving parallel trends in BMI%95th in the pre-tax period (Figure 1).

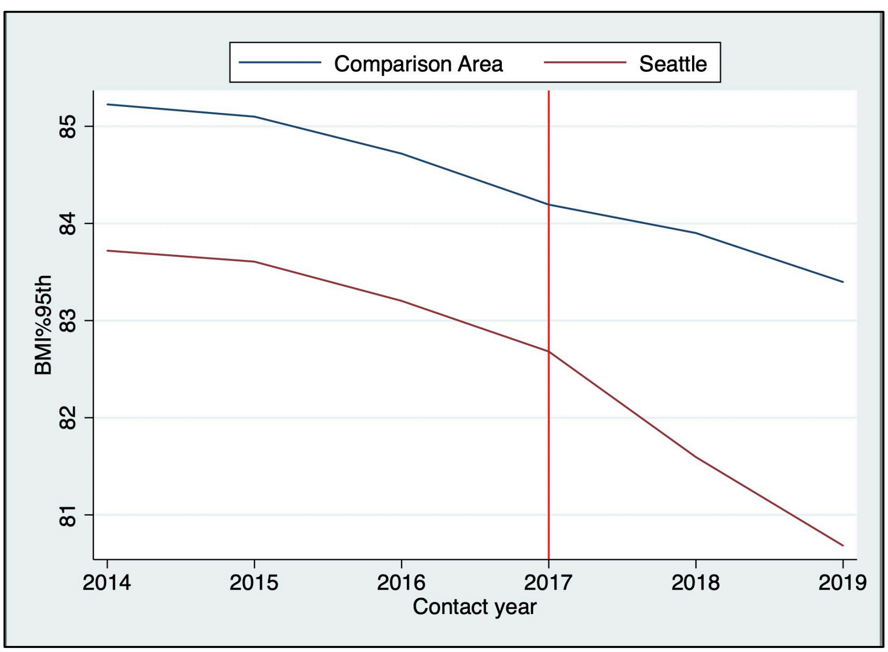


Figure 1. Estimated trends in BMI%95th in Seattle and the comparison area in pre-tax and post-tax periods

TABLE 4. SYNTHETIC CONTROL DIFFERENCE-IN-DIFFERENCE ESTIMATE OF THE ASSOCIATION BETWEEN THE SBT AND BMI%95TH		
	COEFFICIENT (95% CI)	P-VALUE
SYNTHETIC DIFFERENCE-IN-DIFFERENCE ESTIMATE	-0.999 (-1.23, -0.76)***	<0.001

****p<0.01*

DISCUSSION

Overall, we find evidence that Seattle's Sweetened Beverage Tax was associated with a statistically significant reduction in youth's BMI, expressed as a percentage of the 95th percentile for an age- and sex-matched reference population. The first difference models suggested an impact of a reduction of 1.56 percentage points in BMI%95th. With a sample average of BMI%95th of 85%, that equates to a 2% reduction in this BMI metric. The synthetic control models suggest a somewhat smaller magnitude of effect—a 0.99 percentage point reduction, which would be a 1.2% reduction in BMI%95th. While the magnitude of this effect is modest, this is consistent with what would be expected owing to the modest scale of the tax and the complex social and behavioral mechanisms hypothesized to underlie current obesity trends. It is also important to keep in mind when interpreting this effect that many children and youth in Seattle may not consume any sweetened beverages prior to the tax, and therefore would be unaffected by the tax, and yet we cannot identify who these individuals are, so the effect we estimate is diluted and would be expected to be larger among those who actually consumed any sweetened beverages at baseline.

Our preferred estimate is that from the synthetic control difference-in-difference because there was evidence of differential trends in BMI%95th in the pre-tax period that were not entirely accounted for using the FSATE weights. The synthetic control difference-in-difference explicitly derives a weighted sample of comparison area participants who have similar pre-tax trends in the outcome. In this way, we can have more confidence that the effect we find can be attributed to the tax and not pre-existing factors. The caveat to this is that these models include only a subset of all patients in our sample. In particular, only youth who had at least one BMI measurement in each of the six years of the study period were included in this model. Additionally, this model was not a pre-specified analytic approach, but rather one we had to turn to after our prespecified approaches appeared to inadequately control for factors creating different BMI%95th trajectories.

The differences in pre-tax trends between Seattle and the surrounding counties are consistent with other findings including in the Moving 2 Health study, which found that that higher population density (which Seattle has relative to the comparison areas) was associated with less weight gain over time.[6]

Our findings are consistent with previous findings reported by Powell and Leider of net reductions in taxed beverage purchasing and in net reductions in added sugar from beverages. They are inconsistent with findings from our team in the longitudinal cohort study of consumption. That study found at both 12 and 24 months, no greater reduction in consumption for Seattle children and parents versus those in the comparison area.

The strengths of this study include a longitudinal rather than cross-sectional cohort, measured height and weight rather than self- or other-reported, limited or no likelihood of study reactivity – there was no attachment between the measurement and the tax (i.e., children were not part of a study specifically looking at changes in weight status as a result of the tax).

Limitations of this analysis are that we used medical records for children and youth demographic and BMI information. This likely results in more measurement error in height and weight compared to if these had been measured on a research protocol. Additionally, we have only limited information on children's economic status or other characteristics.

[6] Cruz, Maricelaa,b; Drewnowski, Adamc,d; Bobb, Jennifer F.a,b; Hurvitz, Philip M.e,f; Vernez Moudon, Annee; Cook, Andreaa,b; Mooney, Stephen J.d; Buszkiewicz, James H.c,d; Lozano, Paulaa; Rosenberg, Dori E.a; Kapos, Flaviad; Theis, Mary Kaya; Anau, Janea; Arterburn, David. Differences in Weight Gain Following Residential Relocation in the Moving to Health (M2H) Study. Epidemiology 33(5):p 747-755, September 2022.

However, we do use "child-level fixed effects" which compare children to themselves over time in both of our models and therefore control for all time-invariant child-level confounders. Our initial propensity score-based weighting, the FSATE weights, did not adequately eliminate differential pre-tax trends in BMI%95th between Seattle and the comparison area, so we had to employ a synthetic control difference-in-difference model to better control for these differential trends. However, this model required that all children have the same number of outcome measurements at the same time interval. This led to a significant reduction in the sample, limiting to children who had at least one BMI measurement in each of the six years of the study period. Nevertheless, the tradeoff for the smaller sample and potentially lower generalizability is an internally valid estimate of the tax impact on children and youth's BMI%95th. Finally, the newly recommended metric of BMI, the BMI%95th, is cumbersome to describe and interpret. However, it replaces a BMI z-score that has been shown to inaccurately describe changes in BMI.

CONCLUSION

Overall, the results from both the first difference models and the synthetic control difference-in-difference models indicate that the tax was associated with less increase in BMI%95th as evidenced by lower increases from before to after the tax among children living in Seattle versus the comparison area. Our preferred, more conservative model, the synthetic control difference-in-difference, suggested the tax was associated with a 0.99 percentage point decrease in BMI%95th, which would be a 1.2% reduction from baseline levels of BMI%95th in Seattle (which was approximately 84%). This is a small, but reasonable, beneficial effect associated with the timing of Seattle's Sweetened Beverage Tax.

APPENDIX

METHODS

Detailed methods are the same as those described in the accompanying report on the association between Seattle's SBT and adult BMI outcomes. However, there were some important differences in the methods among children. First, the FSATE weighting among children did not result in equalizing differential trends in BMI%95th among children. This was evidenced in the comparative interruptive time-series models and the event study models and we describe those results below. This led us to pursue the synthetic control difference-in-difference models as a way to explicitly equalize the pre-tax trends in BMI%95th between Seattle and the comparison area.

Comparative interruptive time-series model

The comparative interruptive time-series model incorporates as many observations as possible and takes advantage of the multiple measurements both before and after the tax for a large proportion of the sample in the electronic health record, we conducted a controlled interrupted time-series analysis. **Appendix Table 1** displays these results. Because our health outcomes are from electronic health records, patients have their BMI measured almost every time they see a health care provider. Thus, the data are unbalanced, meaning that individuals contribute different numbers of BMI observations and BMI is not measured at the same calendar time for everyone.

The estimates indicate that on average BMI%95th did not change significantly in the comparison area over the pre-tax years (Row 1 **Appendix Table 1**; 0.000781 (0.00849); p-value=0.927) and that there was no significant change from pre-to-post tax years in the comparison area (Row 3; 0.00515 (0.00398); p-value=0.196). Among youth in Seattle, the estimates suggest that the slope of BMI%95th was significantly lower in the pre-tax period compared to the slope in the comparison area (Row 2; -0.03** (0.0136); p-value=0.021). However, there was no significant difference in the change in slope of BMI%95th for Seattle as compared to the analogous change from pre to post tax in the comparison area (Row 4; the difference-in-difference estimate: -0.00696 (0.00652); p-value=0.286). The point estimate was negative but not statistically significant. The results of this model suggest that children in Seattle were experiencing lower gains in BMI%95th before the tax went into effect.

Unfortunately, the differential trend in BMI%95th between Seattle and the comparison area children before the tax indicates that our FSATE weighting was not successful at balancing the sample such that trends in BMI%95th were similar pre-tax.

APPENDIX TABLE 1: CITS MODEL FOR CHANGES IN SLOPE OF BMI%95TH (N=221,484 VISITS)

		COEFFICIENT (SE)	P-VALUE
ROW 1	PRE-TAX TREND IN BMI%95TH IN THE COMPARISON AREA	0.000781 (0.00849)	0.927
ROW 2	DIFFERENCE BETWEEN SEATTLE AND COMPARISON AREA IN THE PRE-TAX TREND IN BMI%95TH	-0.03** (0.0136)	0.021
ROW 3	DIFFERENCE BETWEEN TREND IN BMI%95TH FROM PRE-TO- POST TAX IN THE COMPARISON AREA	0.00515 (0.00398)	0.196
ROW 4	DIFFERENCE-IN-DIFFERENCE ESTIMATE: DIFFERENCE BETWEEN CHANGE IN PRE TO POST TREND FOR SEATTLE COMPARED TO CHANGE IN PRE-TO-POST TREND FOR COMPARISON AREA	-0.00696 (0.00652)	0.286

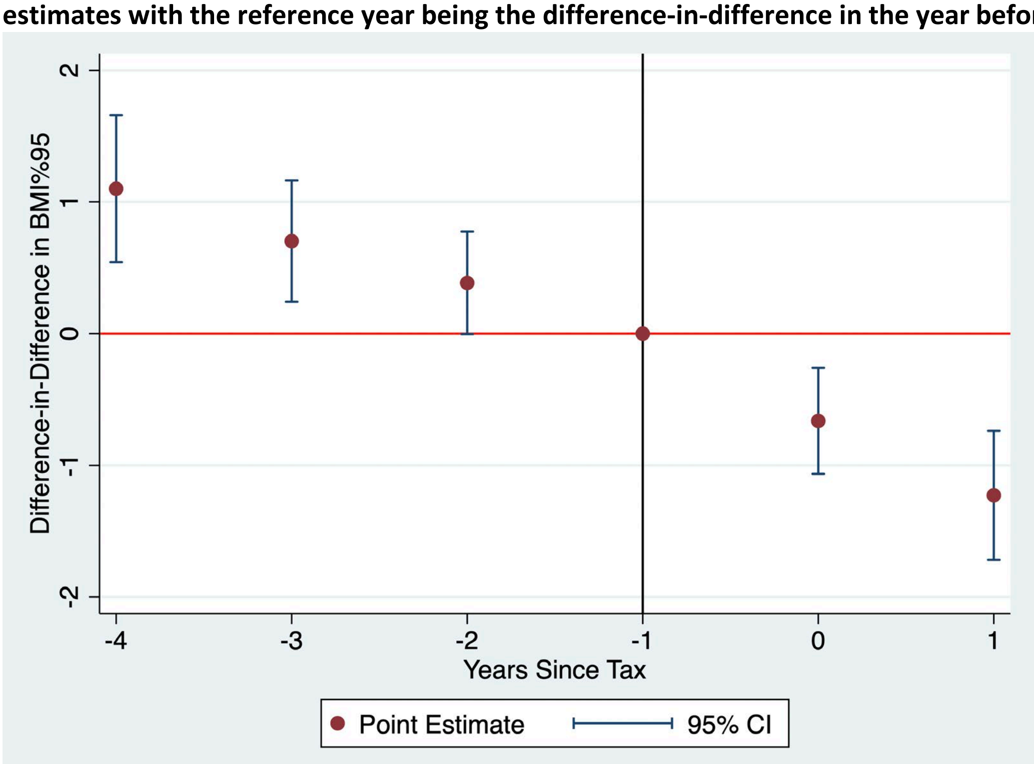
**p<0.10; **p<0.05; ***p<0.01*

Event study model
We also fitted an "event study" model. This model computes a difference-in-difference estimate comparing the change in BMI in Seattle to the change in the comparison area using the year before the tax as the referent year. It is different from the first differences model because it uses multiple observations from each child. It is different from the interruptive time-series model because it allows for the estimated tax impact to be different for each year. It does not require that youth have a BMI measurement in each year.

Because the event study approach allows for a different impact to be estimated each year (including the pre-tax years), it allows us to visualize the pre-tax trends in youth BMI%95th to assess the degree to which the trends in BMI%95th are parallel for Seattle and the comparison area during the pre-tax period (**Appendix Figure 1**).

An indication that trends in the two groups are parallel would be that the estimates of the difference-in-difference in the pre-tax years (2014-2017) in Appendix Figure 1 would be close to zero in all pre-tax years. The positive estimates in the pre-tax period suggest that Seattle was experiencing lower BMI gains over time (despite the counterintuitive interpretation). But most notably, there is a trend pre-tax that continues post-tax and this indicates, similar to the comparative interrupted time-series that the FSATE weighting is not equalizing the BMI%95th trends in the pre-tax period, and therefore, it raises concerns that our statistical models are unable to fully account for the difference between the Seattle population and the comparison area population. We observe that the negative point estimates in the post-tax period are consistent with an interpretation that the tax was associated with decreases in BMI%95th in Seattle. However, this is a continuation of a trend that is apparent in the pre-tax period. Seattle youth are gaining in the BMI%95th at a slower pace than those in the comparison area, pre-tax. To assess whether there were additional declines in Seattle post-tax on top of the identified trend, we calculated the year-over-year change in BMI%95th based on the model estimates. **Appendix Table 2** displays these estimates. The average year-over-year change in the pre-tax period is approximately -0.4 while it is approximately -0.7 in the post-tax years, suggestive of a possible tax impact on child weight status with lesser increases (or greater decreases) in Seattle versus comparison area children.

Appendix Figure 1. Event study model for association between Seattle's SBT and BMI%95th: difference-in-difference estimates with the reference year being the difference-in-difference in the year before the tax (set to zero by design)



APPENDIX TABLE 2: EVENT STUDY MODEL FOR ASSOCIATION BETWEEN SEATTLE'S SBT AND BMI%95TH: DIFFERENCE-IN-DIFFERENCE ESTIMATES WITH THE REFERENCE YEAR BEING THE DIFFERENCE-IN-DIFFERENCE IN THE YEAR BEFORE THE TAX (SET TO ZERO BY DESIGN)

	COEFFICIENT (SE) | P-VALUE		YEAR OVER YEAR CHANGE IN COEFFICIENT
2014	1.15*** (-0.284)	0.00375	0.375
2015	0.775*** (-0.235)	0.00330	0.330
2016	0.445** (-0.198)	0.00445	0.445
2017	REFERENT YEAR		0
2018	-0.652*** (-0.205)	0.00205	0.625
2019	-1.25*** (-0.25)	0.01045	1.045

**p<0.10; **p<0.05; ***p<0.01*

Appendix Table 3 displays the estimated change in BMI%95th for the comparison area from before to after the tax. The difference-in-difference estimates reported in the main report are the change that occurred in Seattle above and beyond these changes seen in the comparison area.

APPENDIX TABLE 3: STRATIFIED FIRST DIFFERENCE MODEL OF RELATIVE DEVIATION FROM THE 95%PERCENTILE AS A FUNCTION OF SBT, FSATE WEIGHTED.

	COMPARISON AREA CHANGE OVER TIME		OBSERVATIONS
	COEFFICIENT (SE)	P-VALUE	
FE FSATE WEIGHTED AGE_GP INS	1.131* (0.604)	(0.061)	24,097
SEX			
MALE	1.061 (0.679)	(0.118)	15,177
FEMALE	-0.244 (1.193)	(0.838)	8,920
AGE			
2-5 YEARS	1.039 (0.768)	(0.176)	12,367
6-18 YEARS	-0.017 (1.013)	(0.987)	11,730
INSTITUTION			
KP ONLY	1.096 (0.737)	(0.137)	21,188
OBCC ONLY	1.564** (0.769)	(0.042)	2,909
RACIAL AND ETHNIC IDENTITY			
HISPANIC	0.836 (2.097)	(0.690)	2,564
NON-HISPANIC, AIAN	0.125 (1.905)	(0.948)	88
NON-HISPANIC, ASIAN	-1.4439 (1.275)	(0.258)	3,065
NON-HISPANIC, BLACK	1.393 (1.288)	(0.279)	2,852
NON-HISPANIC, MULTI-RACE	2.345 (3.106)	(0.450)	2,481
NON-HISPANIC, NHOPI	-0.410 (1.929)	(0.832)	275
NON-HISPANIC, (AN)OTHER RACE	0.793 (1.078)	(0.462)	1,490
NON-HISPANIC, WHITE	1.016 (0.698)	(0.145)	11,282
PEDIATRIC MEDICAL COMPLEXITY			
PMCA 1	0.576 (0.782)	(0.462)	15,025
PMCA 2	2.766** (1.325)	(0.037)	5,840
PMCA 3	0.749 (1.375)	(0.586)	2,298

**p<0.10, **p<0.05, ***p<0.01*