Using Healthy Youth Survey Data to Assess Change in Sugar-Sweetened Beverage Consumption and Weight Status Among Adolescent Students

THE EVALUATION OF SEATTLE'S SWEETENED BEVERAGE TAX

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EXECUTIVE SUMMARY

Objective

The Seattle Sweetened Beverage Tax went into effect in January 2018. This report examines the association between the Seattle Sweetened Beverage Tax (SBT) and changes in sugar-sweetened beverage consumption and weight status among adolescent students.

Methods

This study used data from the Washington State Healthy Youth Survey, which sampled cross-sections of adolescents (8th, 10th, and 12th grade students) from public schools in Seattle and elsewhere in King County before (2014 and 2016) and after (2018 and 2021) the implementation of the SBT. The outcomes of interest were daily sugar-sweetened beverage (SSB) consumption (consuming at least one time per day), body mass index (BMI), overweight (BMI >85th percentile), and obese status (BMI >95th percentile). The study used a difference-in-difference analysis to evaluate the association between the SBT and changes in outcomes in Seattle relative to the comparison area (elsewhere in King County). Because the COVID-19 pandemic may have influenced the outcomes, we repeated the analysis with a dataset that excluded the 2021 data.

Results

The final sample for the four years included 63,210 King County adolescents, of whom 11,719 were Seattle students. Among adolescents in Seattle and the comparison area, the prevalence of daily SSB consumption, average BMI, overweight, and obesity generally levelled off or declined between 2016 and 2018 but then increased in 2021. While we did not find a statistically significant association between SBT and changes in daily SSB consumption or obesity over this period (through 2021), we found a signal of a small decrease in the average BMI (by 0.244 unit, p=0.08) and in prevalence of overweight (by 2.9%, p=0.03) in Seattle relative to elsewhere in King County. When we repeated the analysis excluding 2021 data, the findings held up: we again found a signal of a small decrease in the average BMI (by 0.289 unit, p=.09) and in prevalence of overweight status (by 3.2%, p=0.03) in Seattle relative to elsewhere in King County.

INTRODUCTION

Sugar-sweetened beverages (SSB) have been linked to higher caloric intake and obesity. A number of U.S. cities have implemented beverage taxes as a strategy to reduce sugar-sweetened beverage consumption and obesity[1]. The City of Seattle enacted a sweetened beverage tax (SBT) on January 1, 2018[2]. Using data from a school-based survey of adolescents in grades 8, 10, and 12 who were asked to self-report height and weight, and frequency consuming sugar-sweetened beverages, this study examined the impact of the SBT on population-level adolescent weight status and sugar-sweetened beverage consumption, comparing students attending Seattle public schools to those attending public schools in King County, WA outside of Seattle in years before (2014 and 2016) and after (2018 and 2021) the implementation of the SBT in Seattle.

METHODS

Washington State Healthy Youth Survey

Healthy Youth Survey (HYS) is a statewide, cross-sectional survey of adolescents attending public schools in Washington State. The primary sampling unit for the survey is the school and grade[3]. For King County, the survey sample included both a simple random sample of schools for unweighted county level estimates as well as non-sampled schools that agreed to participate that year. Based on school enrollment data with 2014, 2016, 2018, and 2021 surveys combined, 82% of all 8th graders, 70% of 10th graders, and 47% of 12th graders completed the survey. Before 2020, the survey took place every two years in the fall in even years. The 2020 survey was postponed to the fall of 2021 due to the COVID-19 pandemic. For students in grade 8, 10, and 12, HYS provided two forms (A and B) with different sets of questions on each form. Forms A and B were randomly administered in a class but only form B contained questions on height and weight used to compute body mass index (BMI). As a result, only students who answered form B were included in this study. We examined the changes in the outcome variables between before (2014 and 2016) and after (2018 and 2021) the SBT implementation. Seattle students were coded as exposed to SBT and students elsewhere in King County were used as the comparison group.

Outcomes

We examined daily SSB consumption (consuming SSB at least 1 time per day) as a binary outcome. We examined the outcome of BMI as a continuous variable, calculated from self-reported weight and height in the survey. We chose BMI instead of one of the age and sex standardized BMI measures[4] because HYS data consisted of independent yearly cross-sectional samples and there were no significant differences between Seattle and the comparison area in grade distribution and average age in the before and after SBT periods. Therefore, child growth at the individual and group levels was not a concern. In addition, BMI is well understood and easy to interpret. We also examined two binary body weight status variables: overweight defined as BMI>= the CDC 85th percentile of BMI for age and sex; and obese defined as BMI>= the CDC 95th percentile of BMI for age and sex.

Statistical Analysis

We combined grades 8, 10, and 12 respondents. We added survey weights to the data using two weighting methods. A survey weight by year was constructed by adjusting sex and grade by school districts, and then scaled to match King County public school enrollments. Propensity score weights adjusted for differences between Seattle and the comparison area students before and after SBT implementation[5] by variables that were potentially associated with the outcome measures but not related to treatment, including grade, sex at birth, race/ethnicity, physical activity level, food insecurity status, screen time, and school level free or reduced lunch rate (see definitions in Appendix). Physical activity and screen time were entered as continuous variables with missing data imputed to the mean. Screen time was constructed by combining hours spent watching TV or electronic devices and hours spent playing video games on an average school day. Missing data in race/ethnicity were imputed using k-nearest neighbor imputation[6]. Missing data in food insecurity were imputed as no food insecurity. For the school level percentage of students eligible for free or reduced lunch, missing data were imputed using school district level percentages. Also, the time factor variable defining before and after SBT, instead of survey year, was included for the propensity score weight generation. The survey weight was used to generate population level estimates such as by geography. Propensity score weight was used to balance differences in the covariates between Seattle and the comparison area in models for evaluating the SBT effect, which was the focus of this report.

The effect of SBT was evaluated using difference-in-difference (DiD) analysis. In DiD design, the assumption is that in absence of treatment (SBT), the unobserved difference between the treatment and comparison groups would stay unchanged over time. Therefore, the observed change in the difference after treatment is assumed to be the effect of the treatment[7 8]. A main assumption in DiD design is that during the period before treatment there should be at least two time points and the time trends in the outcome between the treatment group and the comparison group should be parallel across the time points. For the HYS data before SBT, we included 2014 and 2016 surveys and examined the parallel trend assumption between Seattle and the comparison area. Propensity score weighting would also help with making the two study group trends parallel pre and post treatment before the treatment effect is included.

For this study, for the BMI outcome, a propensity score weighted multivariate linear regression model with fixed effects was used with BMI as the dependent variable, Seattle versus the comparison area as treatment, combined 2014 and 2016 versus combined 2018 and 2021 as the pre and post treatment time factor, and their interaction term (treatment x time) as the DiD treatment effect. The same set of variables that were used for generating the propensity score weights were included in the model as covariates for double robustness in case the propensity score model was mis-specified[9]. For more refined adjustment, age, instead of grade, was included in the model because it was highly correlated with grade.

For the binary outcomes, the same linear multivariate regression model was used for easier interpretation of the coefficient for the DiD interaction term. The DiD coefficient from the linear model measures the proportional change in the binary outcome and it is believed to be the unbiased estimate of the treatment effect[10]. Because of complications in the interaction term in non-linear models, logistic regression was not used for the binary outcomes in this analysis[11].

Sensitivity analysis
For the post SBT period with 2018 and 2021 combined, the 2018 and 2021 surveys were about nine months and three years nine months after SBT implementation respectively. In addition to a longer duration post SBT, the 2021 data were subject to the impact of the COVID-19 pandemic and high inflation that may have increased the price of sweetened beverages. As a result, we also conducted a sensitivity analysis by excluding 2021 data from the analytic dataset and focused on the shorter-term impact of SBT. Note that compared to the full analytic dataset, the sensitivity analysis has reduced power because of sample size reduction. For the sensitivity analysis, propensity score weights were generated also with 2021 data excluded.

RESULTS

Data characteristics
The total HYS form B sample for the four years was 76,145 respondents. The sample size for the analytic dataset was 63,210 after sequentially excluding 2,126 students from two school districts that only participated in the 2018 survey, 9,521 students with missing BMI, 1,280 students with missing SSB consumption, and eight outliers in BMI (z score <-5). Of the final sample, 11,719 were Seattle students.

Table 1 shows demographic and selected covariate characteristics for students in the Seattle and comparison area by different analytic weights (unweighted, survey weight weighted and propensity score weight weighted). Seattle and the comparison area students were similar in demographics and the covariates with and without weighting. The study sample had higher proportions of 8^{th} and 10^{th} graders than 12^{th} graders. Racial composition was similar to that of the student population in the county. **Table 2** shows that before SBT implementation (2014 and 2016), compared to students in the comparison area, Seattle students had significantly lower prevalence of daily SSB consumption, overweight, and obesity. The difference between the two areas in mean BMI, however, was not statistically significant.

Change in consumption of sugar-sweetened beverages
On SSB daily consumption, the prevalence decreased in both Seattle and the comparison area between 2014 and 2016 and the trends were parallel. The declining trends continued between 2016 and 2018 after the implementation of SBT, but then increased between 2018 and 2021 (Figures 1a and 1b).

Table 3 shows results after controlling for demographic and selected potential confounding variables between Seattle and the comparison area based on propensity score weighted multivariate DiD regression models. For the main and sensitivity analyses, the DiD coefficients (Table 3) were not statistically significant, indicating a lack of association between SBT and SSB daily consumption.

Change in BMI

F**igures 2a and 2b** show that between 2014 and 2016, the trends in BMI appear to be parallel between Seattle and comparison area adolescents. Then in Seattle, the average BMI decreased between 2016 and 2018 but then increased in 2021. In the comparison area, BMI increased continuously from 2014 to 2021. When 2018 and 2021 (and also 2014 and 2016) data were combined (**Table 2**), there was little change in BMI before and after SBT in both Seattle and the comparison area.

In Table 3, for BMI, the model result in the DiD coefficient showed that after controlling for the covariates, the mean change after SBT implementation was 0.244 units lower in Seattle than in the comparison area, which signaled a small decrease (p-value = 0.076) relative to the comparison area. Similarly, sensitivity analysis excluding 2021 data signaled a reduction of 0.289 unit (p-value = 0.087) relative to the comparison area.

The DiD coefficient indicated the average difference in the change of BMI between Seattle and the comparison area. For the sample of students in the study, the BMI ranged from 11.9 to 54.9 with a mean of 21.74. The DiD coefficient of 0.289 units is akin to a reduction in BMI in Seattle from 21.74 to 21.45, assuming the BMI in the comparison area did not change.

Change in the prevalence of obesity and overweight status

The prevalence of obesity and overweight showed relatively parallel trends between 2014 and 2016. The rates in Seattle were either flat or declined from 2016 to 2018 but then increased from 2018 to 2021. The rates in the comparison area, however, increased continuously between 2014 and 2021 (Figures 3a, 3b, 4a, and 4b). The DiD coefficients for obesity from the linear regression models for both the main analysis with 2021 data included in the post SBT period and the sensitivity analysis with 2018 data only, were not statistically significant (**Table 3**). However, the DiD coefficients for overweight were significant in both the main and sensitivity analyses, indicating a significant SBT effect on overweight reduction. The DiD coefficient showed a relative reduction of approximately 3% in overweight prevalence in Seattle compared elsewhere in King County (2.9% with 2018 and 2021 data combined and 3.2% with 2018 only).

Limitations

The results should be interpreted with caution because of several limitations in the study. First, height and weight, as well as the frequency of SSB consumption from HYS were self-reported and therefore were subject to self-report bias. Second, missing data made the study sample less representative of the target population (all 8^{th}, 10^{th}, and 12^{th} grade public school students in Seattle and elsewhere in King County). In particular, 14.6% of students were dropped from the analytic dataset because of missing data for BMI and/or SSB consumption. Missing data in BMI in our data was significantly associated with survey year, grade, and race/ethnicity but not gender: students in later survey years, in lower grades, and who identified as non-white were more likely to have missing BMI. Missing data on SSB consumption were significantly associated with survey year, gender, and race/ethnicity, but not grade. Students in the 2021 survey, who were male, and non-white were more likely to have missing data in SSB consumption. In addition, two school districts in the comparison area, including a very large one, did not participate in the 2021 survey so they only had 2014-2018 data. Third, the COVID-19 pandemic and high inflation may have had negative impacts on obesity and SSB consumption when 2021 data were included. When taking classes from home, students may have increased their SSB consumption and the higher prices in sweetened beverages may have made the increased tax amount less noticeable. Fourth, the SBT treatment effect on BMI reduction was assumed to be preceded by its impact on reducing SSB consumption. While we found an association between SBT and a decrease in overweight as well as a signal of an association with a decrease in BMI, we did not find an association with change in daily SSB consumption. This could be due to a combination of several factors such as: 1) the question on the frequency of SSB consumption during the past seven days was not a precise measurement in the actual quantity of SSB consumption, 2) the Sweetened Beverage Tax in Seattle did not necessarily change the behavior in SSB consumption or its impact might have been mitigated by other factors such as substitution to foods, sweets, and untaxed beverages that increased calorie intake[12], and 3) some Seattle residents, especially those who routinely purchased large quantities of sweetened beverages, may choose to purchase their beverages outside of Seattle and in larger quantity, and therefore maintained or even increased their level of SSB consumption.

CONCLUSION

Among adolescents in Seattle and the comparison area, the prevalence of daily SSB consumption, average BMI, overweight, and obesity generally levelled off or declined between 2016 and 2018 but then increased in 2021. While we did not find a statistically significant association between SBT and changes in daily SSB consumption or obesity over this period (through 2021), we found a signal of a small decrease in the average BMI (by 0.244 units, p=0.08) and in prevalence of overweight (by 2.9%, p=0.03) in Seattle relative to elsewhere in King County. When we repeated the analysis excluding 2021 data, the findings held up: we again found a signal of a small decrease in the average BMI (by 0.289 units, p=.09) and in prevalence of overweight status (by 3.2%, p=0.03) in Seattle relative to elsewhere in King County.

TABLE 1. DISTRIBUTION OF SEATTLE AND COMPARISON AREA RESPONDENTS, 2014, 2016, 2018, AND 2021 COMBINED								
	SAMPLE SIZE N		UNWEIGHTED %^		SURVEY WEIGHTED %^		PROPENSITY SCORE WEIGHTED %^	
	SEATTLE	COMPARISON	SEATTLE	COMPARISON	SEATTLE	COMPARISON	SEATTLE	COMPARISON
YEAR								
2014	2751	13366	23.5	26.0	23.8	24.6	23.3	25.0
2016	3062	13445	26.1	26.1	25.1	25.7	26.7	25.0
2018	2847	13722	24.3	26.6	23.5	25.5	25.8	28.6
2021	3059	10958	26.1	21.3	27.6	24.2	24.5	21.4
GRADE								
8	4741	20229	40.5	39.3	29.6	30.8	38.8	39.5
10	4115	19898	35.1	38.6	30.5	33.8	38.4	38.0
12	2863	11364	24.4	22.1	39.9	22.5	22.8	22.5
AGE (MEAN)	NA	NA	14.9	14.8	15.4	15.3	14.9	14.8
SEX AT BIRTH: MALE	5644	25464	48.2	49.5	50.8	51.9	49.1	49.2
RACE/ETHNICITY								
AI/AN	83	590	0.7	1.1	0.7	1.0	0.9	1.1
ASIAN	2070	10707	17.7	20.8	17.6	20.7	19.7	20.3
BLACK	1140	2766	9.7	5.4	9.7	5.9	6.4	6.2
HISPANIC	822	5573	7.0	10.8	7.2	11.9	9.9	10.2
MULTIPLE	1381	5508	11.8	10.7	11.9	11.0	11.2	10.9
NH/PI	147	1074	1.3	2.1	1.2	2.3	1.7	1.9
WHITE	5673	22608	48.4	43.9	48.7	42.5	45.6	44.6
OTHER	403	2665	3.4	5.2	3.0	4.8	4.5	4.9
PHYSICAL ACTIVITY	2356	11138	20.1	21.6	19.2	20.8	20.9	21.4
FOOD INSECURITY	953	4568	8.1	8.9	8.5	9.3	8.6	8.7
SCREEN TIME (MEAN)	NA	NA	4.9	4.9	4.9	5.0	4.9	4.9
SCHOOL LEVEL ENROLLMENT IN LUNCH PROGRAM								
<10%	2619	13018	22.3	25.3	25.4	23.2	22.2	23.1
10-24%	3345	14115	28.5	27.4	26.6	24.2	32.1	31.5
25-39%	2664	9247	22.7	18.0	21.7	19.3	19.5	19.2
40+%	3091	15111	26.4	29.3	26.3	33.4	26.2	26.3

^These columns are percentages unless mean is indicated in the row header. Age = self-reported age in each survey.
Race/ethnicity = eight mutually exclusive categories.

AI/AN = American Indian/Alaskan Native.
NH/PI = Native Hawaiian/Pacific Islander.
Physical activity = 5+ days physically active for a total of at least 60 minutes per day in the past seven days.
Food insecurity = family had to cut meal size or skip meals because there wasn't enough money for food during the past 12 months.
Screen time = hours spent watching TV or electronic devices + hours spent playing video games.

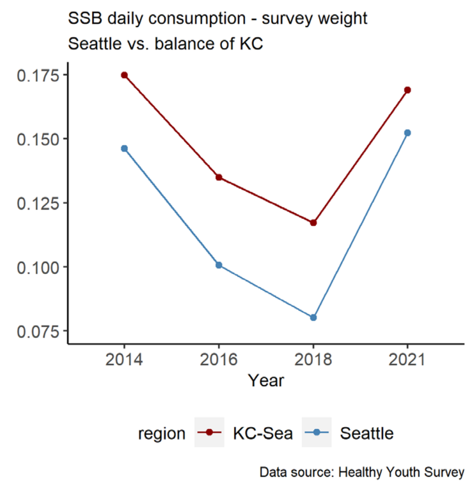
TABLE 2. SSB CONSUMPTION, BMI, OVERWEIGHT, AND OBESITY IN SEATTLE AND THE COMPARISON AREA PRE (2014 AND 2016) AND POST (2018 AND 2021) SBT IMPLEMENTATION BY DIFFERENT ANALYTIC WEIGHTS

OUTCOME MEASURES	UNWEIGHTED %		SURVEY WEIGHTED %		PROPENSITY SCORE WEIGHTED%	
	SEATTLE	COMPARISON	SEATTLE	COMPARISON	SEATTLE	COMPARISON
SSB DAILY CONSUMPTION (%)						
2014+2016	12.1	14.6	12.3	15.5	12.9	15.1
2018_2021	11.1	13.1	11.9	14.2	10.4	12.6
BMI (MEAN)						
2014+2016	21.3	21.7	21.7	22.0	21.4	21.7
2018_2021	21.4	22.0	21.7	22.5	21.4	22.0
OBESE (%)						
2014+2016	6.8	8.7	7.0	9.3	7.4	8.9
2018_2021	7.7	11.0	7.9	12.1	8.3	10.5
OVERWEIGHT (%)						
2014+2016	17.9	20.8	17.8	21.6	19.1	21.1
2018_2021	18.5	24.2	18.8	25.6	18.8	23.6

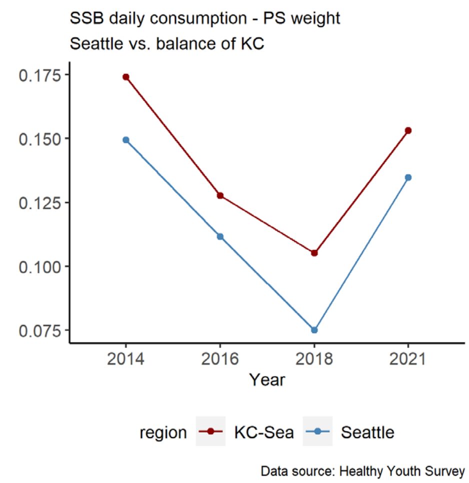
SSB = Sugar Sweetened Beverages BMI =
Body Mass Index

Figures 1 – 4. Trends in SSB, BMI, overweight, and obesity in Seattle and comparison area (2014, 2016, 2018, and 2021)

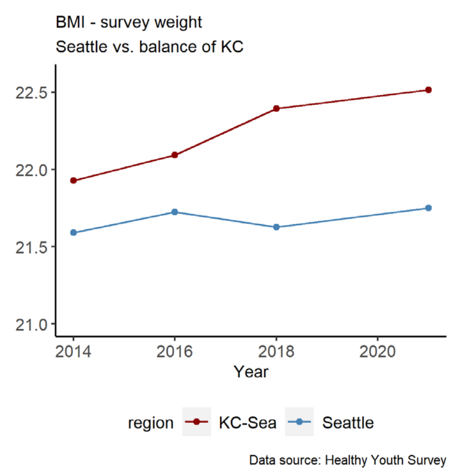
1a.



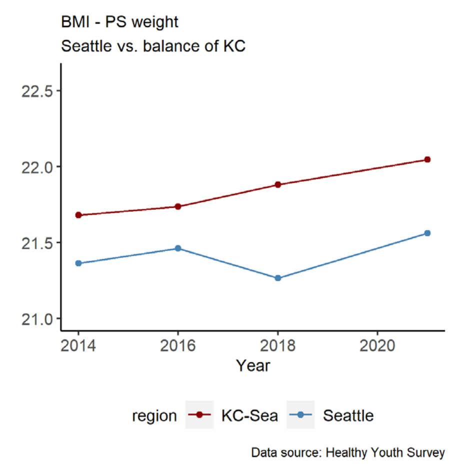
1b.



2a.



2b.



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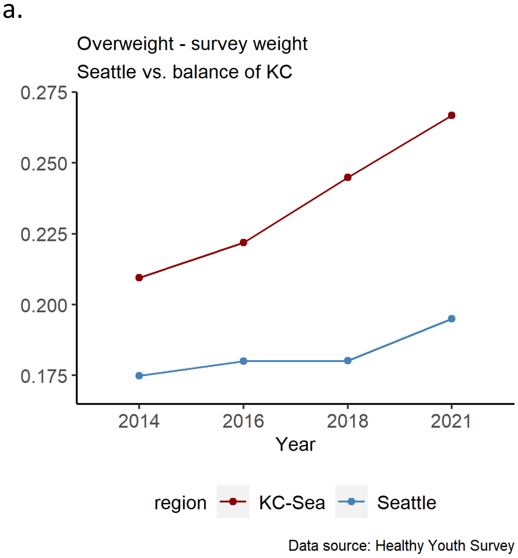

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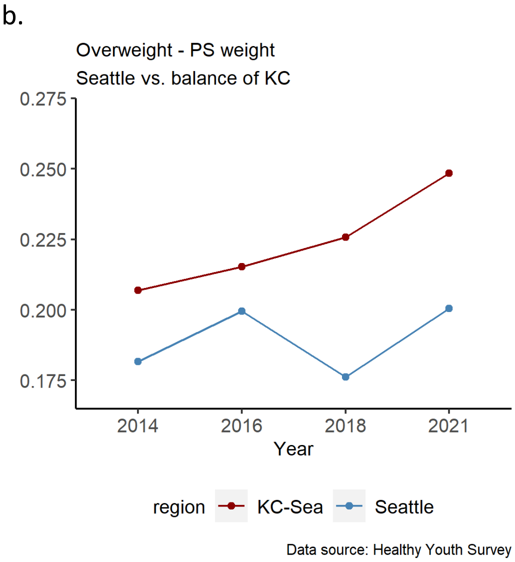

4a.

4b.

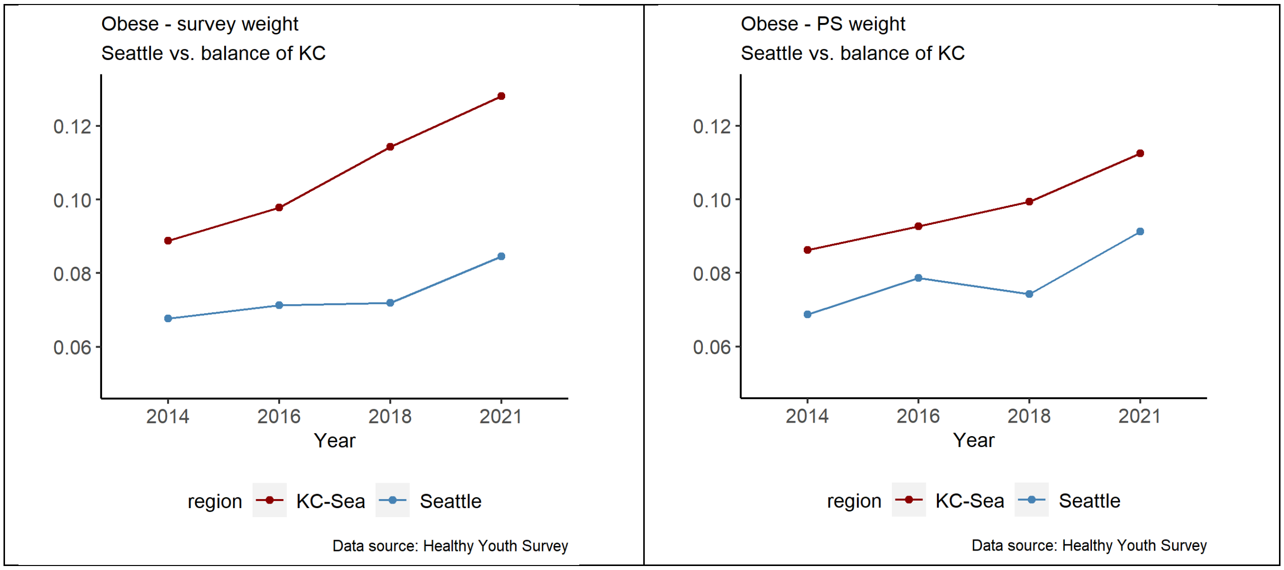

TABLE 3. PROPENSITY SCORE WEIGHTED MULTIVARIATE DID LINEAR

	POST SBT: 2018+2021		POST SBT: 2018 ONLY	
OUTCOME MEASURE	COEFFICIENT	P-VALUE	COEFFICIENT	P-VALUE
SSB DAILY CONSUMPTION	-0.002	0.857	-0.00	0.374
BMI*	-0.244	0.076	-0.289	0.087
OVERWEIGHT**	-0.029	0.025	-0.032	0.028
OBESE	-0.008	0.372	-0.014	0.158

Model includes grade, sex at birth, race/ethnicity, physical activity level, food insecurity status, screen time, and school level free or reduced lunch rate.
*Statistically significant at .10 level.
**Statistically significant at .05 level.

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