24 Month Report: Revenues

THE EVALUATION OF SEATTLE'S SWEETENED BEVERAGE TAX

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Contents

Was Seattle's Sweetened beverage tax associated with a change in small food store business Revenue?

Executive summary

The goal of this portion of Seattle's Sweetened Beverage Tax (SBT) Evaluation was to assess the degree to which the SBT may have affected the business viability of small food stores or convenience stores in Seattle. To do so, we assessed the association between the implementation of the tax and business revenue and store closures. The SBT could affect business revenue if, for example, consumers purchase fewer taxed beverages from retailers but do not substitute purchases of untaxed beverages or other products in their place. Small independent food stores were chosen for these analyses because we hypothesized that they could be the stores most vulnerable to revenue losses and/or potential closure in association with the SBT.

We used store-level tax records that are maintained by the Washington State Department of Revenue to calculate retailer revenues. This analysis is focused on revenues rather than profits due to limitations in the available data, which only include retailer revenue, but contain no information about costs (see Data Sources for details.) As a result, our analysis cannot address the effect of the SBT on retailer profits.

Our primary statistical model uses the synthetic control method. This method uses city-level mean outcomes for the aggregate of Seattle stores versus outcomes for a 'synthetic comparison group.' Outcomes for the synthetic comparison group are constructed as a weighted average of outcomes for all available units in the full comparison group. In this case, the full comparison group is a set of 7 other cities in Washington that did not institute a sweetened beverage tax but that otherwise share similar social and economic characteristics with Seattle. The synthetic control method is a process that assigns weights to the comparison units such that the weighted average outcome produced from those weights (in this case, city-level average store revenue) tracks the same outcome for Seattle closely in all pre-SBT years. This makes it reasonable to assume that the trends would have continued to be similar in Seattle and the comparison group had the SBT not occurred. We additionally use retailer-level analysis in the same seven comparison cities to estimate the association between the SBT and retailer closure in Seattle.

KEY FINDINGS

- While the nature and availability of the business revenue data prevents us from examining changes in business *profits*, we find no evidence that the tax was associated with declines in business *revenue* or business *closure* in small independent food stores in Seattle versus the comparison areas.
- All of the estimates from the primary statistical models indicate that small independent food stores in Seattle experienced either increased revenue or attenuated declines in revenue in the year after the tax was implemented (2018), relative to stores in the comparison areas, but that these differences were not statistically significant. Some models show statistically significant revenue growth in Seattle for small independent food stores in the second year of the tax (2019), relative to the comparison areas.
- We found no association between the tax in Seattle and the likelihood of small food stores going out of business.

Background

The goal of this portion of Seattle's Sweetened Beverage Tax (SBT) Evaluation was to assess the degree to which the SBT may have affected the business viability of small food stores or convenience stores in the city of Seattle. As with any policy, it is possible that there could be unintended consequences of the SBT. Potential unintended consequences include a loss in store revenue or store closures. This could happen if customers decrease their purchasing of taxed beverages and do not replace spending with goods of similar value. We investigate whether the SBT is associated with changes in small store revenue using data on business revenue from the Washington State Department of Revenue. We also examine the association between the SBT and the likelihood of these stores going out of business using data from the same data source**.** An observed increase in business closures after a policy can be an alternative way to detect negative effects of that policy on the profits of affected businesses**.** Small food stores were chosen for this analysis because we hypothesized that they could be the stores most vulnerable to revenue losses in association with the SBT.

Methods

Business Revenue Analysis

Briefly, in order to evaluate the association of the tax with business revenue, we used data from the Washington State Department of Revenue for 5 years prior to the tax implementation on January 1, 2018, and for two years after tax implementation (prior being January 1, 2013 - December 31, 2017; post-tax being January 1, 2018 - December 31, 2019). We end our analysis with the 2019 tax year due to the disruptions of the COVID-19 pandemic that emerged in early 2020.

To approximate retail revenue, we used retailer-reported business income from retail sales from the DOR's Business and Occupation (B&O) tax records. This measure is more appropriate for our purposes compared to an alternative measure such as revenue subject to sales tax because beverages, like other groceries, are not subject to sales tax.

For our primary outcome**,** we calculated annual percent change in revenue for our primary outcome. We calculate percent change in taxable revenue by:

$$Percent\ change\ in\ Revenue = \frac{Revenue_t - \ Revenue_{t-1}}{Revenue_{t-1}}\ X100\%$$

Where t is the year of tax data and t-1 is the previous year. For example, to calculate percent change in revenue for 2018, we subtract each business' 2017 revenue from its 2018 revenue and then divide by the 2017 revenue. We then multiply this quantity by 100 to convert to a percentage.

We adjusted all revenue for inflation using the U.S. Bureau of Labor Statistics (BLS) inflation measures for Seattle-Tacoma-Bellevue area for all cities in our sample except Spokane and Vancouver. For those cities, we used annual inflation calculated by the BLS for all urban areas in the US. All dollar values are adjusted to 2018 US$. For the city-level analyses, we calculated annual revenue growth for each city with >100,000 residents (described in the Comparison Group section below) by calculating the average percent change in taxable revenue from all included retailers in the city.

The average change in business revenue over the study period in each of these cities and Seattle is shown in **Figure 1.**

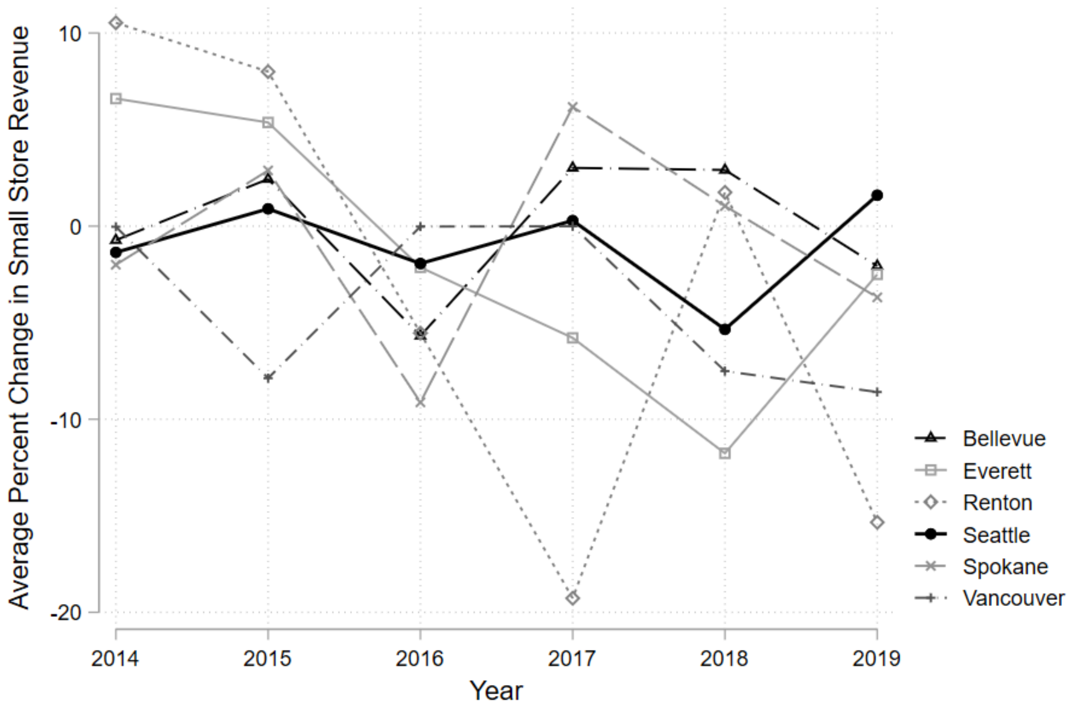


Figure 1- Average Percent Change in Revenue for All Small Food Retailers in Sample, by City and Year

Data limitations

There are important limitations to these data that should be noted while interpreting the results and provide reasoning to why we refer to this study as exploratory, rather than claiming we were able to examine a causal impact of the tax on profits, we can only examine the influence of the tax on revenues and business closures. The business revenues as an outcome have a number or inherent limitations. First, we only have total business revenue and cannot identify revenue from beverages specifically. Second, we have previously found that many retailers raise the price of taxed beverages by nearly the amount of the tax. Since we are calculating changes in gross revenues, not net revenues or ***profits***, we expect that store ***revenues*** might increase or stay steady even as their costs are increasing, because the price of the tax is leading to higher prices, which could produce higher revenues (but not necessarily profit). Specifically, if the tax had no impact on purchasing of these beverages, we would expect to see a small positive change in business revenue (i.e. the tax itself should result in increased prices and increased total revenue for taxed beverages to the extent they are still purchased). If consumers substitute a different, non-taxed beverage all of the time, we'd expect revenue to be approximately unchanged or slightly decline due to not paying the price of the tax. Likely the consumer reaction is somewhere between these two extremes. Any decrease in business revenue in Seattle stores above and beyond secular trends (i.e., relative to the best matched comparison that is not subject to the tax) could be reason for concern. We use the synthetic control method, which is a method aimed at causal inference, however, due to the above-mentioned data limitations, we can only speak to the impact of the tax on revenue and not on net profit.

A second potential limitation to this type of study is the possibility that a second policy differentially affected gross business revenue over this time period. We are not aware of any policy occurring during our study time period that would be expected to affect the gross business revenue of small stores differentially for Seattle versus the other cities that contribute to the synthetic control for Seattle. To our knowledge, the B&O tax is a gross receipts tax in all cities in Washington and there is a core model ordinance that standardizes many features of the tax, with the goal of general uniformity across cities in Washington. Exceptions to the model policy provisions are allowed for non-mandatory provisions. During our study period, according to the archives on MRSC.org, only the city of Renton updated their non-mandatory provisions. While Renton was a candidate "donor" in our synthetic control models, our final preferred models actually do not include Renton, so this would not affect our primary results. Second, the Seattle Minimum Wage Ordinance is a policy that could have affected some Seattle employers differently than those in neighboring cities; however, Washington state also implemented a phased increase in minimum wage during the same time as the Seattle minimum wage. For businesses with 500 or fewer employees, the minimum wage increases in Seattle were the same as those for the rest of Washington state. Because we focus on non-chain small convenience stores, the stores in our study were likely to be experiencing similar changes in minimum wage in Seattle and the comparison area.

Stores included in the analysis

We limited our sample to small independent (non-chain) food stores and convenience stores. After summarizing the data from small stores in the entire state of Washington in comparison to stores in Seattle, we observed large variations in business revenue and revenue growth between cities over time (see **Figure 1**). Therefore, in order to ensure that our comparison group was limited to retailers that can be reasonably assumed to be exposed to similar economic and demographic forces as retailers in Seattle (with the exception of the SBT), we applied a number of inclusion criteria in the construction of our comparison sample. First, we restricted our sample of retailers to stores within cities that had a population size of greater than 100,000. We also excluded stores inside and outside of Seattle reporting >$1 million in total business revenue from our sample. This rule allowed us to focus our analysis on smaller stores that could be most vulnerable to the impacts of the SBT. Finally, we excluded stores inside and outside of Seattle with >200% change in business revenue from year-to-year in order to prevent large changes in a few stores from driving the results. This process left us with 439 unique small retailers reporting taxable business revenue in eight cities, including Seattle. Some of these retailers are not present in all years of the data, either opening or closing their operations during the study period. If we exclude retailers that are not present in all years of the data, we have a sample of 136 unique retailers.

Comparison group

Our primary statistical models use synthetic control methods[1] to construct a comparison group to which we can compare the outcomes observed in Seattle. Synthetic control methods use aggregate outcomes and covariates and are recommended for evaluating policies where it may be difficult to identify appropriate comparison places (e.g., there is no city highly comparable to Seattle in Washington state). Briefly, the goal is to use information from stores in potential comparison cities to create a "synthetic control or comparison area" from potential "donor cities" (in the terminology of the synthetic control literature). There were seven cities in Washington state (aside from Seattle) that had >100,000 people, however we excluded one of these cities (Kent), because there were fewer than 10 qualifying retailers in the city. Consequently, we calculated the average annual percent revenue growth for Seattle and the six

[1] Abadie, Alberto, and Javier Gardeazabal. 2003. "The Economic Costs of Conflict: A Case Study of the Basque Country." *American Economic Review*, 93 (1): 113-132.

remaining comparison cities from the remaining 406 retailers (unbalanced sample) and 133 retailers (balanced sample). Applying the synthetic control methodology to the remaining six cities (Bellevue, Everett, Renton, Spokane, Tacoma, and Vancouver), we created a weight for each city that reflected its similarity to Seattle in demographics as well as pre-tax trends in small food retailer revenues. The method provides researchers with several potential models (and corresponding sets of weights) to choose from. Each model has a level of prediction error associated with it. We chose our primary analysis model based on its low error as well as other considerations suggested by the synthetic control literature. Secondary analysis models were also selected based on these considerations.

Results

Findings from the Synthetic Control Method: Full Sample of Stores

Using the synthetic control methodology described above, we calculated several potential sets of city weights to be used in constructing our synthetic control unit. The method constructs weights based on different combinations of pre-policy outcome variables as well as city-level demographics. The factors included in each model, as well as the calculated weights and associated prediction error (RMSPE in the table) are shown in **Appendix Table 2**. The weights and prediction errors are very similar for almost all of the models explored. This is likely due to the fact that the synthetic control method primarily relies on the pre-SBT outcome variable in constructing weights. Ultimately, we chose **Model 4** as our primary analysis model, since it includes a full set of demographic characteristics as well as an overall average of the pre-SBT outcome variables. In Model 4, as well as in most models for which weights were constructed, only Bellevue, Everett, and Vancouver receive non-zero weights, with weights for Bellevue being the highest. The magnitude of these weights reflects the overall similarity in both our outcome as well as basic demographics between these cities and Seattle.

Figure 2 displays the primary results from the synthetic control model comparing percent change in revenue in Seattle stores versus the weighted average of the percent changes in revenue in the comparison areas or “Synthetic Seattle” (the weighted average of select cities as described above). Seattle is shown in the solid black line and the comparison group/Synthetic Seattle is shown in the dashed line. The pre-SBT trend in the outcomes (annual percent change in revenue) are similar for Seattle and Synthetic Seattle, as we would expect, given that the city weights were constructed to create the best fit possible between these two trend lines.

Our primary result is the difference between the trend lines for Seattle and Synthetic Seattle after the tax was implemented (2018 and 2019 values of the outcome). These results indicate no evidence of an adverse impact on business revenues in Seattle stores for either of the two years after the tax in comparison to the weighted average outcome from the comparison group (i.e., Synthetic Seattle).

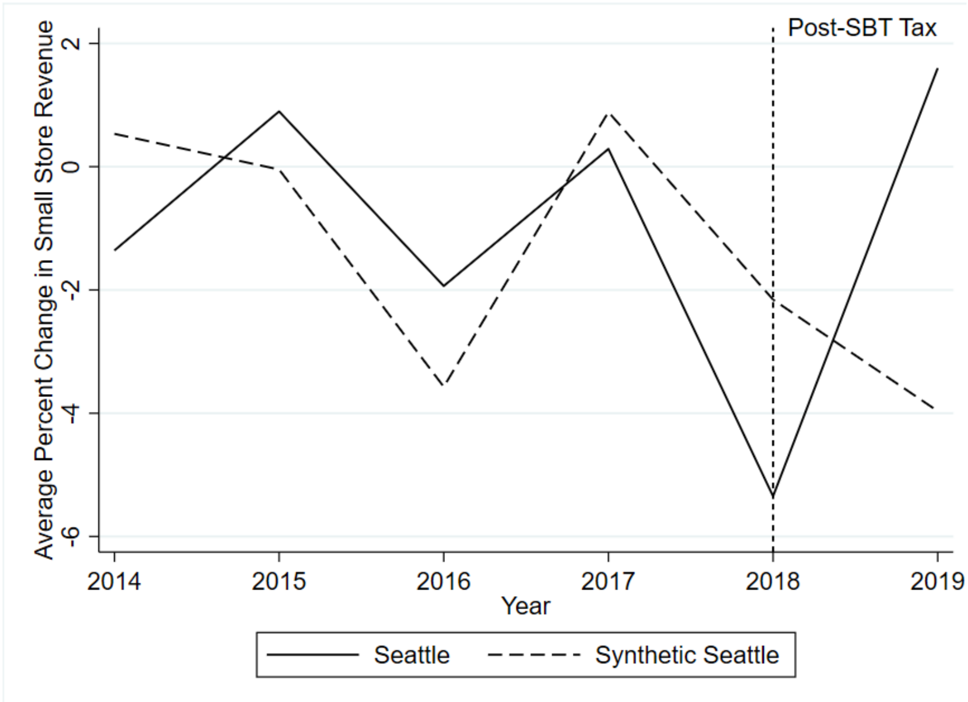


Figure 2- Average Percent Change in Small Food Store Revenue in Seattle and comparison area, 2014-2019. Synthetic Seattle weighted average of outcomes in comparison cities, with weights based on Model 4 in Appendix Table 1. Vertical line marks 2017, last year of data before SBT. The Full Sample of stores is an unbalanced sample, including every operating business in every year, including retailers that open after 2014 or fail during any study year. Results show that average store revenue growth in Seattle is greater than in Synthetic Seattle.

In **Table 1** below, we show the effect of the SBT on percent change in revenue as the difference between this outcome in Seattle and in Synthetic Seattle. A negative effect means that revenue grew faster in Synthetic Seattle than in Seattle, while a positive effect means the opposite. This table also includes a measure of statistical precision of the effects we measure. This value (the p-value) indicates the probability that the effect we identify is different from zero and not the result of noise in our variables. Lower p-values mean that the detected effect is more likely to be due to true differences in outcomes and less likely to be due to noise. Standard thresholds in the synthetic control literature in Economics take p-values < 0.10 to be indicative of a 'statistically significant' difference in outcomes.

As we see in **Table 1**, the difference in percent revenue growth between Seattle and Synthetic Seattle is a negative 3.2 percentage point difference in revenue growth in 2018, but the p-value of 0.33 indicates that this estimated effect cannot be distinguished from zero statistically. In other words, we cannot claim to have found any difference in revenue growth between Seattle and Synthetic Seattle in this first year of the tax. [2] However, in 2019, the second year of the tax, the estimated effect is a positive 5.6 percentage point difference in revenue growth between Seattle and Synthetic Seattle, and the p-value of <0.01 indicates that this difference is likely to be due to real differences in outcomes. Consulting **Figure 2,** we see that this relatively higher growth in Seattle versus Synthetic Seattle is due to declining

[2] McClelland R, Gault S. The synthetic control method as a tool to understand state policy. Washington, DC: The Urban Institute. 2017 Mar.

revenues in Synthetic Seattle, which can be attributed to declining revenues in the cities that make up this weighted average.

TABLE 1. EFFECT OF SBT ON CHANGES IN AVERAGE REVENUE GROWTH FOR SMALL STORES FOR UNBALANCED STORE SAMPLE		
YEAR	PERCENTAGE POINT DIFFERENCE IN REVENUE GROWTH	P-VALUE
2018	-3.2	0.33 (NS)
2019	5.6	<0.01

ns=not statistically significantly different

<u>Sensitivity Analyses for the synthetic control method.</u>

Sensitivity Analysis One:

Different model specification for the synthetic control method in the full sample of stores.

Choosing the most appropriate statistical model in the comparison group method is not always an obvious choice if several models fit the data equally well. For this reason, we repeated the analysis above in a few different ways in order to detect the extent to which our results and subsequent conclusions are sensitive to the model chosen. We conducted several types of sensitivity analysis. First, we chose two other model specifications from **Appendix Table 1** and repeated the analysis above for using those specifications. We found that although our estimated effect sizes varied slightly from those in **Table 1** above, our main conclusions were the same: no statistically significant difference between Seattle and the Synthetic Seattle during the first year of the tax, and a positive and statistically significant difference in revenue growth during the second year of the tax. The effect size graphs for one of these alternative specifications is shown in **Appendix Figure 1**.

Sensitivity Analysis Two:

Synthetic Control Method in a Balanced Sample.

The next sensitivity analysis we conducted was to evaluate whether our assessment of the tax's impact would change if we further limited the sample of stores in Seattle and the comparison group to a balanced sample of 133 stores that are present in the sample for all five years (this is 136 stores in the balanced sample, minus the three stores located in Kent).

Figure 3 shows percent change in revenue growth in Seattle and Synthetic Seattle for this "balanced" sample of retailers. In the figure, we see that revenue growth in Seattle hovers around zero from 2016 to 2019, spanning the pre- and post-SBT introduction period. Revenue growth in Synthetic Seattle, on the other hand, is more volatile over this period, with a sharp decline occurring in 2019 that is not matched in the Seattle sample. **Table 2** below shows the estimates of these effect sizes as well as their p-values. Similar to the results for the primary model in **Table 1**, we find that Seattle retailers experience 0.2 percentage point growth relative to retailers in the comparison group in the first year with the tax (2018), and this difference is not statistically significant. Similar to our primary models, in the second year with the tax (2019) retailers in the comparison group experience a large decline in revenue growth, while the balanced set of Seattle retailers saw revenue change hold steady. The overall difference in growth between Seattle and the comparison group is 6.3 percentage points in 2019 when using only the balanced sample. However, in contrast to our findings for the unbalanced sample of retailers (primary models) this difference between Seattle and the comparison group is not statistically significant.

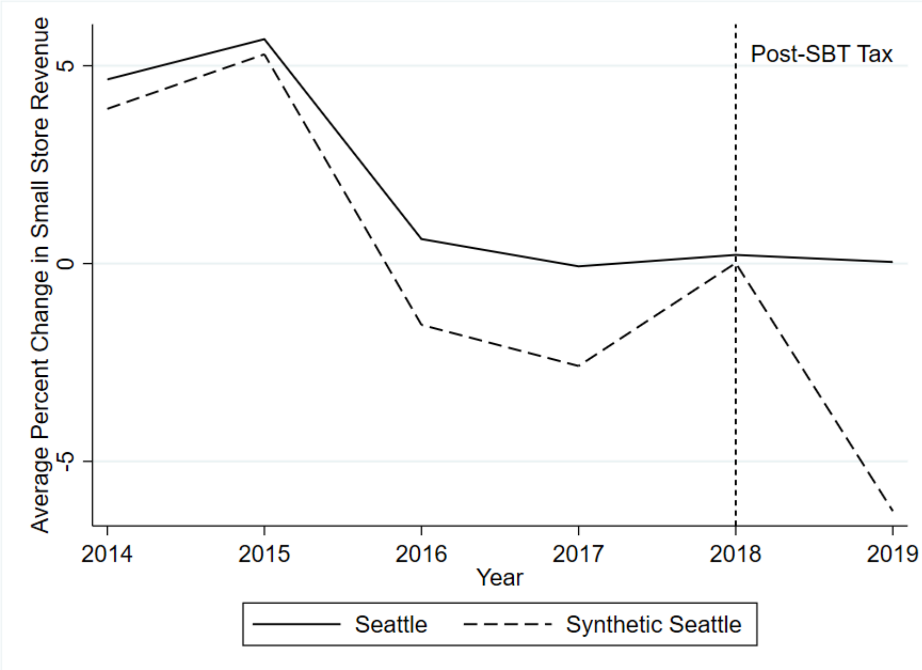


Figure 3- Average Percent Change in Small Food Store Revenue in Seattle and Synthetic Seattle (a weighted average of the outcome variable in 6 comparison area cities), 2014-2019. Balanced sample includes only retailers that are in businesses in 2013 and remain in business through the end of 2019. This figure shows that Seattle retailers experience a slightly higher percent change in revenues relative to retailers in the comparison group in the first year with the tax (2018). In the second year with the tax (2019) retailers in the comparison group experience a large decline in revenue growth, while the balanced set of Seattle retailers saw revenue change hold steady.

TABLE 2. EFFECT OF SBT ON CHANGES IN AVERAGE REVENUE GROWTH FOR SMALL STORES FOR BALANCED STORE SAMPLE		
YEAR	PERCENTAGE POINT DIFFERENCE IN REVENUE GROWTH	P-VALUE
2018	0.21	1.00 (NS)
2019	6.3	0.50 (NS)

ns=not statistically significantly different

Sensitivity Analysis Three:

Expanding store sample inclusion criteria

In another check that our results are not driven by our modeling choices, we tested the sensitivity of our findings with respect to the exclusion of retailers with more than one million dollars in revenue and/or more than 200% revenue growth in a year from our sample. We re-calculated annual percent change in revenue with this larger sample and re-estimated the synthetic control model as above. We found that although city-level revenue growth is more volatile than in our sample that excludes these retailers, growth in revenue is still larger in Seattle than in the comparison area post-SBT, but the difference in revenue growth between the cities is not statistically significant.

Sensitivity Analysis Four:

Synthetic controls for each store (rather than city-wide aggregate).
Finally, we tested whether our results were sensitive to our decision to use average revenue growth at the city level as our outcome, rather than firm-level revenue growth. We used the synthetic control method to generate a synthetic control for each store in Seattle (rather than for the city of Seattle in aggregate). In this analysis, each retailer's synthetic control is made up of a weighted average of the outcomes of the donor stores (all retailers from our data set that were not located in Seattle). We used the same data as in the "balanced" analysis describe above, i.e. stores that remain in our sample during all years, since the synthetic control method requires that all units are present in every year of data. This data set includes the 136 stores from the balanced sample described above (62 of which are in Seattle and 74 are in the comparison areas). As a result, the method produces 62 sets of weights used in forming 62 synthetic controls, which ultimately produces 62 measures of the treatment effect, measured as the post-tax difference in revenue growth between each store and its synthetic comparison. The average of these 62 treatment effects is -0.069 percentage points in 2018 and 0.98 in 2019. Neither of these differences is statistically different from zero, consistent with our findings from the city-level analysis on the balanced sample of stores described above.

In summary, our primary analysis using the synthetic control method, as well as a number of similar analyses that vary assumptions from our primary model, do not provide evidence of an association between the SBT and a loss of business revenue. Instead, the models suggest that the trends seen in business revenue in small independent stores in Seattle show growth after the SBT (at least in 2019), or attenuated declines relative to the stores in the comparison group, but differences are generally not statistically significantly different between Seattle and the comparison group.

<u>Findings from the difference-in-differences method</u>.
Difference in differences is an alternative modeling method in the policy impact evaluation literature. While synthetic control methods are more widely accepted for evaluating the impact of a policy in only one city, we employ difference-in-differences as an alternative method of determining the effect of the tax, both because this method is more widely known than the synthetic control method and because it provides easy to interpret estimates of the average treatment effect for individual stores.

Similar to the synthetic control models used above, the difference-in-differences statistical models estimate the average change in store revenue growth in Seattle post-SBT, above and beyond the change in revenue growth in the comparison cities during the same time period. Where this analysis differs from the synthetic control analysis is that all stores in all comparison cities are given equal weight as comparison units when calculating the treatment effect. Additionally, difference-in-differences calculates the treatment effect for each store and reports and average of those treatment effects, rather than first averaging revenue growth at the city level and performing the analysis on that outcome as was done in the majority of our synthetic control models. For this analysis, we also limited our sample to small food retailers only for years when those retailers reported $1 million or less in revenue and less than 200% annual revenue growth. Additionally, we limited our sample to stores in the same sample of Washington cities with more than 100K residents, with the exception of Kent because of the extreme values mentioned above.

As with our synthetic control analysis, we use difference-in-differences to estimate the effect of the SBT on store revenue growth for both the full/unbalanced sample of stores (the N=439 stores present in any year of our data) and the balanced sample of stores (the N=136 stores that appear in all years of our data). Our estimates are reported in **Table 3**. Like the results from our primary synthetic control analysis, the estimates in **Table 3** consistently indicate that percent change in business revenues was higher in Seattle stores compared to stores in comparison cities from before to after the tax. However, similar to the results from the synthetic control method, this difference is not statistically significant. For example, in the model that includes stores that remain in business over the entire period (i.e., balanced) and adjust for all baseline time-invariant store characteristics ("store fixed effects") the results indicate that small food stores in Seattle, on average, had 2.04 percentage points higher change in business revenue compared to the small food stores in comparison cities, but that this difference did not reach statistical significance (p=0.95).

TABLE 3. ESTIMATED ASSOCIATION BETWEEN SEATTLE'S SWEETENED BEVERAGE TAX AND PERCENT CHANGE IN BUSINESS REVENUE AMONG SMALL FOOD RETAILERS USING DIFFERENCE-IN-DIFFERENCES METHOD

MODELS	DIFFERENCE-IN DIFFERENCES (UNIT= PERCENTAGE POINTS) (95% CONFIDENCE INTERVAL)	P-VALUE	NUMBER OF STORE-YEAR OBSERVATIONS	NUMBER OF UNIQUE STORES
FULL SAMPLE/UNBALANCED MODEL WITH STORE FIXED EFFECTS	-0.24 (-6.55, 6.07)	0.94	1,576	439
FULL SAMPLE/UNBALANCED MODEL WITHOUT STORE FIXED EFFECTS	2.13 (-3.15, 7.42)	0.53	1,576	439
BALANCED MODEL WITH STORE FIXED EFFECTS	2.02 (-4.24, 8.30)	0.52	816	136
BALANCED MODEL WITHOUT STORE FIXED EFFECTS	0.86 (-3.93, 5.64)	0.72	816	136

Business Closure Analysis.

In addition to store revenue, we assessed whether the SBT was associated with a higher likelihood of small stores going out of business. In this analysis, we use linear probability models to examine whether there is any association between the SBT and stores in Seattle going out of business by testing whether the likelihood of business closure increased in Seattle after the tax versus before the tax. The outcome in this model is an indicator variable for whether each store went out of business or not. The model controls for the contribution of a number of factors, including city, neighborhood socio-demographics, business tenure, and average taxable income during our study period. Our key variable of interest is an indicator for whether or not the retailer was exposed to the SBT in Seattle. This is an indicator variable that is one for Seattle retailers that report being operational at the start of 2018 and zero otherwise. The estimated coefficient for this variable shows the association between exposure to the SBT and business closure (over and above any association between being located in Seattle at any time in our study period and business closure). We perform this analysis on two samples – our primary analysis sample (the full unbalanced sample of stores with <$1million in revenue and <200% change in yearly revenue) – and the fullest sample of relevant retailers (including those with over one million dollars in revenue and those with over 200% yearly growth in revenue). Additionally, we classify a business as open until they officially report closure to the Department of Revenue. Consequently, we have more businesses in this analysis than in the previous analyses based on taxable income growth.

Table 4 shows the results of the analysis estimating the association between SBT exposure and business closure. Results for both samples show that businesses exposed to the SBT (operating in Seattle post-

2018) are no more or less likely to fail than those that were located in in non-taxed cities during that same period.

TABLE 4. ESTIMATED ASSOCIATION BETWEEN SEATTLE'S SWEETENED BEVERAGE TAX EXPOSURE AND RETAILER CLOSURE USING LINEAR PROBABILITY MODELS			
MODELS	SBT EXPOSURE (95% CONFIDENCE INTERVAL)	P-VALUE	NUMBER OF UNIQUE STORES
FULL/UNBALANCED SAMPLE	-0.015 (-0.065, 0.035)	0.56	566
ALL BUSINESSES, INCLUDING THOSE WITH >$1MILLION REVENUE AND >200% REVENUE GROWTH	-0.015 (-0.053, 0.021)	0.40	893

As a sensitivity analysis for the outcome of business closure, we analyzed the effect of exposure to the SBT in Seattle on the city-level rate of food retailer closure. We conducted this analysis using the synthetic control method. Using the sample of small food retailers stores with <$1 million in revenue and <200% change in revenue, we calculated the proportion of these businesses that failed in each year by dividing the number of businesses that closed during the year by the number of businesses operating at the beginning of the year. We constructed this measure for each of our seven cities in each year. We find that the closure rate for small food retailers included in our sample hovers around 7-8% in Seattle from 2014 to 2018. However, it raises close to 10% in 2019. To investigate whether this rise in business failure in Seattle could be explained by the SBT, we conduct a synthetic control analysis for this outcome using the same methods outlined above.

Figure 4 shows the evolution of the business closure rate in Seattle and the comparison group. This figure shows that the business closure rate increases to over 12% in Seattle and over 14% in the comparison group by 2019, but the difference between failure rates in Seattle and comparison area are not statistically significant. **These findings suggest that the increase in business closure observed in Seattle is likely driven by changes in economic conditions experienced in other larger cities in Washington, not just in Seattle. This suggests that the SBT is not driving the observed changes in Seattle.**

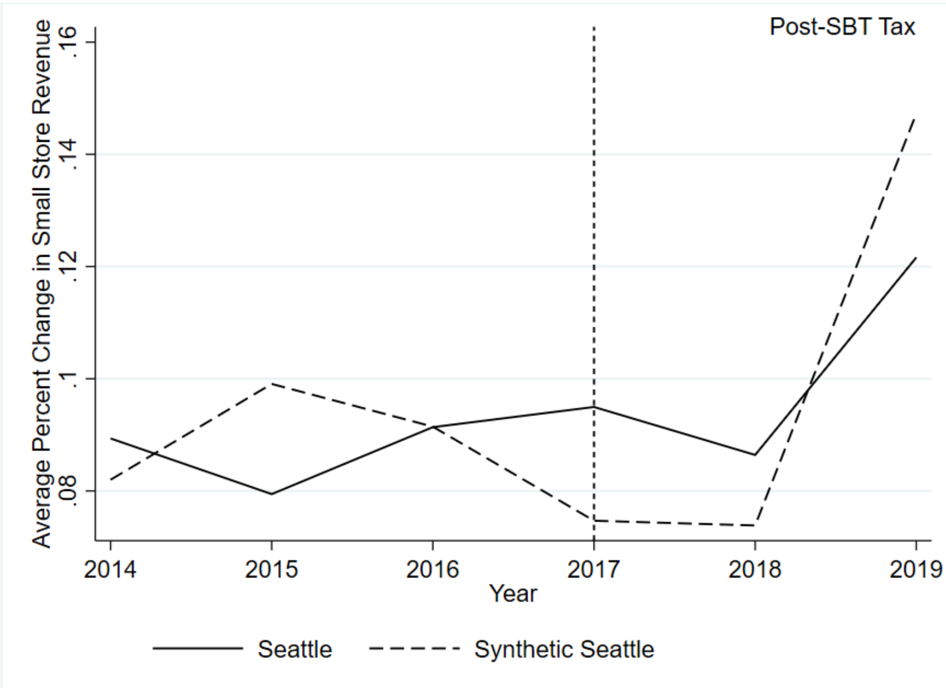


Figure 4- Business Failure Rate in Seattle and Synthetic Seattle, 2014 – 2019. All non-chain food retailers included in our primary analysis sample –the full (unbalanced sample of stores with <$1million in revenue and <200% change in yearly revenue.

Conclusion

We used multiple statistical methods to assess the degree to which Seattle's SBT was associated with potential negative unintended consequence of lost revenue in small independent food stores. While the nature and availability of the business revenue data prevents us from examining changes in business ***profits***, we find no evidence that the tax was associated with declines in business ***revenue*** in small independent food stores in Seattle versus similar stores in other larger Washington cities, none of which have a sweetened beverage tax. All of the estimates from the primary statistical models indicate that small independent food stores in Seattle had either increases or attenuated declines in revenue in the year after the tax was implemented (2018), relative to stores in the comparison areas, but that these differences were not statistically significant. Some models show statistically significant revenue growth in Seattle in the second year of the tax (2019), relative to comparison. The synthetic control model performed well in that we were able to create a synthetic comparison group that was well-matched to Seattle. In addition, findings were consistent across various primary and secondary models, and in balanced and unbalanced samples.

We also assessed whether the SBT was associated with an increased likelihood of stores going out of business in Seattle versus outside of Seattle. We find no evidence that the tax was associated with a greater likelihood of going out of business.

Findings were consistent in suggesting no adverse association between the tax and retailer revenue or retailer closure across various primary and secondary models, and in balanced and unbalanced samples.

Appendix

Detailed Methods.
Below we provide more detailed descriptions for the methods used in this section. Some of the information below also appears in the main section of this report.

Data Sources

Washington State Department of Revenue. We used microdata from the Washington State Department of Revenue (DOR). Our observation period covers calendar years 2013-2019, providing 5 years of pre-SBT data and 2 years of post-SBT data. We end our analysis with the 2019 tax year due to the disruptions of the COVID-19 pandemic that emerged in early 2020.

We use retailer-reported business income from the DOR's Business and Occupation (B&O) tax records. The B&O tax is on gross receipts, and revenue is reported in the records by type of business activity. We are able to isolate a measure of retail sales revenue from these records. Since nearly all revenue from retail transactions is subject to the B&O tax, it is a more appropriate measure of revenue of beverage sales, given that beverages, like other groceries, are not subject to sales taxes in Washington.

We limit our analysis to revenue from small food stores and non-chain convenience stores for two main reasons. First, as mentioned above, we hypothesize that these stores are at greatest risk for being negatively impacted since the sale of beverages may make up a more sizable portion of total sales than for larger stores. Second, because the DOR data does not consistently disaggregate revenue for chain stores across their various locations, we could not reliably identify revenue for locations inside versus outside of Seattle for some chain stores.

There are important limitations to these data that should be noted while interpreting the results and are the reasons we refer to this study as exploratory and associational, rather than claiming a causal impact of the tax. First, we only have total business revenue and cannot identify revenue from beverages specifically. Second, we have previously found that many retailers raise the price of taxed beverages by nearly the amount of the tax. Since we are calculating changes in gross revenues, not net revenues or profits, we expect that store revenues might increase or stay steady even as their costs are increasing, because the price of the tax is leading to higher prices, which could produce higher revenues (but not necessarily profit). This could occur even if overall retailer sales were declining, and therefore could mask a negative impact of the tax on retailers. Specifically, if the tax had no impact on purchasing of these beverages, we would expect to see a small positive change in business revenue (i.e. the tax itself should result in increased prices and increased total revenue for taxed beverages to the extent they are still purchased). If consumers substitute a different, non-taxed beverage all of the time, we'd expect revenue to be unchanged. Likely the consumer reaction is somewhere between these two extremes. Any decrease in business revenue in Seattle stores above and beyond secular trends could be reason for concern.

King County Categorized Food Permit List. We used the King County Categorized Food Permit List to check the validity of the North American Industry Classification System (NAICS) codes (industry codes to classify businesses) in the DOR dataset to see how well these codes identified small, independent food retailers. We sought to identify small businesses that would be the most likely to be impacted by the tax—small stores that sell beverages, such as convenience stores or small grocery stores. To identify these types of stores, we first eliminated chain stores and restaurants through key word matching. Then we conducted an analysis of the codes to see how well these codes identified small, independent food retailers. We used the categorized list of permitted food stores in King County as a gold standard against which we compared the NAICS codes for correctly identifying small independent food retailers. For stores that were present in both datasets (DOR and the categorized King County permit list), we found 92% accuracy in the NAICS codes classification for identifying small, independent food retailers. This provided us with confidence in the identification of the larger set of stores (i.e., throughout Washington state) that appear in the data set of tax revenue and have relevant NAICS codes.

American Community Survey. We utilized the American Community Survey 5-year estimates for annual city-level demographic characteristics, including: population size, population density, per capita income, age distribution, educational attainment distribution, and race/ethnicity distribution. We use ACS 1-year estimates for each year from 2013 to 2018 for median home prices, which are used to calculate growth in housing prices (see below for analyses that included housing prices).

Sample Inclusion Criteria

After summarizing the data from small stores in the entire state of Washington in comparison to stores in Seattle (described in more detail in the previous progress report), we observed large variations in business revenue and revenue growth between cities. Therefore, in order to ensure that we create our comparison group from retailers that can be reasonably assumed to be exposed to similar economic and demographic forces as retailers in Seattle, we applied a number of inclusion criteria in the construction of our main analysis sample. First, we restricted our sample of retailers to stores within cities that had a population size of greater than 100,000. We also excluded stores reporting >$1 million in total business revenue from our sample. This rule allowed us to focus our analysis on smaller stores that could be most vulnerable to the impacts of the SBT. Finally, we excluded stores with >200% change in business revenue from year-to-year in order to prevent large changes in a few stores from driving the results.

Outcome variable

Revenue Growth. We used percent change from pre-SBT to post-SBT in business revenue subject to the B&O tax on retail activity as our primary outcome of interest since there was a wide variation in absolute business revenue among stores. Business revenue subject to the B&O tax was chosen as the outcome since this tax covers the widest range of goods sold and may be reported more reliably than gross revenue (as described above). We adjusted all revenue for inflation using the U.S. Bureau of Labor Statistics (BLS) inflation measures for Seattle-Tacoma-Bellevue area for all cities in our sample except Spokane and Vancouver. For those cities, we used annual inflation calculated by the BLS for all urban areas in the U.S. All dollar values are adjusted to 2018 US$.

We calculate percent change in taxable revenue by:

$$\frac{Revenue_t - Revenue_{t-1}}{Revenue_{t-1}} \, X100$$

For the city-level analyses, we calculated annual revenue growth for each city by calculating the average percent change in taxable revenue from all included retailers in the city.

Business Closure. As a secondary analysis, we use business closure as our outcome variable. We defined a variable indicating if one of the retailers in our sample closes during any year in the study period (yes=1, no=0). Our analysis explores the question of whether businesses are more likely to close in Seattle post-SBT implementation, and looks at the likelihood of business failure at the individual level as well as the proportion of businesses failing in each city by year as outcomes.

Statistical Analyses

Descriptive analyses. We summarized the available demographic characteristics from cities in our sample, including population size, population density, per capita income, age distribution, educational attainment distribution, race/ethnicity distribution, age distribution, median home prices, and percent change in median home prices. **Appendix Table 1** shows means and frequencies of these characteristics for each of the cities in Washington population with >100,000.

Synthetic Control Method. The synthetic control method entails multiple steps. First, we limited the potential comparison cities to those with >100,000 people. Using the terminology of the synthetic control method, we call these potential donor cities. **Appendix Table 1** displays the cities in Washington that met these criteria. Second, we selected variables that we hypothesized to be correlated with small food store revenue to use as covariates (see paragraph above). In this method, it is important that Seattle does not have the lowest or highest values of any of the selected covariates and instead that a weighted linear combination of the values from the donor cities could equal the value of Seattle. The value of these variables for Seattle and the seven potential donor cities are displayed in **Appendix Table 1**. Based on the criteria above (Seattle should not be the extreme value on any of the chosen variables), we selected as variables to include in the synthetic control model selection process: percent of the population with a college degree or higher; race/ethnicity distribution; income per capita; growth in housing prices. Given Seattle was at or near the ends of the distribution, population density, resident age, and income were not included in the synthetic control model selection process.

APPENDIX TABLE 1. DEMOGRAPHIC CHARACTERISTICS OF SEATTLE AND POTENTIAL DONOR (COMPARISON) CITIES (5-YEAR AVERAGE FOR 2013-2018)

	BELLEVUE	EVERETT	KENT*	RENTON	SEATTLE	SPOKANE	TACOMA	VANCOUVER
POPULATION								
• TOTAL POPULATION	142,242	108,941	128,057	101,054	**708,823**	214,804	210,103	178,413
• POPULATION DENSITY	4,251	3,277	3,796	4,310	**8,452**	3,124	4,226	3,646
AGE								
• UNDER 5 YEARS OLD	6.0%	6.0%	7.0%	7.0%	**5.0%**	6.0%	6.0%	7.0%
• 5-9 YEARS OLD	6.0%	6.0%	7.0%	7.0%	**5.0%**	6.0%	6.0%	7.0%
• 10-14 YEARS OLD	6.0%	6.0%	6.0%	5.0%	**4.0%**	6.0%	5.0%	6.0%
• 15-17 YEARS OLD	4.0%	4.0%	5.0%	4.0%	**2.0%**	4.0%	3.0%	4.0%
• 18-24 YEARS OLD	7.0%	10.0%	10.0%	8.0%	**11.0%**	10.0%	10.0%	9.0%
• 25-34 YEARS OLD	18.0%	18.0%	17.0%	19.0%	**23.0%**	16.0%	17.0%	16.0%
• 35-44 YEARS OLD	14.0%	13.0%	13.0%	16.0%	**16.0%**	13.0%	13.0%	13.0%
• 45-54 YEARS OLD	15.0%	13.0%	12.0%	14.0%	**12.0%**	12.0%	13.0%	12.0%
• 55-64 YEARS OLD	12.0%	12.0%	12.0%	11.0%	**11.0%**	13.0%	12.0%	12.0%
• 65-74 YEARS OLD	8.0%	7.0%	7.0%	6.0%	**7.0%**	9.0%	8.0%	9.0%
• 74-84 YEARS OLD	5.0%	3.0%	3.0%	3.0%	**3.0%**	4.0%	4.0%	4.0%

• 85 AND OLDER	2.0%	2.0%	1.0%	2.0%	**2.0%**	2.0%	2.0%	2.0%
RACE								
• WHITE	49.8%	63.5%	43.7%	44.6%	**64.5%**	81.4%	58.7%	72.1%
• BLACK	2.7%	4.4%	12.4%	9.7%	**6.9%**	2.1%	9.7%	2.0%
• AMERICAN INDIAN/ALASKA NATIVE	0.2%	0.7%	0.8%	0.4%	**0.5%**	1.5%	1.4%	0.5%
• ASIAN	35.3%	9.1%	19.8%	23.3%	**14.9%**	2.6%	9.1%	5.4%
• HAWAIIAN/PACIFIC ISLANDER	0.3%	1.3%	1.6%	1.9%	**0.3%**	0.8%	1.2%	1.4%
• OTHER	0.5%	0.1%	0.1%	0.3%	**0.3%**	0.1%	0.3%	0.2%
• TWO OR MORE RACES	4.3%	5.3%	5.5%	5.9%	**6.0%**	5.1%	7.8%	5.2%
• HISPANIC	6.9%	15.6%	16.1%	13.9%	**6.6%**	6.5%	11.9%	13.3%

	BELLEVUE	EVERETT	KENT*	RENTON	SEATTLE	SPOKANE	TACOMA	VANCOUVER
EDUCATION (ALL LEVELS)								
• LESS THAN HS	4.6%	12.5%	14.2%	9.2%	**5.4%**	7.1%	11.9%	9.1%
• HS GRAD	9.2%	26.3%	26.3%	22.2%	**9.8%**	23.3%	25.7%	24.7%
• SOME COLLEGE	18.7%	38.6%	34.5%	32.5%	**22.0%**	39.2%	34.1%	38.2%
• BACHELOR'S DEGREE	37.0%	15.8%	18.2%	25.7%	**36.2%**	18.7%	18.2%	18.5%
• MASTER'S DEGREE	22.5%	5.1%	4.9%	8.5%	**17.7%**	7.9%	7.2%	6.8%
• PROFESSIONAL DEGREE	4.1%	1.1%	1.2%	1.0%	**5.1%**	2.4%	1.8%	1.5%
• PHD	3.9%	0.6%	0.6%	0.9%	**3.8%**	1.4%	1.2%	1.2%
EDUCATION								
• % OF POPULATION WITH BACHELOR'S OR HIGHER	67.6%	22.6%	24.9%	36.1%	**62.8%**	30.4%	28.4%	28.1%
INCOME								
• MEDIAN HH INCOME	112,283	57,205	68,880	74,756	**85,562**	47,822	58,617	58,865
• INCOME PER CAPITA	63,115	30,670	29,561	37,460	**55,789**	28,274	31,252	31,352
HOUSING PRICES								
• MEDIAN HOME PRICE 2013	589,170	266,642	293,238	320,733	**486,823**	173,505	243,187	217,719
• MEDIAN HOME PRICE 2014	593,157	254,320	276,579	311,179	**481,974**	168,465	228,095	209,861
• MEDIAN HOME PRICE 2015	610,962	250,908	272,759	316,679	**492,249**	169,366	221,338	212,611
• MEDIAN HOME PRICE 2016	647,182	257,597	279,506	333,429	**515,406**	169,299	225,902	228,680
• MEDIAN HOME PRICE 2017	687,042	276,386	294,034	350,694	**555,042**	171,509	234,484	245,175
• MEDIAN HOME PRICE 2018	737,000	293,200	316,400	369,300	**605,200**	174,300	250,400	260,400
• GROWTH IN HOME PRICE 2013-2014	0.7%	-4.6%	-5.7%	-3.0%	**-1.0%**	-2.9%	-6.2%	-3.6%
• GROWTH IN HOME PRICE 2014-2015	3.0%	-1.3%	-1.4%	1.8%	**2.1%**	0.5%	-3.0%	1.3%
• GROWTH IN HOME PRICE 2015-2016	5.9%	2.7%	2.5%	5.3%	**4.7%**	0.0%	2.1%	7.6%
• GROWTH IN HOME PRICE 2016-2017	6.2%	7.3%	5.2%	5.2%	**7.7%**	1.3%	3.8%	7.2%
• GROWTH IN HOME PRICE 2017-2018	7.3%	6.1%	7.6%	5.3%	**9.0%**	1.6%	6.8%	6.2%

**Kent is included in this table because it has a population >100,000; however, further investigation revealed that Kent had few small food stores and extreme volatility in percent change in revenue so we ultimately excluded Kent from the analysis.*
Housing Prices adjusted for inflation in 2018 prices.
All other variables are 2018 ACS 5-year estimates

The third step in building synthetic control model is to implement a set of candidate synthetic control models with different combinations of predictor variables, or specifications. The fit of each specification is tested using model fit statistics (the root mean squared prediction error) and the data-driven weights for each donor city and each predictor variable. In addition to including the predictors above, synthetic control models also include the outcome of interest (i.e., business revenue) in the years prior to the policy intervention (lagged outcome). The candidate specifications tested include different combinations of pre-intervention lagged outcomes. For example, researchers often test models with pre-treatment outcomes from only even years, only odd years, only the year immediately previous to the policy intervention, the average of all years, and all years. It is not recommended to rely on a model that includes the exact pre-intervention values of the outcome variable for all years because this makes the other covariates moot and may create a complicated model that fits the existing data too closely at the expense of reducing its accuracy to predict. During the candidate selection process, we also discovered that the city of Kent had extreme volatility in average business revenue, likely driven by having only a small number of small food stores. For this reason, we eliminated Kent from the donor pool of cities.

Appendix Table 2 shows the root mean squared prediction error and the donor weights for 11 candidate synthetic control models. Models with a lower RMSPE indicate a better match for the trends in pre-intervention business revenue in stores between Seattle and the comparison area. The weights given to each of the covariates in these models are shown in **Appendix Table 3.**

APPENDIX TABLE 2. ROOT MEAN SQUARED PREDICTION ERROR AND WEIGHTS FOR DONOR CITIES FOR 11 CANDIDATE SYNTHETIC CONTROL MODELS

MODEL	OUTCOME LAGS AND ALL COVARIATES	RMSPE	BELLEVUE	EVERETT	RENTON	SPOKANE	TACOMA	VANCOUVER
1	2017 ONLY + ALL COVARIATES (RACE, EDUCATION, PER CAPITA INCOME, GROWTH IN HOUSING PRICES)	1.4	0.57	0.14	0	0	0	0.28
2	2014 AND 2016 + ALL COVARIATES (RACE, EDUCATION, PER CAPITA INCOME, GROWTH IN HOUSING PRICES)	1.4	0.57	0.14	0	0	0	0.28
3	2016 AND 2017 + ALL COVARIATES (RACE, EDUCATION, PER CAPITA INCOME, GROWTH IN HOUSING PRICES)	1.4	0.57	0.14	0	0	0	0.28
4	AVERAGE OF ALL YEARS + ALL COVARIATES (RACE, EDUCATION, PER CAPITA INCOME, GROWTH IN HOUSING PRICES)	1.4	0.57	0.14	0	0	0	0.28
5	ALL YEARS + ALL COVARIATES (RACE, EDUCATION, PER CAPITA INCOME, GROWTH IN HOUSING PRICES)	1.4	0.57	0.14	0	0	0	0.28
6	AVERAGE OF ALL YEARS + 3 COVARIATES (RACE, PER CAPITA INCOME, GROWTH IN HOUSING PRICES)	1.4	0.57	0.15	0	0	0	0.28
7	AVERAGE OF ALL YEARS + 2 COVARIATES (RACE, GROWTH IN HOUSING PRICES)	1.4	0.57	0.14	0	0	0	0.28
8	AVERAGE OF ALL YEARS + 1 COVARIATE (RACE)	1.4	0.44	0.17	0	0.075	0	0.31
9	ALL YEARS + NO COVARIATES	1.4	0.57	0.14	0	0	0	0.28
10	NO LAGGED YEARS + 3 COVARIATES (RACE, PER CAPITA INCOME, GROWTH IN HOUSING PRICES)	1.4	0.57	0.15	0	0	0	0.28
11	NO LAGGED YEARS + 2 COVARIATES (RACE, GROWTH IN HOUSING PRICES)	1.5	0.57	0	0.07	0.045	0	0.31

Appendix Table 3 shows the weights for the covariates in each of the models.

APPENDIX TABLE 3. DATA-DRIVEN WEIGHTS OF COVARIATES IN CANDIDATE MODELS											
COVARIATES	**MODEL 1**	**MODEL 2**	**MODEL 3**	**MODEL 4**	**MODEL 5**	**MODEL 6**	**MODEL 7**	**MODEL 8**	**MODEL 9**	**MODEL 10**	**MODEL 11**
AVG OF ALL YEARS				.1		.14	.39	.26			
PCT CHANGE 2014		.11			.0032				.24		
PCT CHANGE 2015					.41				.38		
PCT CHANGE 2016		.00084	.18		.29				.15		
PCT CHANGE 2017	.44		.037		.1				.24		
PCT W/ BACHELOR DEGREE+	.044	.019	0.0000	.000048	.00045						
PER CAPITA INCOME	.26	.1	.14	.13	.015	.25				.24	
HOME PRICE GROWTH	.02	.55	.22	.52	0.0000	.35	.52			.45	1
PCT WHITE	.00015	.021	.029	.093	.031	.02	.021	.11		0.0000	0.000012
PCT BLACK	.000088	0.0000	.017	.006	0.0000	.00043	.0055	0		0.0000	0.0000
PCT AIAN	.000087	.0022	.0026	.00011	.0002	.00009	.00065	.18		0.0000	0.0000
PCT ASIAN	.18	.0009	.0037	.033	0.0000	.13	.013	0		.14	0.0000
PCT HAWAIIAN NATIVE/PI	.000012	.00096	0.0000	.00035	.00024	.00034	.00096	.00055		0.0000	0.0000
PCT OTHER	.041	.15	.29	.075	.013	.072	.026	.45		.11	0.0000
PCT 2 OR MORE RACES	.02	.041	.018	.043	.011	.035	.014	.0024		.042	0.0000
PCT HISPANIC	.00085	.0017	.07	.000091	.12	.0012	.012	0		.0073	0.0000
RMSPE	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.4	1.5

Based on the results above, we observed that the RMSPE is lowest and the same for all models except Model 11. **We chose Model 4 as the primary model (reported above in the main section of the report) because it includes the average of all pretreatment years, which is a recommended practice, and it includes all four covariates (race, education, per capita income, and growth in housing prices). This model weights Bellevue the highest, followed by Everett and Vancouver).** We ran sensitivity analyses with Model 5 and Model 7 because they have similarly low RMSPE and use a wide range of different covariates (results shown in **Appendix Figure 1**).

For each of these 3 models, we performed the synthetic control analysis to: 1) estimate the magnitude of the association between the SBT and change in business revenue at small food stores; and, 2) conduct statistical inference assessment to assess whether the change in Seattle is likely statistically different from the change in comparison.

In additional sensitivity analyses, we limit the sample of stores to a balanced panel of those that are in the sample for all five years of the observation period (both pre- and post-SBT) and run the statistical analyses described above.

<u>Difference-in-differences analysis.</u> We additionally conducted difference-in-differences analyses to assess whether results would be consistent if we were to use this methodology. The first difference-in-

differences analysis uses the traditional difference-in-differences framework, comparing the average change in the outcome in Seattle to the average change in the outcome in the comparison cities. The difference-in-differences analyses are also limited to cities with >100K residents in Washington with the exception of Kent because of the extreme values mentioned above. The models are implemented with ordinary least squares regression and take the following general form:

$$Y_{it} = \beta_0 + \beta_1(\text{city})_i + \beta_2(\text{time})_t + \beta_3(\text{city}_i \text{X} \text{time}_t) + \beta_4(\text{store})_i + \varepsilon_{it},$$

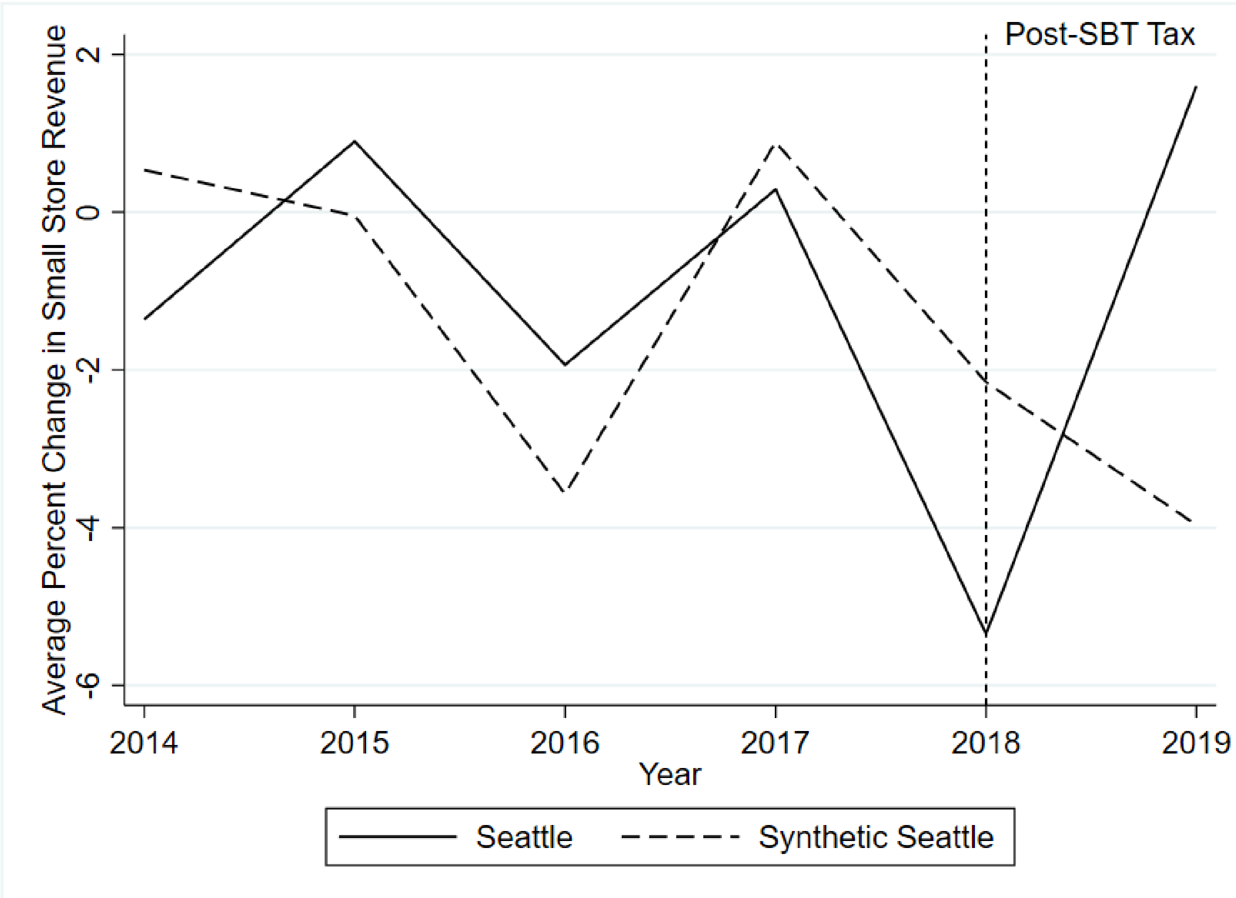
where, Y_{it} is the percent change in business revenue of store i at time t. *City* is an indicator variable that takes the value of 1 for observations in Seattle and 0 for observations in the comparison cities; this controls for baseline differences in business revenue between Seattle and the comparison cities. *Time* is an indicator variable that takes the value of 1 for business revenue measured in the post-tax period and 0 for business revenue measured in the pre-tax period; this controls for the time trend we would have expected to see had Seattle not implemented the tax. The coefficient on the interaction between city and time (cityXtime), β_3, is the difference-in-difference estimator. It estimates the average change in revenue growth in Seattle above and beyond the change in revenue growth in the comparison cities and is our estimate of the association between the SBT and business revenue. Our primary difference-in-differences model includes β_4, which is the indicator variable for each store to control for differences in baseline income by store. In sensitivity analyses, we 1) remove the store fixed effects but keep the same sample of stores (only stores that are observed at least once in the pre period and observed in the post period); 2) limit the sample to stores observed in all 6 years, with and without store fixed effects (results shown in **Table 1.**)

<u>Business Closure Analysis.</u> In this analysis, we use linear regression to examine the effect of exposure to the SBT on business closure. The variable indicating business closure is our outcome, and our model estimates the contribution of a number of factors, including city, neighborhood socio-demographics, business tenure, and average taxable income to business failure during our study period. We also include with our explanatory factors a variable that is one for Seattle retailers that report being operational at the start of 2018 and zero otherwise. The estimated coefficient for this variable shows the association between exposure to the SBT and business closure (over and above any association between being located in Seattle and business closure). We used the full sample of businesses in this analysis, including those with over one million dollars in revenue and those with over 200% yearly growth in revenue.

As a supplemental analysis for this outcome, we construct a measure that shows the proportion of businesses failing in each of our seven cities in each year. For this measure, we use all identified non-chain food retailers in all of our seven cities and do not exclude retailers with over $1 million in revenues or >200% revenue growth. We conduct a synthetic control analysis on this outcome to estimate whether the proportion of businesses failing in each year increases in Seattle post-SBT, relative to changes in the same outcome in a weighted average of our comparison area.

Appendix Figure 1. Sensitivity Analyses (Model 5) Results from synthetic control Models 5 and 7.

Model 5



Appendix Figure 1 - Average Percent Change in Small Food Store Revenue in Seattle and comparison area, 2014-2019. Synthetic Seattle weighted average of outcomes in comparison cities, with weights based on Model 5 in Appendix Table 3 in Appendix. Vertical line marks 2017, last year of data before SBT. Unbalanced sample includes every operating business in every year, including retailers that open after 2014 or fail during any study year. Results show that average store revenue growth in Seattle is greater than in Synthetic Seattle.