The Effect of Singapore's Sugar-Sweetened-Beverage Advertising Ban on Product Entry

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The Effect of Singapore's Sugar-Sweetened-Beverage Advertising Ban on Product Entry

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Abstract

We estimate causal effects of Singapore's 2019 announcement of an advertising ban on sugar-sweetened beverages (SSBs). The announced ban stipulated that beverages with added sugar content beyond a threshold would no longer be allowed to be advertised. Our focus is on how the ban announcement affected companies' SSB product launch decisions in subsequent years. Specifically, we quantify whether the ban announcement reduced the average amount of added sugar in newly launched products in four most popular SSB categories. We find a significant impact in three of the four categories. The average sugar content in newly launched products decreased by 11.7% in Juice, 22.2% in Iced Tea, and 23% in Instant Coffee. We find that these declines are primarily driven by higher rates of product introduction at the low end of the sugar distribution.

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1 Introduction

Singapore has one of the highest prevalence rates of diabetes among developed nations (Magliano et al., 2021; Ministry of Health Singapore, 2019; International Diabetes Federation, 2021). Singapore also has one of the highest death rates associated with diabetes (Magliano et al., 2021). As a result, diabetes has become a major public health concern. One of the leading causes of diabetes is the excessive sugar intake from packaged food sources (Ministry of Health Singapore, 2019). A significant portion of this sugar intake comes from sugar-sweetened beverages (SSB) (Singh et al., 2015; Ministry of Health Singapore, 2019). It is estimated that 52% of the total sugar intake among adults in Singapore comes from SSB (National Nutrition Survey, 2022). With the objective of reducing sugar intake, in October 2019, the Singaporean government announced that an advertising ban would be imposed on SSB with high levels of added sugar. In this paper, we estimate the causal effects of the ban announcement on the sugar content of SSB products that entered the market in subsequent years.

Specifically, we quantify how the ban announcement affected the sugar content of newly launched products in four of the most popular SSB categories in Singapore: instant coffee[1], ready-to-drink (iced) tea, ready-to-drink (iced) coffee and juice. As is the case in several other Asian markets, soft drinks are not the most popular SSB, with coffee and tea exceeding soft drinks in popularity by a significant margin.[2]

Our analyses are carried out using detailed nutritional data from Mintel between 2016 and 2023. Mintel records details of every product launch in food manufacturing around the world. Of interest to our work is that Mintel also reports the sugar content for each product launch. As such, our study focuses on a supply side effect of the policy: sugar content in newly introduced products. Due to data availability, we are unable to analyze demand-side responses or other supply-side effects (e.g., reformulation of previously launched products). Our methodology relies on difference-in-difference methods that use product launches in the neighboring countries of Malaysia, Hong Kong, Vietnam, and the Philippines as a control group.

Our results show a significant impact of the advertising ban announcement in three of the four categories studied, the exception being Iced Tea. We find a significant impact in three of the four categories. The average sugar content in a newly launched product decreased by 11.7% in Juices (-0.94 gr per 100 ml), 22.2% in Iced Coffee (-1.49 gr per 100 ml), and 23% in Instant Coffee (-1.30 gr per 100 ml). We also study how different portions of the sugar content distribution contribute to the decline and find that the observed reductions are primarily driven by a substantially higher rate of product introductions at the low end of the sugar distribution.

At the time of the ban announcement, the government did not determine what constituted a product with a "high level" of added sugar and left the precise determination for a future

[1] Sometimes also referred to as "soluble" coffee.

[2] Due to data limitations, we are unable to study soft drinks, the third most popular beverage by volume in Singapore. In Section 4, we provide more details of the SSB market in Singapore.

date. Specifically, the announcement of the advertising ban was accompanied by a second (related) announcement: the government would develop and implement a nutrient scale to rate the healthfulness of manufactured food products. This scale, which was implemented a few years later, would have added sugar as one of its key determinants[3] This scale would, in turn, be used to determine the level of sugar content at which the advertising ban would be implemented.[4]

Although the nutrient scale was not finalized until 2021 (see Section 3 for details), we argue that firms started to reduce the sugar content of product launches starting in 2019. First, the discussions and consultation that led to the announcement of the advertising ban and the nutrient score policy show that the nutrient score that the Singaporean government planned to adopt followed the structure of the system implemented in several European countries (the so-called "Nutri-Score"). Thus, there was a fairly high degree of certainty among industry participants about what levels of sugar content would ultimately be considered high (and thus affected by the ban). Second, the Singaporean government publicly announced its intentions to adopt strict policies (including the advertising ban) at least one year before the 2019 announcement; further food manufacturers participated as stockholders in the consultation process leading to the announcement. In other words, industry was not caught by surprise when the policies were announced. From a managerial perspective, it makes sense to adapt to imminent and strict regulations by responding before they become effective.[5] Finally, as we later show, our graphical and econometric evidence is indeed consistent with the hypothesis that firms started to reduce the sugar content in new products after the ban was announced.

Advertising bans exist around the world, but they are mostly targeted to highly addictive products. To our knowledge, the advertising ban on sugary drinks in Singapore is the first attempt of this kind by a government in its efforts to reduce the presence of sugary products and limit sugar intake. This paper contributes to the literature on policies designed to improve diets, as well as to the literature on advertising, mandatory front-of-package labeling (FoPL) policy, and product reformulation (see Section 2 for more details). More specifically, our paper contributes to the scant empirical evidence on the supply-side effects of advertising bans, in particular, as they pertain to product reformulation in the context of front-of-package labeling (FoPL) policies. To our knowledge, this is the first study on supply-side responses to an advertising ban on sugary drinks. We argue that our results can have significant implications for policy efforts aimed at tackling obesity, diabetes, and other diseases.

The rest of the article is organized as follows. Section 2 reviews the relevant literature.

[3] As we later explain, the government enacted a labeling rule that mandated products with the two lowest grades in the scale to display their nutrient score while making it voluntary for other products; see Section 3 and Figure 1.

[4] The scale, which was released in 2021 and placed in effect in 2022, not only considers added sugar but also saturated fat. However, in the case of sugary beverages, the main determinant of their nutrient score is the amount of added sugars, with saturated fat playing a limited role (and for some beverages, such as juice, no role). The scale effectively breaks up drinks into four groups, from most healthy (A) to least healthy (D), depending on the amount of sugar in the product. The advertising ban became effective in December 2022 and was imposed on products in category D. See Section 3 and Figure 1.

[5] The clearest example of this type early reaction by industry is the trans-fat ban in the US: firms started to remove trans fat content from products much earlier than the date when it became effective (2018) (see Rojas et al., 2023)

Section 3 provides details on the advertising ban in Singapore. Section 4 discusses the data and presents some preliminary analyses. Section 5 presents the main empirical analyses. Section 6 presents a placebo test and Section 7 concludes.

2 Literature Review

Advertising bans have been introduced around the world for various reasons. The large majority of these restrictions have been aimed at limiting the consumption of addictive or unhealthy products (e.g., cigarettes, alcohol, and other nicotine products). There are some examples of advertising restrictions related to food. In 1978, Quebec introduced an advertising ban on foods and beverages aimed at children under 13 years of age (extended to all Canada in 2008) (Potvin, Dubois and Wanless, 2012). In 2014 Mexico approved an advertising ban on sweetened beverages and other foods where 35% of the broadcast audience are under 13 years old (Bergallo et al., 2018). In Asia, advertising bans have been introduced for certain products, TV channels, and hours of the day. Ads for selected unhealthy foods on children's TV channels have been banned in South Korea (2010) and Taiwan (2016) during evening hours (Kim et al., 2013). What sets the Singaporean advertising ban apart is that it is aimed at all consumers and is applicable to all advertising channels. We are unaware of advertising bans of this scope for SSB anywhere in the world.

Only a handful of empirical studies have investigated the effect of an advertising ban (Dubois, Griffith and O'Connell, 2018; Radesky et al., 2020; Taillie et al., 2021). Most of these studies focus on consumers' responses to the ban. For example, Dubois, Griffith and O'Connell (2018) study UK's advertising ban on junk food and quantify how this policy could make consumers change their choices towards healthier options. Another strand of literature focuses on how advertising regulations can affect market concentration (e.g., Eckard Jr, 1991; Sass and Saurman, 1995).

Empirical studies of how an advertising ban aimed at promoting healthy eating could affect supply-side variables are almost non-existent. The closest study to our work is Alé-Chilet and Moshary (2022). Chile introduced an advertising ban in 2016 on foods and beverages with a high content of calories, saturated fat, sugar, and sodium. This ban was implemented in advertising outlets where at least 20% the audience consisted of children under 14 years of age. Alé-Chilet and Moshary (2022) study both supply and demand responses to this advertising ban by focusing on the ready-to-eat cereal market. Consistent with our findings, the authors find that the advertising ban induced companies to reduce the sugar content of their products.

More broadly, our study is related to empirical work on how advertising affects market outcomes. The majority of empirical analyses in this literature study whether advertising is effective in improving volume sales (Assmus, Farley and Lehmann, 1984; Bruce, Peters and Naik, 2012; Gatignon, 1984; Shapiro, Hitsch and Tuchman, 2021; Bayer et al., 2020; Rosengren et al., 2020) or market share (Rosengren et al., 2020; Hydock, Paharia and Blair, 2020; Johnson, Shriver and Du, 2020). Some of this empirical research focuses on more nuanced consumers' responses to advertising, such as determining whether advertising plays an informative or a persuasive role (Dubois, Griffith and O'Connell, 2018; Bagwell, 2007; Rojas and Peterson, 2008).

3 The Advertising Ban in Singapore

In 2016, the Ministry of Health (MOH) established a task force (Diabetes Prevention and Care Task Force) dedicated to combating diabetes. From the beginning of its establishment, the task force championed several key initiatives, one of which was "healthy living", emphasizing the importance of healthy eating along with regular physical activity. In addition, the Health Promotion Board (HPB)[6] adopted similar initiatives. For example,in 2001, the Healthier Choice Symbol (HCS) was introduced as a visual identifier for healthy foods. Products with the HCS logo generally referred to products with reduced levels of sugar, saturated fat, and/or salt within their product category. Similarly, in 2017 the HPB implemented an initiative aimed at reducing the consumption of beverages with high sugar content in government premises. [7]. Soon after, the MOH escalated its efforts to tackle the issue on a larger scale. The MOH initiated a consultation process designed to define the most appropriate policies to increase public awareness and curb the consumption of sugary drinks. The consultation process included the administration of consumer surveys and the participation (feedback) of various stakeholders that included industry and consumer advocacy groups.

The original set of possible policies that were subject to the consultation process contained four different types of interventions. Using the information collected during the consultation process, the MOH and the HPB decided to implement two measures (Health Promotion Board, 2022). The first was to require food manufacturers to display a front-of-package nutritional score label. The second was to ban advertising for SSBs that fell into the category with the "least healthy" nutritional score.[8]

On 10 October 2019, the Singapore government announced its decision to implement these two policies. The two policies would apply exclusively to SSB. The advertising ban would take effect across all advertising channels, including television, print, billboards, and all online channels (including social media platforms). As it involved the front-of-packaging nutrient score (and the corresponding threshold for determining the least healthy SSBs), the government's announcement indicated that these details would be provided once the nutrient score guidelines were finalized. On 30 December 2021, the government released the details of the nutrient score. The scale was labeled "Nutri-Grade" and determined 4 levels of healthiness (from most to least healthy): A, B, C, and D. Figure 2 shows an example of a product with an "A" score.[9] Displaying the Nutri-Grade logo was mandatory for beverages

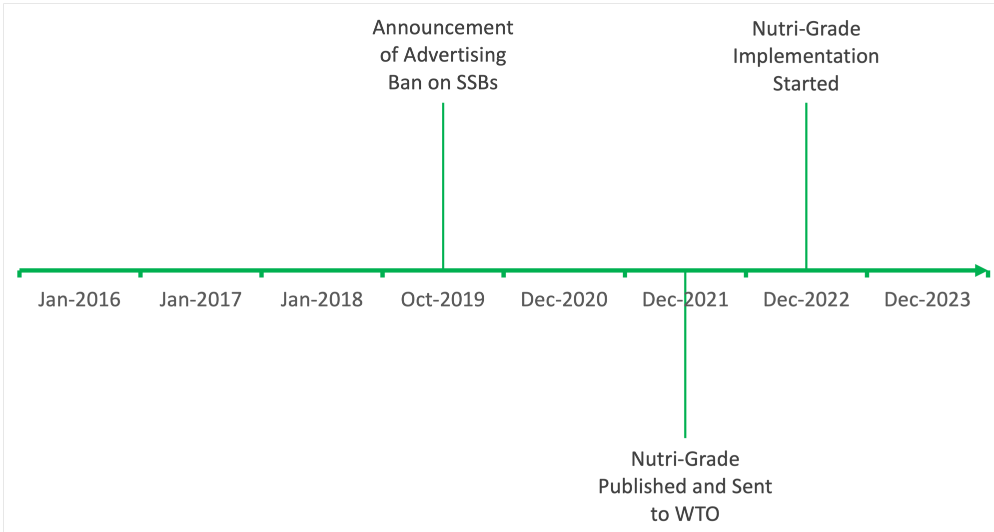
[6]The Health Promotion Board (HPB) is a statutory board under the Ministry of Health of the Government of Singapore. It was established in 2001 to lead the promotion of health at a national level, among other things through disease prevention programs.

[7]The initiative was called "Whole-of-Government (WOG) Healthier Drinks Policy"

[8]The consumer survey administered by the MOH comprised about 4,000 respondents. Approximately 84% of the participants showed their preference for a mandatory front-of-package label policy and 71% supported advertising regulations for the least healthy SSBs (Ministry Of Health, 2019).

[9]The Nutri Grade labeling policy became effective on December 30, 2022.

Figure 1: Advertising Ban Announcement Timeline



with Nutri-Grade C and D and voluntary for beverages with scores A and B. The advertising ban was imposed on beverages with a D score.

Figure 2: Nutri-Grade Logo

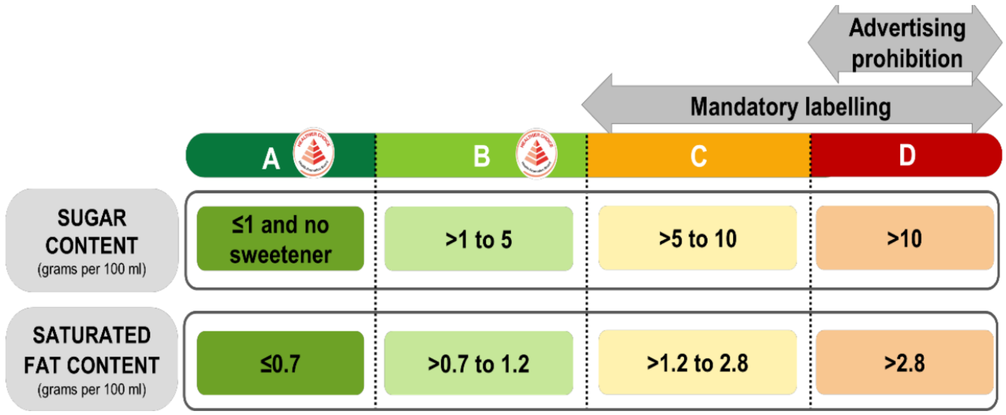
NUTRI-GRADE

A B C D 0% sugar

The letter assigned on the Nutri-Grade scale is a function of sugar and saturated fat, as depicted in Figure 3. Thus, a product would be considered to be in the least healthy category (D) if it exceeded a sugar content of more than 10 grams of sugar per 100 ml or 2.8 grams of saturated fat per 100 ml. In other words, the Nutri-Grade scale takes the rating given by the worst rating of the two attributes (sugar and saturated fat). For example, if sugar content falls within the B range (for sugar) and saturated fat falls within the C range, then the product's Nutri-Grade will be C (Shin, Puri and Finkelstein, 2023).

As stated in the Introduction, we argue that firms did not wait for the details of the policies to be finalized to react to the policy. Instead, as supported by our empirical analysis, food manufacturers began reformulation efforts to reduce sugar right after the 2019 announcement. An important reason for why firms' reactions are likely to have started as the announcement was made is that the policy announcement did not take industry by surprise. The news of an intervention of this type had been widely disseminated among and discussed by industry

Figure 3: Mandatory Labeling, Advertising Ban and Nutri-Grade Design



Source: Health Promotion Board, Singapore

participants for a couple of years. Thus, firms' managerial decisions on how to react to the policy had already had time to be proposed and analyzed by the time the 2019 announcement was made. Furthermore, although the exact threshold for determining which products would be affected by the ban was not known at the time of the announcement of the advertising ban, it was not difficult for companies to look at the distribution of sugar content in their product lines and identify which levels of sugar content would likely be considered as "high" by the government.[10]

4 Data and Preliminary Analysis

Our main data source is new product launch data from Mintel Global New Product Database (GNPD) between 2016 to 2023. This data availability span provides us with a sufficient time period before and after the ban announcement to estimate the causal impact of the ban announcement on the beverage market in Singapore. We use nutritional information and product launch time variables from Mintel GNPD data in the analysis. Mintel also contains information on each product's brand name, price, ingredients, serving size, category, package size, among other information. Mintel also includes photos of the product package, including different labels and nutritional facts, which allowed us to verify the accuracy of the nutritional information in the data or correct any discrepancies.

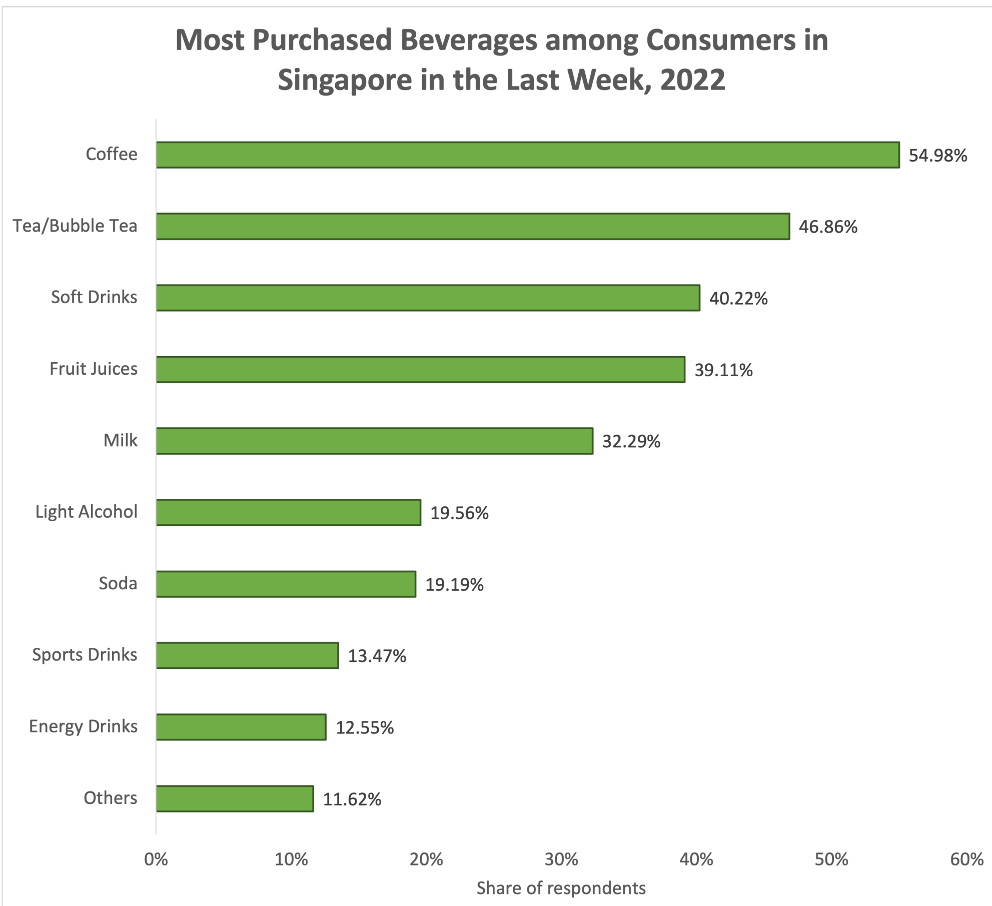
We choose the four most popular beverages in the database for the case of Singapore. Given that our data is composed of product launches, we determine a category's popularity based on the number of product introductions. These categories are instant coffee, ready-to-drink (iced) tea, juice, and ready-to-drink (iced) coffee. Importantly, the popularity of

[10]In addition, during the consultation process, the MOH had indicated that the nutrient scoring system would be similar (and likely the same) as the Nutri-score system implemented in Europe. Although Singapore's final version of this score differed from that used in Europe, both systems would have resulted in a similar threshold to determine the least healthy category.

a product category based on the intensity of product launches seems to align well with the popularity of a category based on sales.

Figure 4 shows the results of a survey that measures consumers' buying habits by type of beverage in Singapore (Statista Search Department, 2022). As in our product launch data, coffee occupies the first position. However, in our data, coffee products are divided into two categories: instant coffee and ready-to-drink coffee (often referred to as iced coffee).[11] In our data, RTD coffee occupies the fourth position (Table 1). In Figure 4 tea occupies the second position, which is the same position it occupies in our data (Table 1). Juices occupy the fourth position in Figure 4 while in our data this category occupies the third position. The main difference is that soft drinks appear within the top four categories in Figure 4 but this category in our data is outside the top four. We attempted to include soft drinks, but unfortunately there are insufficient observations to carry out a reliable analysis.

Figure 4: Leading Beverages Purchased Among Consumers in the Last Week in Singapore in 2022



Source: Statista

[11]As is the case in several Asian countries, instant coffee is the most popular way to drink coffee. It is so popular that in several countries it is (once mixed with water) the most consumed beverage (Statista Search Department, 2022).

Of the four beverage categories we study, RTD coffee, RTD tea and juice are sold in a liquid presentation, whereas instant coffee is sold as a powder mixed with cream and sugar.[12] Figure 5 depicts examples of different beverages introduced in Singapore. The picture from left to right indicates instant coffee, ready-to-drink iced tea, juice, and ready-to-drink iced coffee drinks.

Figure 5: Images of Beverages

The labeling and advertising regulations apply on a 100 ml basis (see Figure 3), and they explicitly include instant coffee, although it is not a product that is sold as a ready-to-drink beverage. Thus, we need to convert the sugar content of instant coffee mix to a per 100 ml serving equivalent. To do this, we compiled information on the powder-to-water ratio recommended by the manufacturer in these packages (information available from the Mintel database). Since this information is not always available for every product launch, we used the observations for which such information was feasible to extract an average recommended ratio.[13]

Due to the sparsity of the data at the monthly level, we aggregate product launches at the annual level and perform analyses at this level of aggregation. Product launch data in the four beverage categories in our analysis are shown in Table 1. Coffee has the largest volume of product launches among the four categories, followed by tea, juice, and RTD (iced) coffee. As controls, we choose product launches in neighboring countries. We select these countries based on their geographic proximity to Singapore, taking into account similar temperature ranges and, most importantly, the nonexistence of SSB policies similar to those implemented by Singapore. The countries we select for this control group are Hong Kong, Malaysia, the

[12] While there are some instant coffee products that do not contain sugar and/or cream, the typical instant coffee product contains significant levels of these two constituents.

[13] More specifically, we determined that, on average, the recommended amount of water for each instant coffee serving (typically a small packet) is 180 ml. We then used the number of grams of sugar in a serving (as stated by the manufacturer and reported in the Mintel database) to obtain the grams of sugar per 100 ml equivalent. For example, if a product is listed as having 15 grams of sugar per serving (i.e., per packet), then the grams of sugar per 100 ml are computed to be 8.33 (i.e., $\frac{15}{180} \times 100 = 8.33$).

Philippines, and Vietnam. The number of product launches by country and category are shown in Table 2.

Table 1: Number of Product Launches in GNPD Mintel Database, by year and cateogry

Year	Instant Coffee	RTD (Iced) Tea	Juice	RTD (Iced) Coffee
2016	191	138	127	63
2017	120	145	129	81
2018	148	173	188	86
2019	165	154	137	62
2020	193	119	120	60
2021	182	137	98	86
2022	204	152	52	84
2023	224	204	66	86
Total	1,427	1,222	917	608

Note: Instant coffee must be mixed with hot water. The other three categories are sold in liquid versions.

Table 2: Number of Product Launches in GNPD Mintel Database, by country and cateogry

Country	Instant Coffee	RTD (Iced) Tea	Juice	RTD (Iced) Coffee
Hong Kong	174	276	326	80
Malaysia	394	279	113	236
Philippines	251	143	189	92
Singapore	328	249	148	112
Vietnam	280	275	141	88
Total	1,427	1,222	917	608

Note: Instant coffee must be mixed with hot water. The other three categories are sold in liquid versions.

A first glance at the possible effects of the announcement of the advertising ban is presented in Table 3. The table compares the average sugar content in product launches in Singapore versus control countries (both individually and as a group) before (up to and including 2019) and after the advertising ban (2020 and beyond). We make two observations regarding this Table. First, using the before period as a reference point, the juice category has the highest sugar content: 8.06 grams per 100 ml. RTD coffee is second with 6.69 grams per 100 ml, followed by instant coffee and tea with a content slightly below 6 grams per 100 ml. The Table shows that there is a generalized tendency for sugar content to decline over time: in all but a few entries (in Singapore and in control countries), the sugar content is

Table 3: Descriptive Statistics of Sugar Content in Beverages

	Before 2019		**After 2019**	
	Mean	SD	Mean	SD
Instant Coffee				
Singapore	5.63	3.38	3.64	3.42
All Control	5.41	3.08	4.55	3.21
Hong Kong	2.35	2.72	1.68	2.69
Malaysia	5.89	3.08	4.67	3.05
Philippines	5.79	3.03	5.51	3.08
Vietnam	5.81	2.27	5.58	2.65
RTD (Iced) Tea				
Singapore	5.87	2.97	4.97	3.23
All Control	6.56	4.48	5.43	4.94
Hong Kong	5.68	4.16	4.62	3.78
Malaysia	7.20	5.71	4.33	3.00
Philippines	6.66	3.11	7.27	10.09
Vietnam	6.71	3.58	6.25	2.88
Juice				
Singapore	8.06	2.74	7.20	3.08
All Control	9.44	3.99	9.52	3.21
Hong Kong	9.18	3.63	9.53	3.55
Malaysia	10.19	6.57	9.95	4.30
Philippines	10.28	2.38	9.93	2.37
Vietnam	8.26	3.10	8.72	2.52
RTD (Iced) Coffee				
Singapore	6.69	2.78	4.80	3.15
All Control	6.44	3.08	5.86	3.21
Hong Kong	5.90	2.70	3.37	3.75
Malaysia	6.18	2.95	5.78	2.65
Philippines	8.15	3.20	6.81	3.41
Vietnam	5.62	2.93	7.59	2.74

lower after 2019 than before 2019. In other words, without a control group, the inferred impact of the announced policy would be overstated. Second, we see that the declines in sugar content are more pronounced in Singapore than in the category "All Control" for instant coffee, juice and RTD coffee. These initial descriptive results are later confirmed in our more formal difference-in-differences (DiD) exercises.

To better understand which portion of the sugar distribution may be driving the observed reductions in sugar content in Singapore, Figure 6 shows the empirical cumulative distribution function (ECDF) of sugar content in all product launches in Singapore during the before period compared to the corresponding ECDF during the post period. The Figure displays the results separately for each of the four categories. The Figure displays an important jump (greater mass) after 2019 in the lower tail of the distribution for both instant coffee and RTD coffee. This suggests that product reformulation (sugar reductions) in product launches in these categories mainly took the form of sugar-free (or near-sugar-free) versions. In contrast, a comparison of pre and post ECDFs in the juice and RTD tea categories suggests that reformulation occurred primarily in products in the midrange of the distribution, notably around the 5 gram per 100 ml mark. [14]

To complement and confirm the patterns observed in Figure 6, Figure 7 depicts its histogram (i.e., empirical density) version. As can be seen, there is a substantial increase in the frequency of observations in the "A' category products both in the instant coffee and RTD coffee categories (and some in the tea category). As observed in Figure 6, tea and juice register a substantial increase in the frequency of observations in the "B" category; notably, this increase in tea occurs just below the 5 gram per 100 ml mark.

5 Results

In this section, we use difference-in-differences (DiD) methods to estimate the effects of the announcement of the advertising ban on the level of sugar content in new product launches. Our specification uses the sugar content in product launches in Singapore in one year and compares it with the sugar content of the product launches in the control countries. The reason for using several countries as a control group (instead of a single country) is that the number of observations in the control group decreases significantly if only one country is used as a control. An alternative specification would be to use synthetic control methods, where the different control countries are combined into a single synthetic (i.e., weighted average) control group. However, this specification is not practical in our setting, as a synthetic control would collapse the number of observations to one per country-year tuple, which wipes out the power from the econometric analysis.

[14] Interestingly, the 5 gram per 100 ml is the threshold that determines whether labeling is mandatory or not (see Figure 2). Although "bunching" type of analysis would at first appear appealing in this setting, note that the exact thresholds were not known by industry until 2021 (and were not implemented until 2022). We carry out some regressions that are mechanically similar to a bunching test but use these results to characterize where in the distribution of sugar content the effect is more pronounced. See details in Section 5.

Figure 6: Empirical CDFs of Sugar Content

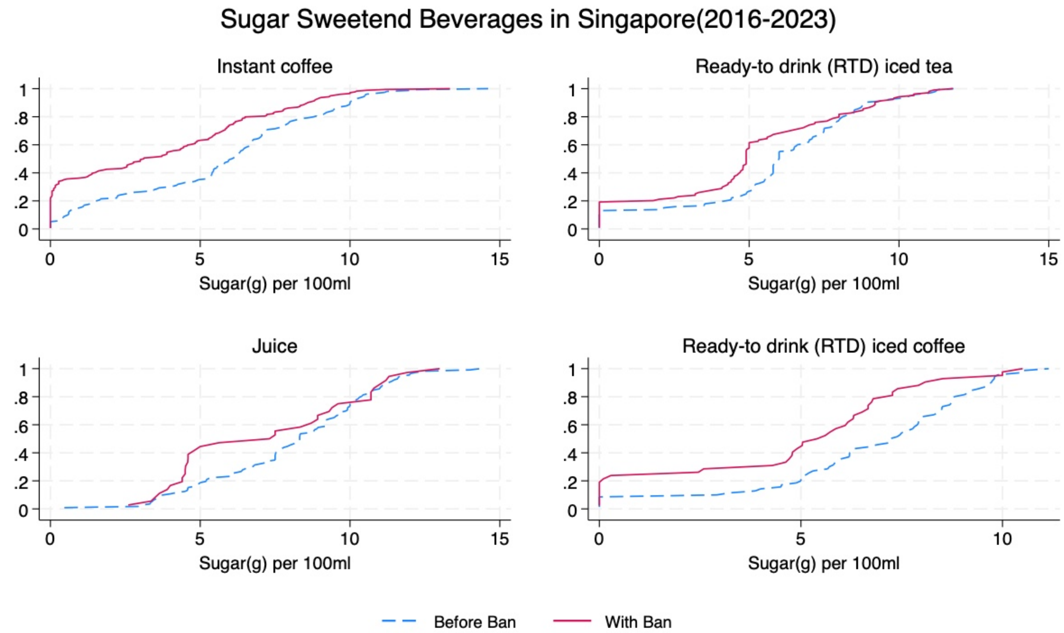
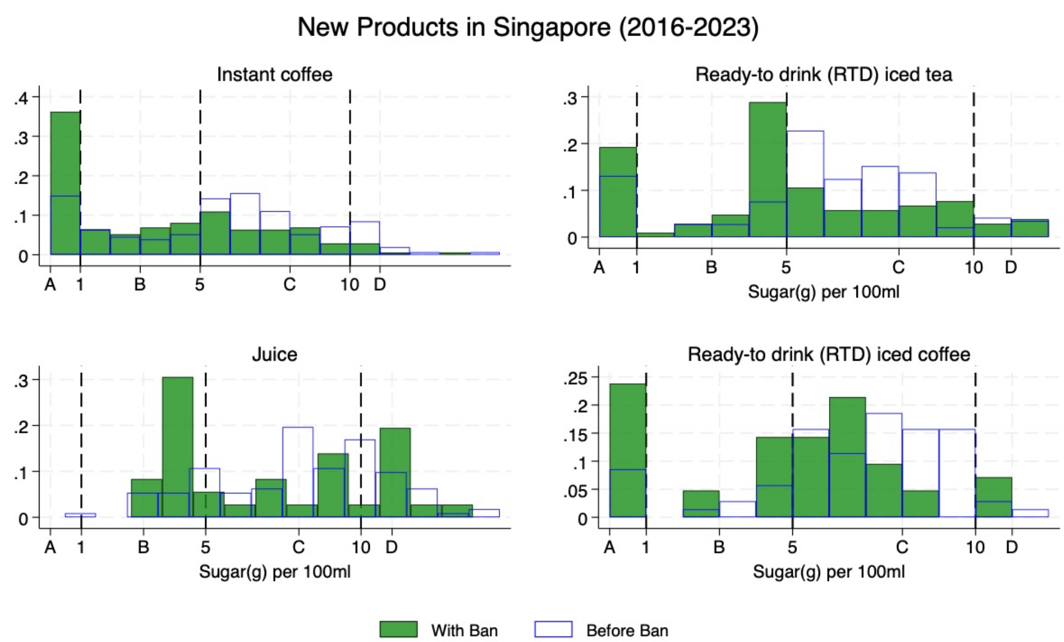


Figure 7: Histograms of Sugar Content in Major Beverages in Singapore



5.1 Identification

The DiD assumption in our case requires that the time trends of the average sugar content in newly launched products in Singapore and control countries prior to 2019 are parallel. We check the validity of this assumption graphically and with a formal parallel trends test.

Figure 8: Average sugar content in new product launches, by year and group (treatment v. control)

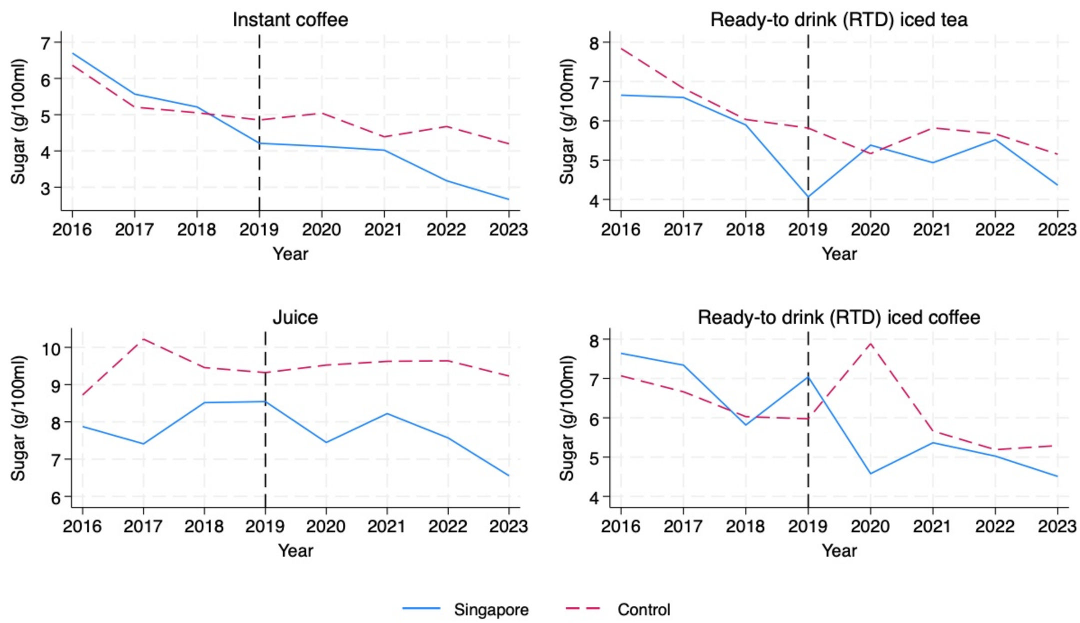


Figure 8 shows the evolution of the average sugar content in all product launches in every year, separately for Singapore and the control countries. The parallel trend assumption in the 2016-2018 period seems to be reasonably appropriate for instant coffee, iced tea, and iced coffee. The case of juice is not evident. To probe the assumption more formally, we perform a parallel trend test. Specifically, we estimate a regression using data for the 2016-2019 period and run the following model regression:[15]

$$s_{itc} = \rho_c + t + (\rho_c \cdot t)\delta + \epsilon_{itc} \tag{1}$$

where s_{itc} is the sugar content for product i in country c and year t, ρ_c is an indicator of whether the observation is in the treatment country, t is a linear time trend, and ϵ_{itc} is the error term. A statistically significant δ would reject the hypothesis that the trends in both groups are different from each other.

[15]We also run a pre-trends test with the smaller 2016-2018 span and also fail to reject the null at the 95% confidence level.

Table 4: Parallel Pre-Trends Analysis for Sugar Content

Sugar (g/100ml)	(1) Instant Coffee	(2) RTD (Iced) Tea	(3) Juice	(4) RTD (Iced) Coffee
Singapore × Time Trend	-0.300	-0.156	0.221	-0.032
	(0.241)	(0.429)	(0.182)	(0.176)
N	624	610	581	292

Note: Table shows coefficient and heteroskedasticity-robust standard errors (in parentheses). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The estimated δ for each beverage category is shown in Table 4. The take away of these results is that, for each beverage category, we fail to reject the null hypothesis that the pre-treatment linear trends in sugar content are parallel between treatment and control countries.

5.2 Difference-in-Differences Results

We estimate the following model to estimate this causal effect of the announcement of the 2019 advertising ban:

$$s_{itc} = \delta_t + \gamma_c + D_{tc}\beta + \varepsilon_{itc} \tag{2}$$

where s_{itc} indicates the sugar content for product i in country c and year t, δ_t denotes time (year) fixed effects, γ_c captures country fixed effects, D_{tc} is an indicator equal to 1 for products brought to market in Singapore after the ban (2020 and beyond) and zero otherwise, and ε_{itc} denotes the usual error term. We cluster standard errors at the country level.[16]

We estimate equation 2 separately for each of the four SSB categories. The estimated results are shown in Table 5. Instant coffee and juice show the strongest statistical evidence of a causal effect: the null hypothesis of no effect is rejected at the 99% confidence level in both cases. A statistically significant difference is detected at the 90% confidence level for iced coffee, but no effect is detected in iced tea. Taking the three categories where results are statistically significant (including the more weakly significant case of iced coffee) and the pre-2019 mean sugar values observed in Table 3, our results imply that average sugar content

[16]We also ran a specification that contain 2019 in the treatment period. The instant coffee category shows a significant DiD coefficient, but the juice and iced coffee decrease in magnitude and cease to be statistically significant. This is not surprising given that the ban announcement occurred at the end of 2019. Furthermore, this result supports our assumption that the announcement generated an effect that can be detected in the data since at least 2020.

Table 5: Impact of Advertising Ban on Product Composition of Beverages in Singapore

Sugar (g/100ml)	(1) Instant Coffee	(2) RTD (Iced) Tea	(3) Juice	(4) RTD (Iced) Coffee
Post Advertising Ban Singapore	-1.298***	0.343	-0.939***	-1.493*
	(0.187)	(0.659)	(0.151)	(0.551)
Year FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
R-squared	0.176	0.052	0.059	0.130
N	1427	1222	917	608

Note: Standard errors clustered at the country level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

in a newly launched product has decreased by 11.7% in Juices (a reduction of -0.94 gr per 100 ml with respect to 8.06 gr per 100 ml in the pre-2019 period), 22.2% in Iced Coffee (a reduction of -1.49 gr per 100 ml with respect to 6.69 gr per 100 ml in the pre-2019 period), and 23% in Instant Coffee (a reduction of -1.30 gr per 100 ml with respect to 5.63 gr per 100 ml in the pre-2019 period).

5.3 Where is the effect coming from?

To complement our main analysis, we study how different portions of the sugar content distribution contribute to the decline. The reduction in the average sugar content in product launches can be driven by firms' tendency to stop introducing unhealthy versions or by a greater tendency to introduce healthier products (or both). To gauge the intensity of these two forces, we estimate a DiD equation, similar to 2, except that the left-hand side is now replaced by an indicator variable that is equal to one if the product is located in a particular segment of the sugar distribution.

We run this test in two areas of the distribution. In the first, we consider the most unhealthy products (highest sugar content) and in the second, we consider the healthiest versions. We use the Nutri-Grade thresholds (see Figure 3) as cut-off points for these two cases. In the first case, we look at products that fall in category D (sugar content $>$ 10 gr per 100 ml) and in the second case we consider products that fall in either category A or category B (sugar content $<$ 5 gr per 100 ml).[17] To facilitate the interpretation of the results, we run this regression using a linear probability model.[18]

Table 6 shows the results for the most unhealthy portion of the distribution, while Table 7

[17]In both cases, we run equation 1) to verify that the assumption of parallel trends holds.

[18]Conclusions are similiar if either a probit or a logit model are used.

Table 6: Effect of Advertising Ban on Entry of Least Healthy Beverages in Singapore

	(1) Instant Coffee	(2) RTD (Iced) Tea	(3) Juice	(4) RTD (Iced) Coffee
Post Advertising Ban Singapore	-0.089**	0.070*	-0.065	0.010
	(0.020)	(0.025)	(0.038)	(0.027)
Year FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
R-squared	0.074	0.036	0.041	0.085
N	1427	1222	917	608

Note: Standard errors clustered at the country level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Impact of Advertising Ban on Entry of Most Healthy Beverages in Singapore

	(1) Instant Coffee	(2) RTD (Iced) Tea	(3) Juice	(4) RTD (Iced) Coffee
Post Advertising Ban Singapore	0.157**	0.155	0.220***	0.088
	(0.041)	(0.117)	(0.018)	(0.085)
Year FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
R-squared	0.143	0.086	0.059	0.068
N	1427	1222	917	608

Note: Standard errors clustered at the country level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

shows the result for the healthy portion of the distribution. Together, these two tables suggest that the observed sugar reductions are driven primarily by a higher intensity of product introductions in the healthier spectrum. Table 7 shows economically large coefficients for all four cases, ranging from 8.8% in iced coffee to 22% in juice, although only two categories show statistically significant results (instant coffee and juice). In contrast, Table 6 shows smaller magnitudes and only two of them are negative (juice and instant coffee). Instant coffee, the only statistically significant negative result registers an 8.9% decrease in the probability of product launches in category D. Taken together, these results indicate that the reduction in average sugar content generated by the announcement of the advertising ban was primarily driven by firms' strategy to introduce healthier versions and only to a limited extent by a decline in the introduction of unhealthier products.

6 Robustness and Additional Results

6.1 Placebo Test

To probe the causal nature of the effect we measure, we perform a placebo test in which we replace SSB with other sugary categories. The idea is that if we do not find a sugar reduction in categories that were not targeted by the policy (and that also contain high levels of sugar), then we would have some reassurance that the effect we measure is due to the SSB advertising ban announcement and not to some other generalized tendency of Singaporean food manufacturers to introduce less-sugary products across the board. For this test, we chose chocolates and desserts. The results of these regressions, shown in Table 8, show that such effects are not observed in these two food categories, further supporting our causal inference.

6.2 Additional regressions

We ran the main DiD specification (equation 2) by moving the treatment period one year back (to 2019). The results are displayed in Table 9. The instant coffee category shows a significant DiD coefficient, but the juice and iced coffee decrease in magnitude and cease to be statistically significant. This is not surprising given that the ban announcement occurred at the end of 2019 and the inclusion of this entire year in the treatment period would dampen the measured effect. More importantly, this result supports our argument that the announcement generated an effect that can be detected in the data since at least 2020 (the first full year after the ban announcement). Finally, we also checked whether our results were sensitive to excluding "private label" products from the analysis.[19]

[19] Results available upon request.

Table 8: Impact of Advertising Ban on Sugar Content in Other Sugary Categories

Sugar(g/100ml)	(1) Chocolate	(2) Dessert
Post Advertising Ban Singapore	-0.326	-1.684
	(1.689)	(1.497)
Year FE	Yes	Yes
Market FE	Yes	Yes
R-Squared	0.688	0.722
N	4155	1573

Note: Standard errors clustered at the country level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Impact of Advertising Ban (from year 2019 and onward) on Product Composition of Beverages in Singapore

Sugar (g/100ml)	(1) Instant Coffee	(2) RTD (Iced) Tea	(3) Juice	(4) RTD (Iced) Coffee
Post Advertising Ban Singapore	-1.425***	-0.230	-0.249	-0.842
	(0.284)	(0.872)	(0.140)	(0.397)
Year FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
R-squared	0.177	0.052	0.057	0.124
N	1427	1222	917	608

Note: Standard errors clustered at the country level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

7 Conclusion

Prior empirical work on advertising has largely focused on how and whether consumers respond to firms' advertising intensity. In this paper, we take a different approach and ask whether firms react to a shock that limits their ability to advertise products. We carry out this exercise in the context of a nationwide policy aimed at limiting consumers' sugar intake. We find evidence that firms change their product introduction strategy by shifting their attention toward products that are not subject to the advertising ban.

We find that the sugar content of new product launches decreases in three of the four categories we study, including the most popular category of instant coffee. This effect coincides with the objective of the policy, which was to limit consumers' exposure to products with high sugar content. The study has significant policy implications around the world as it pertains to governments' efforts to combat obesity, diabetes, and related noncommunicable diseases. There is evidence that SSB taxes can work in reducing sugar intake. Our study shows that policy makers may have another effective tool at their disposal.

Due to data limitations, our study only focuses on the supply-side impact of the advertising ban announcement. Future research on the demand side will be useful in complementing our results. Moreover, there is scope for future work on how the advertising ban may impact consumption across different demographics and other manufacturers' marketing strategies (such as price), all of which have significant policy implications.

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