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# The effect of implicit and explicit taxes on the purchasing of 'high-in-calorie' products: A randomized controlled trial

Brett Doble, Felicia Ang Jia Ler, Eric A. Finkelstein*

*Programme in Health Services and Systems Research, Duke-NUS Medical School, Singapore*

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ABSTRACT

Public health taxes on less healthy food and beverage products have been shown to be effective in various settings. However, it is unclear if observed reductions in the quantity of taxed products purchased is a result of price increases due to the tax or the accompanying messaging and if the effects are influenced by the level of support for such taxes within the population. 941 adults residing in Singapore were randomized and asked to shop in one of four versions of a fully functional on-line experimental grocery store: 1) no tax control; 2) implicit tax showing only post-tax prices (i.e., 20 % higher than control prices) on high-in-calorie products; 3) fake tax showing pre-tax prices and a label falsely indicating that the price includes a 20 % tax on high-in-calorie products; and 4) explicit tax showing the same label as in 3) and an actual 20 % price increase applied to the high-in-calorie products. The proportion of high-in-calorie products purchased was 14 % in the control arm. We were unable to reject the null hypothesis of no effect in the implicit tax arm compared to control (0.08, 95 % CI −3.31 to 1.77) or in the fake tax arm compared to the control (2.59, 95 % CI −5.04 to 0.00) but observed a statistically significant 3.35 percentage point decrease (95 % CI −6.01 to −0.5) in the explicit tax arm compared to control. We were unable to reject the null hypothesis of no effect in any of the outcomes related to diet quality. Individuals who support the tax showed greater responsiveness to the explicit and fake taxes compared to those who do not (price elasticities of demand of −1.38 and −0.51 respectively). Results suggest that reductions in the proportions of high-in-calorie products purchased may be largely attributable to explicit messaging rather than to price increases. However, even when effective, policymakers should recognize that changes in purchasing patterns may not improve diet quality and that results may not generalize to other areas where levels of support differ.



## 1. Introduction

The link between poor diet and rising rates of obesity and non-communicable diseases is well documented, with dietary factors contributing almost 10 % of the global disease burden (G. B. D. Risk Factors Collaborators, 2015). To tackle this issue, policymakers world-wide have implemented targeted public health taxes on products identified to be less healthy due to high levels of calories, sugar, saturated fat and/or salt. These taxes are expected to decrease consumption of targeted products but also could increase social welfare given that many individuals lack self-control (Laibson, 1997) and/or engage in myopic behavior (Bhattacharya, 2004), particularly when it comes to diet and exercise choices. Although paternalistic, such an approach can help individuals overcome these lapses (Bhattacharya and Sood, 2011; Gruber and Köszegi, 2001; OöDonoghue and Rabin, 1999).

The effectiveness of these taxes, however, has been mixed. After implementation of taxes on sugar-sweetened beverages (SSBs) and/or nonessential high energy dense foods, Mexico, Chile and Berkeley, California reported varying levels of initial (Batis et al., 2016; Nakamura et al., 2018; Silver et al., 2017) and sustained (Colchero et al., 2017) reductions in consumption of taxed products, whereas taxes on saturated fat in Denmark was not shown to be effective (Toft et al., 2014).

Despite the mixed evidence, the logic behind these taxes is compelling. According to the law of demand in economics, an inverse relationship exists between price and quantity demanded. If a tax increases the price of a product, then the quantity demanded of that product is expected to decrease. However, the law of demand does not indicate the expected degree of change in demand for a particular price increase, which will vary from product to product. For SSBs, consumers are relatively insensitive to price changes (Andreyeva et al., 2010; Green et al., 2013). For this

* Corresponding author at: Programme in Health Services and Systems Research, Duke-NUS Medical School, 8 College Road, 169857, Singapore.
*E-mail address:* eric.finkelstein@duke-nus.edu.sg (E.A. Finkelstein).

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reason, a recent review suggested that taxes would need to be at least 20 % to be effective (Mytton et al., 2012).

One of the reasons for the high tax is that not all of the tax is likely to be passed along to consumers. Suppliers may find it profit maximizing to absorb some, or even all, of the tax rather than increase prices to consumers, as has been observed in the market for tobacco products (Gilmore et al., 2013). Yet, even a modest tax could reduce consumer demand if the tax is accompanied by a clear and salient message that the taxed products are less healthy and should be avoided. Contrarily, taxes that are not salient or clearly identifiable to consumers at the time of selection may be less likely to be effective (Finkelstein, 2009). For example, diminished effects have been observed for taxes added at the time of payment as opposed to being clearly visible on the price tags on store shelfs (Chetty et al., 2009). A salient and clearly delineated targeted public health tax not only has a price effect but also provides a signal to consumers that the government considers the taxed products to be less healthy (Licari and Meier, 2000). In such cases, a tax could potentially be effective even if suppliers were willing to absorb the entire tax. Yet, some consumers may be less supportive of these taxes and therefore less likely to moderate their purchases, which is problematic if those who support the tax are least likely to benefit (i.e., they already purchase relatively small quantities of less healthy products). It is even possible that consumers who are less supportive of these taxes could increase purchases as a form of protest. Consumers often use their purchasing power to make political statements (Glickman, 2009; Shaw et al., 2006) and reactance behaviors in response to SSB taxes have been observed.(Debnam, 2017) The effectiveness of targeted public health taxes may therefore be diminished in locales with low support for such taxes.

It is also unclear if targeted public health taxes have differential impacts in populations most likely to benefit (e.g., individuals living with diabetes, those who are overweight/obese, from low-income households and/or lower educational backgrounds) (Batis et al., 2016; Nakamura et al., 2018). If these groups are less likely to moderate their purchases, the effectiveness of the tax could be reduced. Furthermore, a negative mood has been associated with greater impulsivity and less control (Atalay and Meloy, 2011) and hungry grocery shoppers have been found to buy more calories (Tal and Wansink, 2013), which both could influence the effectiveness of a tax.

Given the multitude of mitigating factors, it is important to identify the extent of their impact to ensure that any targeted public health tax is most likely to have the desired effect, which is an improvement in diet quality, and more so for those most likely to benefit. Using a randomized control trial, the aim of the study was therefore four-fold: 1) to determine if targeted public health taxes that result in higher prices reduce demand for taxed products; 2) to determine if the effectiveness is greater if the tax is clearly delineated; 3) to determine if a salient and clearly delineated tax will reduce demand for taxed products, even in the absence of a price increase; and 4) to determine if demand responses in the presence of salient and clearly delineated taxes are moderated by the level of support for the tax and by health status.

## 2. Methods

### 2.1. Design and participants

The study was approved by the Institutional Review Board, National University of Singapore (S-18-209) and registered in the American Economic Association's registry for randomized controlled trials (AEARCTR-0003176). All investigations were conducted according to the principles expressed in the Declaration of Helsinki and all participants provided written (electronically online) informed consent before being enrolled in the study.

Participants were recruited from three different sources, Facebook, Instagram and an online web panel (LightSpeed GMI). For all sources prospective and enrolled participants completed all study-related procedures online. Prospective participants were directed to a study website (https://nusmart.duke-nus.edu.sg/IMPEX), where after being screened for eligibility, they could access the online grocery store, called NUSMart. NUSMart mirrors an actual online grocery store, containing over 4000 food and beverage products, with pictures of each product, associated retail prices and product descriptions. Products are also searchable by 24 different categories (e.g., dairy products, carbonated soft drinks, fresh meats & seafood and snacks) and participants can add and remove products to and from their cart and review their total cart cost. Nutrition Information Panels for packaged products are also available as viewable pictures and on click-through under product details.

Participants were eligible for the study if they were Singapore residents and aged ≥21 years. If eligible, participants were asked to complete: 1) an online registration form (Text A3); note that participants recruited from LightSpeed GMI did not complete this form; 2) an online consent form (Text A4); and 3) after obtaining consent, an online baseline questionnaire (Text A5) that collected demographics, grocery shopping and food purchasing behaviors, medical conditions afflicting the participant or members of their household and levels of support for various government interventions aimed at improving diet quality.

Those who consented and completed the baseline questionnaire were randomized into one of four study arms and asked to spend between S$50 and S$100 (US$37 and US$73) on NUSMart. The minimum and maximum expenditures were intended to ensure sufficient purchasing data per shop and that results would not be unduly influenced by a few participants with large expenditures. During study enrolment, participants were told that there would be a 50 % chance of having to purchase the products that they had selected. The outcome of which would only be revealed upon spinning a digital "Wheel of Purchase" (Figure A1) when checking out of NUSMart and submitting their sales order on completion of their shop. However, no participants were actually required to purchase their selected products (i.e., "Wheel of Purchase" outcome was always "No Purchase"). This design was chosen so that participants thought they had a positive probability of having to purchase their selected products, thereby increasing the likelihood that their selected products were an accurate reflection of their actual shopping patterns. Such a design increases the credibility of the results over alternative designs that rely only on hypothetical shops.

Following completion of their shop, participants completed a brief survey to assess their mood and hunger level (Text A6) and were debriefed that they were deceptively told there was a positive probability that they would have to purchase the products that they had selected. Participants fulfilling all the study elements were compensated with a S$20 (US$15) Lazada electronic gift voucher (a popular eCommerce website in Singapore, https://www.lazada.sg).

### 2.2. Interventions and outcomes

Participants were randomized to shop in one of four versions of NUSMart (four study arms) that differed only in terms of the application and labelling of a tax on a select group of high calorie products. The application and labelling of the tax followed a similar approach previously used to incentivize responses to subsidies and taxes on various products within a computer-based retail environment (Muller et al., 2017). Within each product category, with the exception of fresh fruits and vegetables (not targeted for taxation), 20 % of products with the highest calories per serving (hereafter referred to as 'high-in-calorie products') were targeted for application of a 20 % tax that was fully passed on to consumers in terms of higher prices. In each intervention arm the same 20 % of high-in-calorie products were targeted. The four arms were: 1) no tax control, which did not display any label or tax on any product; 2) implicit tax showing only post-tax prices (i.e., 20 % higher than control prices) on the high-in-calorie products; 3) fake tax showing pre-tax prices and a label falsely indicating that the price includes a 20 % tax on the high-in-calorie products; and 4) explicit tax showing the same label as in 3) and an actual 20 % price increase applied to the high-in-calorie products. An example of how the taxes and labels were displayed on the same product across the four study arms is shown in Fig. 1.

All outcome measures were calculated using the sales orders submitted online by participants after completing their shop on NUSMart. The primary outcome was the proportion of products purchased that were the target of the tax (hereafter referred to as "proportion of targeted/taxed products purchased"). Secondary outcomes were based on measures of overall purchasing patterns, including kilocalories per serving, to quantify the effect of implicit, fake and explicit taxes on calories purchased. It should be noted that we standardized serving sizes for each product by using the mean serving size within each food and beverage subcategory. This was done as serving sizes can be arbitrarily set by manufacturers and some products lacked information on an appropriate serving size. Other secondary outcomes related to measures of expenditure and diet quality were considered, including kilocalories per dollar spent, total spend and expenditure on targeted/taxed products, as well as a modified (due to lack of available data, we were unable to account for the presence of polyunsaturated fats) version of the Alternative Health Eating Index-2010 (AHEI-2010) (Chiuve et al., 2012), to test for any unintended consequences of introducing a tax, and lastly a measure of consumers' sensitivity to price changes in the targeted/taxed products under implicit, fake and explicit taxes, price elasticities of demand. Price elasticities of demand for food and non-alcoholic beverages typically range from -0.27 to -0.81 (Andreyeva et al., 2010), but have been shown to be larger for soft drinks (-1.06) and sugar-sweetened beverages (−1.16) (Colchero et al., 2015).

### 2.3. Statistical methods

Sample size was calculated based on previously conducted NUSMart studies, using a 20 kilocalories per serving mean difference between the intervention arms and the control group, a two-tailed *t*-test with a 5 % level of significance, four separate comparisons, a standard deviation of 65 kilocalories per serving and a power of 0.8. This suggested a required sample size of 235 participants in each arm. An attrition rate of 25 % was estimated; therefore, we aimed to include 1175 participants. It should be noted that the trial was powered to quantify differences in kilocalories per serving (secondary outcome) rather than differences in the proportion of targeted/taxed products purchased (primary outcome) as the ultimate objective of a tax on less healthy products is to reduce caloric intake. Furthermore, we chose the proportion of targeted/taxed products purchased as the primary outcome as it is the most proximal effect of the interventions. However, given an intervention may affect the primary outcome, but not affect kilocalories per serving purchased, we powered our study using the latter with the expectation that if the study were powered for kilocalories per serving purchased the study would also be powered for the primary outcome.

After completing the baseline questionnaire, participants were randomly allocated with equal probability to one of the four arms. Allocation was done using a computer random number generator administered through NUSMart. Allocation results were recorded within NUSMart and all investigators, including the study data analyst, were blinded for group allocation.

Baseline data were analyzed by analysis of variance (ANOVA) and paired t-tests for continuous variables and Chi-squared tests for categorical variables. All analyses were based on intention to treat, included all available data collected in the study, and regressed the outcome of interest on study arm indicators for each of the three tax interventions (implicit, fake and explicit taxes). The effects of implicit, fake and explicit taxes on the primary outcome was assessed using a fractional logit model (Papke and Wooldridge, 1996). For the secondary outcomes, ordinary least squares; OLS

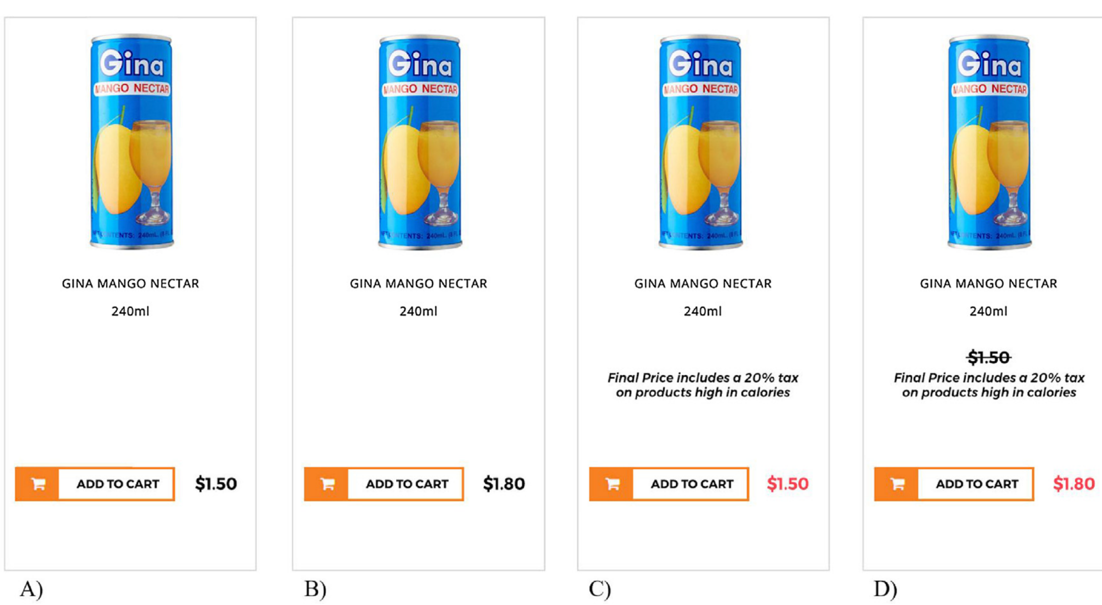


**Fig. 1.** Example product from NUSMart showing how the taxes and labels were presented across the four study arms. A) no tax control arm; B) implicit tax arm; C) fake tax arm; and D) explicit tax arm.

(kilocalories per serving, total spend and AHEI-2010) or an appropriate specification of the generalized linear model; GLM identified using Box-Cox and Modified Park tests (Deb et al., 2017) (kilocalories per dollar spent and expenditures of targeted/taxed products) was used. To model expenditures on targeted/taxed products and to estimate price elasticities of demand, a two-part model (logistic regression followed by appropriately selected GLM specification) (Deb et al., 2017) was used to account for the fact that not all participants purchased taxed/targeted products. Price elasticities of demand were calculated using mean differences for each of the three intervention arms relative to control and predicted mean quantities of targeted/taxed products purchased in the control arm to estimate the percentage change in the quantity of targeted/taxed products purchased. This was then divided by the percentage change in the price of targeted/taxed products in each intervention arm (i.e., 20 % in all three arms).

To test whether the level of support for taxes on less healthy products influenced outcomes, additional models were estimated that included interaction terms between the intervention arms and level of support. Similarly, we also tested whether outcomes were influenced by the presence of an individual (either participant and/or family member) within the participants' household who was living with diabetes, who was overweight/obese or living with a chronic disease and whether the participant was hungry or happy during their shop and whether the participant was from a high income household or university-educated. As the study was not powered to detect differences in these subgroups, data from the participants in the fake and explicit tax arms were combined to increase power. All models were estimated both with and without covariates to gauge the stability of the estimates. Covariates included age, body mass index (BMI), sex, household size, ethnicity, monthly household income and an indicator for participants recruited via the online panel. Age, BMI and household size were mean centered to improve interpretation of the effects.

All statistical analyses were performed using Stata/MP 15.1 (StataCorp LLC, Texas, USA). All results are given as mean values with 95 % confidence intervals (CIs) estimated using the percentile method from a nonparametric bootstrap (DiCiccio and Efron, 1996). Statistical significance was assessed using 95 % CIs, in that, a CI that includes zero does not allow for the null hypothesis, that a particular statistic is zero given the other predictors in the model, to be rejected.

## 3. Results

Fig. 2 outlines the flow of participants during the trial. Recruitment of participants via Facebook and Instagram advertisements started on 3 August 2018 and stopped on 22 October 2018 due to slower than expected recruitment. LightSpeed GMI commenced recruitment through their platform on 22 October 2018 and continued until 13 November 2018, but they were unable to fulfill our required sample size. Recruitment via Facebook and Instagram advertisements therefore recommenced on 19 November 2018. The final data collection date for the primary outcome measure was 24 November 2018. After screening for eligibility, 1144 participants consented to participate and were randomized to one of the four study arms, of which 941 completed the study. Table 1 shows the baseline characteristics of the participants. Across the four arms, participants were largely ethnic Chinese and the mean age was 36 years. The average body mass index (BMI) was 23 kg/m$^2$ and roughly half of participants were female. There were no significant differences in participant characteristics between groups.

Table 2 shows the model-based analyses for the primary and secondary outcomes, reporting the predicted values of the dependent variables for each analysis by study arm and the differences between each of the three intervention arms (implicit, fake and explicit taxes) and the control group. The regression coefficients for

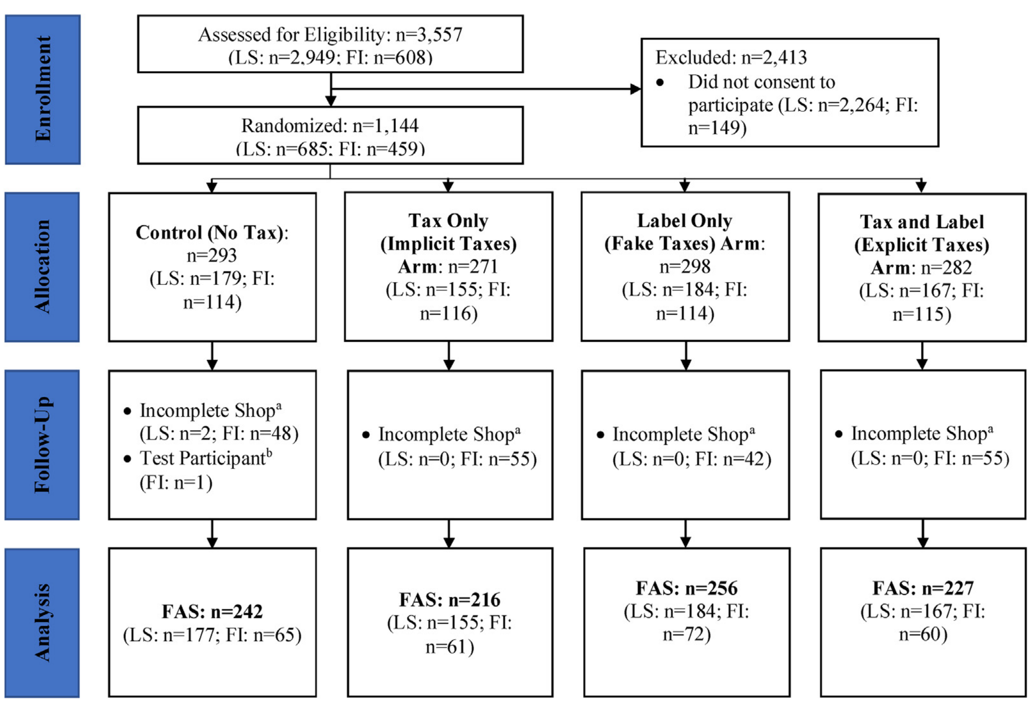


**Fig. 2.** CONSORT Diagram for the study.
FAS: full analysis sample; LS: Light Speed Participants; FI: Participants recruited via Facebook and Instagram advertisements
[a]Incomplete Shop: Participants were randomized, and were able to log into NUSMart, but did not check out/complete their purchase.
[b]Test Participant: A dummy account used to test the online shopping platform and therefore data from this shop was excluded from analysis.
One participant also shopped twice due to a glitch in NUSMart's programming, resulting in duplicate data. This has not been noted in the CONSORT diagram, but the sales order from the second (duplicate) shop were excluded from the analysis.

**Table 1**
Characteristics of all participants included in the IMPEX study.

| Baseline Characteristic | Control Arm (n = 242) | Implicit Taxes Arm (n = 216) | Fake Taxes Arm (n = 256) | Explicit Taxes Arm (n = 227) |
|---|---|---|---|---|
| **Age (years)** | 35.6 ± 10.0 | 37.0 ± 10.7 | 36.2 ± 10.9 | 36.5 ± 10.4 |
| **BMI (kg/m²)** | 22.8 ± 3.6 | 23.3 ± 3.7 | 22.7 ± 3.7 | 22.7 ± 4.0 |
| **Household size** | 3.0 ± 1.5 | 3.2 ± 1.4 | 3.2 ± 1.5 | 3.1 ± 1.4 |
| Sex | | | | |
| Male | 110 (45.5) | 103 (47.7) | 133 (52.0) | 114 (50.2) |
| Female | 132 (54.6) | 113 (52.3) | 123 (48.1) | 113 (49.8) |
| Ethnicity | | | | |
| Chinese | 212 (87.6) | 185 (85.7) | 233 (91) | 200 (88.1) |
| Malay | 10 (4.1) | 15 (7.0) | 7 (2.7) | 12 (5.3) |
| Indian | 14 (5.8) | 14 (6.5) | 11 (4.3) | 8 (3.5) |
| Other | 6 (2.5) | 2 (0.9) | 5 (2.0) | 7 (3.1) |
| High income household (≥$10,000/month) | | | | |
| Yes | 94 (42.0) | 80 (40.0) | 98 (41.5) | 79 (37.8) |
| No | 130 (58.0) | 121 (60.0) | 138 (58.5) | 130 (62.2) |
| University educated | | | | |
| Yes | 142 (58.7) | 136 (63.0) | 164 (64.1) | 133 (58.6) |
| No | 100 (41.3) | 80 (37.0) | 92 (35.9) | 94 (41.4) |
| Support for taxes on high-in-calorie products | | | | |
| Oppose | 72 (29.8) | 62 (28.7) | 76 (29.7) | 61 (26.9) |
| Support | 170 (70.3) | 154 (71.3) | 180 (70.3) | 166 (73.1) |
| Household with at least one person living with diabetes | | | | |
| Yes | 32 (13.2) | 34 (15.7) | 33 (12.9) | 28 (12.3) |
| No | 210 (86.8) | 182 (84.3) | 223 (87.1) | 199 (87.7) |
| Household with at least one individual who is overweight or obese | | | | |
| Yes | 28 (11.6) | 26 (12.0) | 20 (7.8) | 17 (7.5) |
| No | 214 (88.4) | 190 (88.0) | 236 (92.2) | 210 (92.5) |
| Household with at least one individual living with a chronic disease | | | | |
| Yes | 119 (49.2) | 113 (52.3) | 131 (51.2) | 103 (45.4) |
| No | 123 (50.8) | 103 (47.7) | 125 (48.8) | 124 (54.6) |
| Mood when shopping during the study | | | | |
| Happy | 136 (56.7) | 119 (55.1) | 137 (53.5) | 118 (52.0) |
| Not happy | 104 (43.3) | 97 (44.9) | 119 (46.5) | 109 (48.0) |
| Hunger when shopping during the study | | | | |
| Hungry | 121 (50.0) | 104 (48.2) | 129 (50.4) | 119 (52.4) |
| Not hungry | 121 (50.0) | 112 (51.9) | 127 (49.6) | 108 (47.6) |

Observed data are presented as mean ± standard deviation or number of participants.
Missing data is 0 for all variables except for household size, where 1 is missing in Implicit, BMI, where 36 are missing in total (14 in Control, 4 in Implicit, 8 in Fake and 10 in Explicit), high income household, where 71 are missing in total (18 in Control, 15 in Implicit, 20 in Fake and 18 in Explicit) and mood, where 2 are missing in Control.

the adjusted analyses are presented in Table A1. Results from the unadjusted analyses are presented in Tables A2 and A3.

### *3.1. Primary outcome - proportion of targeted/taxed products purchased*

In the adjusted analysis, the proportion of targeted/taxed products purchased was 14 % in the no tax (control) group (Table 2). Compared to the control group the proportion of targeted/taxed products purchased was a statistically significant three percentage points (or 27 %) lower in the explicit tax group (−0.03, 95 % CI −0.06 to −0.005). A similar magnitude was observed for the fake tax group (−0.03, 95 % CI −0.05 to 0.00) but a slightly larger confidence interval meant that we could no longer reject the null hypothesis of no effect. In the unadjusted analysis (Table A2), statistically significant three percentage point reductions in the proportion of targeted/taxed products purchased compared to control were observed for both the fake tax group (−0.03, 95 % CI −0.05 to −0.003) and the explicit tax group (−0.03, 95 % CI −0.07 to −0.003). We were unable to reject the null hypothesis of no effect between the implicit tax group and the control for both the adjusted (−0.01, 95 % CI −0.03; 0.02) and unadjusted (0.00, 95 % CI −0.03 to 0.02) analyses.

### *3.2. Secondary outcomes*

Predicted mean values for each of the five secondary outcomes were very similar across the four study arms in the adjusted analyses (Table 2). In no case were we able to observe statistically significant differences for any of the interventions arms relative to control. Results were similar in the unadjusted analyses (Table A2) with the exception of a statistically significant 1.26 point decrease in the AHEI-2010 score in the explicit tax arm compared to control (95 % CI −2.50 to −0.09).

**Table 2**
Primary and secondary outcomes for full analysis sample – adjusted analyses.

| Outcome | No Tax Group (Control) (n = 210) | | Implicit Taxes Group (n = 196) | | Implicit Taxes and Control Comparison | | Fake Taxes Group (n = 228) | | Fake Taxes and Control Comparison | | Explicit Taxes Group (n = 200) | | Explicit Taxes and Control Comparison | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | 95 % CI | Mean | 95 % CI | Diff | 95 % CI | Mean | 95 % CI | Diff | 95 % CI | Mean | 95 % CI | Diff | 95 % CI |
| Proportion of taxed / targeted products purchased | 0.14 | 0.12, 0.16 | 0.13 | 0.12, 0.15 | −0.01 | −0.03, 0.02 | 0.11 | 0.10, 0.13 | −0.03 | −0.05, 0.00 | 0.11 | 0.09, 0.13 | **−0.03** | **−0.06, -0.005** |
| kCal per serving | 137 | 126, 149 | 138 | 125, 150 | 8.62 | −7.87, 28.31 | 138 | 126, 149 | 5.55 | −10.65, 23.73 | 143 | 130, 155 | 13.00 | −4.16, 31.53 |
| kCal/$ | 253 | 230, 280 | 236 | 213, 261 | −11.28 | −44.27, 22.85 | 254 | 233, 274 | 4.96 | −28.62, 36.56 | 258 | 235, 284 | 9.28 | −26.45, 44.46 |
| Total spend ($) | 67 | 65, 69 | 69 | 66, 71 | 1.86 | −1.38, 5.39 | 66 | 64, 69 | −0.32 | −3.40, 2.82 | 66 | 64, 68 | −0.79 | −3.83, 2.34 |
| Expenditure on taxed / targeted products ($) | 2.33 | 1.84, 2.90 | 2.29 | 1.96, 2.66 | −0.07 | −0.64, 0.48 | 2.11 | 1.78, 2.48 | −0.24 | −0.82, 0.32 | 1.90 | 1.47, 2.38 | −0.47 | −1.06, 0.21 |
| AHEI-2010 | 42.74 | 41.81, 43.76 | 41.87 | 41.87, 42.79 | −0.99 | −2.30, 0.33 | 42.45 | 41.63, 43.17 | −0.30 | −1.57, 0.93 | 41.42 | 40.48, 42.39 | −1.30 | −2.70, 0.08 |

AHEI-2010 - Alternative Health Eating Index-2010; Diff – discrete difference; kCal – kilocalories.
Bold numbers are significantly different to control.
Outcomes are adjusted for age, body mass index, household size, sex, ethnicity, income category and Light Speed participant indicator.
95 % CIs are derived from a bootstrap using the percentile method; the CI is equivalent to the z test statistic, therefore, if the CI includes zero, we would fail to reject the null hypothesis that a particular statistic is zero given the other predictors are in the model.

### *3.3. Moderator analyses*

Table 3 shows the model-based analyses for the primary outcome assessing the effects of implicit, fake and explicit taxes in different participant subgroups. Note that the fake and explicit tax arms have been combined to increase power. Predicted values of the dependent variables for each analysis for the two intervention groups (implicit tax arm and combined fake and explicit taxes group) by participant subgroup and the discrete differences between the two intervention groups and the control arm are presented. The regression coefficients for the adjusted analyses are presented in Table A4 and the discrete differences and coefficients from the unadjusted analyses are presented in Table A5 and Table A6 respectively. With the exceptions outlined below, results of the adjusted and unadjusted analyses were similar.

#### *3.3.1. Support for tax on high-in-calorie products*

A statistically significant increased effect in the combined fake and explicit taxes group compared to control was observed for those who support taxes on less healthy products (−0.07, 95 % CI −0.10 to −0.03), with a seven percentage point (30 %) reduction in the proportion of targeted/taxed products purchased (Table 3). The difference between non-supporters and supporters was about five percentage points, but this difference was not statistically significant. No increase in the effect in the implicit tax arm was observed and we were unable to reject the null hypothesis of no effect for both non-supporters (−0.02, 95 % CI −0.07 to 0.02) and supporters (−0.03, 95 % CI −0.07 to 0.01).

#### *3.3.2. Other moderators*

Other moderators tested had varying impacts on the magnitude of effect of the taxes on the proportion of targeted/taxed products purchased (Table 3). Statistically significant differences in the combined fake and explicit taxes group compared to control were observed only for households without an individual living with diabetes (−0.03, 95 % CI −0.06 to −0.002) or without an individual who is overweight or obese (−0.03, 95 % CI −0.06 to −0.003). However, for the combined fake and explicit taxes group we were unable to reject the null hypothesis of no effect between non-diabetes households and diabetes households and between non-overweight/obese households and overweight/obese households.

We found statistically significant differences in the combined fake and explicit taxes group compared to control for participants living in a household with (−0.06, 95 % CI −0.09 to −0.02) and without (−0.04, 95 % CI −0.07 to −0.003) an individual living with a chronic condition, for participants that were hungry (-0.06, 95 % CI −0.10 to −0.03) and not hungry (−0.04, 95 % CI −0.08 to −0.003) during their shop, for participants that were happy (−0.07, 95 % CI −0.11 to −0.3) and not happy (−0.05, 95 % CI -0.09 to −0.003) during their shop and for participants from a high income household (−0.05, 95 % CI −0.09 to −0.02) and low income household (−0.04, 95 % CI −0.07 to −0.01). We were, however, unable to reject the null hypothesis of no effect between each of these participant subgroups. We also did not find a statistically significant effect in the combined fake and explicit taxes group compared to control for either university (−0.01, 95 % CI −0.04 to 0.03) or non-university (−0.01, 95 % CI −0.05 to 0.04) educated participants.

For all the moderator analyses we were unable to reject the null hypothesis of no effect in the implicit taxes arm compared to control for non-chronic disease (−0.02, 95 % CI −0.05 to 0.02) and chronic disease (−0.03, 95 % CI −0.07 to 0.01) households, not hungry (-0.02, 95 % CI -0.05 to 0.02) and hungry (−0.04, 95 % CI −0.08 to 0.00) shoppers, not happy (−0.03, 95 % CI −0.07 to 0.01) and happy (−0.03, 95 % CI -0.08 to 0.01) shoppers and low-income (-0.01, 95 % CI -0.04 to 0.02) and high-income (−0.03, 95 % CI -0.07 to 0.01) participants.

### *3.4. Price elasticities of demand for taxed/targeted products*

The mean quantity of targeted/taxed products purchased was 2.33 in the no tax group (control) and slightly lower in the implicit, fake and explicit taxes arms (2.29, 2.11 and 1.90 respectively) (Table 4, Table A7 and Table A8). Using this data to calculate price elasticities of demand for each intervention arm indicated that participants were more price sensitive to targeted/taxed products in the explicit tax arm (elasticity of −0.97), followed by the fake tax arm (elasticity of −0.46) and, consistent with our hypothesis, least sensitive to price changes in the implicit tax arm (elasticity −0.10).

Participants who support taxes on less healthy products were more sensitive to price changes in targeted/taxed products in both the implicit tax arm and combined fake and explicit taxes group (elasticities of −0.68 and −1.38 respectively) (Table A9 and Table A10). Non-supporters were less sensitive to price changes in targeted/taxed products in the combined fake and explicit taxes group (elasticity of -0.51) and were nearly completely insensitive

**Table 3**
Primary outcome (proportion of taxed/targeted products purchased) for full analysis sample with moderators – adjusted analyses.

| Outcome | No Tax Group (Control) | | | Implicit Taxes Group | | | Implicit Taxes and Control Comparison | | Explicit Taxes and Fake Taxes Groups Combined | | | Explicit/Fake Taxes and Control Comparison | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | 95 % CI | N | Mean | 95 % CI | Discrete difference | 95 % CI | N | Mean | 95 % CI | Discrete difference | 95 %CI |
| Non-supporters[a] | 63 | 0.17 | 0.13, 0.21 | 58 | 0.14 | 0.10, 0.17 | −0.02 | −0.07, 0.02 | 122 | 0.14 | 0.11, 0.16 | −0.02 | −0.07,0.02 |
| Supporters[a] | 147 | 0.13 | 0.10, 0.16 | 138 | 0.13 | 0.11, 0.16 | −0.03 | −0.07,0.01 | 306 | 0.10 | 0.09, 0.11 | **−0.07** | **−0.10, -0.03** |
| Non-diabetes household[b] | 184 | 0.14 | 0.11, 0.17 | 164 | 0.14 | 0.12, 0.16 | −0.01 | −0.03,0.02 | 375 | 0.11 | 0.10, 0.12 | **−0.03** | **−0.06, 0.002** |
| Diabetes household[b] | 26 | 0.15 | 0.10, 0.20 | 32 | 0.12 | 0.08, 0.18 | −0.02 | −0.07, 0.04 | 53 | 0.11 | 0.08, 0.15 | −0.03 | −0.07,0.02 |
| Non-overweight/obese household[c] | 185 | 0.14 | 0.11,0.16 | 171 | 0.14 | 0.12,0.16 | 0.00 | −0.03,0.03 | 396 | 0.11 | 0.09,0.12 | **−0.03** | **−0.06, 0.003** |
| Overweight/obese household[c] | 25 | 0.17 | 0.10, 0.25 | 25 | 0.12 | 0.08, 0.15 | −0.01 | −0.06, 0.04 | 32 | 0.14 | 0.10, 0.20 | 0.00 | −0.06, 0.06 |
| Non-chronic disease household[d] | 108 | 0.16 | 0.12, 0.20 | 97 | 0.14 | 0.11, 0.17 | −0.02 | −0.05, 0.02 | 224 | 0.12 | 0.10, 0.14 | **−0.04** | **−0.07, -0.003** |
| | 102 | 0.12 | 0.09, 0.15 | 99 | 0.13 | 0.10, 0.15 | −0.03 | −0.07, 0.01 | 204 | 0.10 | 0.08, 0.12 | **−0.06** | **−0.09, -0.02** |
| Chronic disease household[d] | 102 | 0.12 | 0.09, 0.15 | 99 | 0.13 | 0.10, 0.15 | −0.03 | −0.07, 0.01 | 204 | 0.10 | 0.08, 0.12 | | |
| Not hungry shoppers[e] | 100 | 0.17 | 0.13, 0.21 | 97 | 0.15 | 0.12, 0.17 | −0.02 | −0.05, 0.02 | 201 | 0.12 | 0.10, 0.14 | **−0.04** | **−0.08, -0.003** |
| Hungry shoppers[e] | 110 | 0.12 | 0.09, 0.15 | 99 | 0.12 | 0.10, 0.15 | −0.04 | −0.08, 0.00 | 227 | 0.10 | 0.08, 0.11 | **−0.06** | **−0.10, -0.03** |
| Not happy shoppers[f] | 83 | 0.18 | 0.13, 0.23 | 85 | 0.14 | 0.11, 0.17 | −0.03 | −0.07, 0.01 | 195 | 0.12 | 0.10, 0.15 | **−0.05** | **−0.09, -0.003** |
| Happy shoppers[f] | 126 | 0.11 | 0.09, 0.14 | 111 | 0.13 | 0.11, 0.16 | −0.03 | −0.08, 0.01 | 233 | 0.10 | 0.09, 0.11 | **−0.07** | **−0.11, -0.03** |
| Not high income[g] | 122 | 0.15 | 0.13, 0.18 | 117 | 0.14 | 0.12, 0.16 | −0.01 | −0.04, 0.02 | 257 | 0.11 | 0.10, 0.13 | **−0.04** | **−0.07, -0.01** |
| High income[g] | 88 | 0.12 | 0.09, 0.16 | 79 | 0.12 | 0.09, 0.16 | −0.03 | −0.07, 0.01 | 171 | 0.10 | 0.08, 0.12 | **−0.05** | **−0.09, -0.02** |
| Not university educated[h] | 87 | 0.12 | 0.09, 0.16 | 73 | 0.14 | 0.10, 0.18 | 0.02 | −0.03, 0.07 | 159 | 0.11 | 0.09, 0.14 | −0.01 | −0.05, 0.04 |
| University educated[h] | 123 | 0.16 | 0.13, 0.19 | 123 | 0.13 | 0.11, 0.15 | 0.02 | −0.02, 0.07 | 269 | 0.11 | 0.09, 0.12 | −0.01 | −0.04, 0.03 |

N – number of participants.
Bold numbers are significantly different to control.
Outcomes are adjusted for age, body mass index, household size, sex, ethnicity, income category (not included in high-income/not high-income analysis) and Light Speed participant indicator.
95 % CIs are derived from a bootstrap using the percentile method; the CI is equivalent to the z test statistic: if the CI includes zero, we would fail to reject the null hypothesis that a particular statistic is zero given the other predictors are in the model.

[a] Study participants were identified as either supporters or non-supporters of taxation of high-in-calorie products if they selected either "Support" or "Strongly support" and "Oppose" or "Strongly oppose" respectively in response to the question: "*Please let us know your support or opposition to the following interventions: Taxes on less healthy foods, such as sugary drinks*".

[b] Study participants were classified as belonging to a diabetes household if they indicated anyone in their household (including themselves) had ever been told by their doctor or other health professional that they had diabetes.

[c] Study participants were classified as belonging to an overweight/obese household if they indicated anyone in their household (including themselves) had ever been told by their doctor or other health professional that they were overweight or obese.

[d] Study participants were classified as belonging to a chronic disease household if they indicated anyone in their household (including themselves) had ever been told by their doctor or other health professional that they had at least one of the following: diabetes, high cholesterol, high blood pressure (hypertension), heart disease/stroke, gastrointestinal disorders or kidney aliments (weak or failing kidneys).

[e] Study participants were classified as hungry and not hungry shoppers if they selected 5 or below and 6 and above respectively on a scale of 1–10 (1 being not hungry at all and 10 being extremely hungry) of how hungry they felt at the moment they had completed their online shopping.

[f] Study participants were classified as happy and not happy shoppers if they selected either "Very happy" or "Happy" and "In between", "Unhappy" or "Very unhappy" respectively on a scale of their current mood at the moment they had completed their online shopping.

[g] Study participants were classified as a high income household if they reported monthly household income of $10,000 and over.

[h] Study participants were classified as university educated if they reported their highest level of education attained to be "University & above".

**Table 4**
Mean quantity of tax/targeted products purchased and own price elasticities for full analysis sample – adjusted analysis.

| | Mean quantity of tax / targeted products purchased | 95 % CI | Elasticity |
|---|---|---|---|
| No Tax Group (Control) (n = 210) | 2.33 | 1.84, 2.90 | |
| Implicit Taxes Group (n = 196) | 2.29 | 1.96, 2.66 | −0.10 |
| Fake Taxes Group (n = 228) | 2.11 | 1.78, 2.48 | −0.46 |
| Explicit Taxes Group (n = 200) | 1.90 | 1.47, 2.38 | −0.97 |

Outcomes are adjusted for age, body mass index, household size, sex, ethnicity, income category and Light Speed participant indicator.
Elasticities were estimated using a two-part model (logit model and generalized linear model using an inverse Gaussian family with log link).

to price changes in the implicit tax arm (elasticity of 0.01) (Table A9 and Table A10).

## 4. Discussion

Consistent with economic theory, we find that targeted public health taxes on less healthy food and beverage products will reduce demand for the taxed products. However, the effectiveness of the tax may depend on it being salient and clearly delineated. Whereas we show that large price increases that are not salient are likely to have only small effects, salient and clearly delineated taxes, even if they come with no price increase, will reduce demand for the taxed product, with our 20 % tax showing reductions of as much as 27 % on taxed products. We further show these reductions are possible even without a price increase. This is an important finding in that it shows that taxes can be effective even if suppliers do not pass along any price increase to consumers. Our results, therefore, support the need to make any tax on less healthy products salient and clearly delineated at the time that consumers are making their selections.

We posited that salient, clearly delineated taxes may be affected by the level of support for such taxes. This may explain the positive impacts of taxes on SSBs observed in Berkley, California, a community known for its support of such policies (Silver et al., 2017) and less successful efforts in Chile and Denmark, where the populations were less supportive of the taxes (Nakamura et al., 2018; Toft et al., 2014). In that respect, policy makers looking to implement taxes on less healthy products should be cognisant of the level of support and understand that the desired effects may be reduced if a large proportion of the population is not supportive. Although, we did not find any evidence of reactance or an increase in demand for the taxed/targeted products in non-supporters of taxes, emotional responses to policy changes like public health taxes can induce significant deadweight loss (Just and Hanks, 2015) and have been specifically observed in reaction to SSB taxes (Debnam, 2017). Policy makers should therefore be aware of the potential counter-productive effects of public health taxes.

We found some indication that the effect of salient, clearly delineated taxes may not be as effective in some populations who would be the main targets or most likely to benefit from such a tax (e.g., households with either individuals living with diabetes and/or who are overweight/obese). Importantly, we also show that the effects of salient clearly delineated taxes are effective regardless of shoppers' mood, hunger and income level. In terms of the latter, this is somewhat inconsistent with evidence from Chile that showed larger reductions in the consumption of SSB in higher socioeconomic groups (Nakamura et al., 2018) and evidence from Mexico that showed the opposite result, in that, no change in consumption of non-essential energy-dense foods was observed in high socioeconomic households (Batis et al., 2016). These differences may be explained by the vastly different populations living in Chile, Mexico and Singapore as well as differences in study design (real-world impacts of taxes in an observational study compared to one-off shops from a randomized controlled trial). However, caution is advised in interpreting our subgroup results, given the small number of participants that self-reported being in these subgroups and that the study was not powered for these comparisons.

Our results also indicate that despite a reduction in the demand for the taxed products, the tax, whether salient or not, had no detectable impact on the mean number of kilocalories per serving purchased or the overall quality of the baskets of products purchased according to the AHEI-2010 score. Based on the 95 % CIs for both these outcomes the interventions are unlikely to be associated with reductions greater than 11 kilocalories per serving and improvements in AHEI-2010 score of more than one point. Given that the ultimate objective of a targeted sin tax on less healthy products is to improve diet quality, our results indicate that taxes alone may be insufficient to achieve that objective.

Overall, we show that reductions in the proportions of high-in-calorie products purchased may be largely attributable to explicit messaging rather than to price increases, but careful consideration in implementing such taxes should be made as the effects may be moderated by the level of support for the taxes and health status of the population.

A number of countries and cities have passed legislation mandating excise taxes on soda and SSBs (Borges et al., 2017; Studdert et al., 2015). In fact the World Health Organization is also promoting the uptake of such taxes (World Health Organization, 2015) and a number of other jurisdictions are considering the introduction of such policies, including Singapore. As we have shown that it is important to consider the salience of taxes in order to maximize the effectiveness of the tax, any jurisdiction that has implemented or is considering implementing such taxes should ensure legislation includes mandates for explicit messaging, alongside any price increase.

In terms of generalizability, our study population was limited to Singaporean adults, who largely identified as ethnic Chinese (88 %) and the majority of the sample (73 %) were recruited from an online survey panel. Although representative of the population in Singapore, these individuals were likely to be highly computer literate and had time available to participate in the study. Our study was also conducted using a fully-functional online grocery store, which may have resulted in recruitment of individuals who were more comfortable with this type of grocery shopping. Future studies should test the results with different populations and with different shopping venues.

Our study also further highlights the limited evidence available (Batis et al., 2016; Nakamura et al., 2018; Silver et al., 2017) indicating that taxes (implicit or explicit) on less healthy food and beverage products will result in reductions in overall energy intake and/or improvements in diet quality. This is problematic as the ultimate goal of a tax on less healthy food products is not just to reduce consumption, but also reduce caloric intake, in order to have an impact on rising rates of obesity and chronic conditions. To realize the full benefits of taxes on less healthy products (Cobiac et al., 2017; Lin et al., 2011) it will therefore be necessary to fully understand the nuances in their implementation. Our study begins to address some of these nuances, recommending salient and clearly delineated messaging and consideration of levels of support, but further understanding will be required to maximize the impact of such taxes on diet quality and health outcomes.

In our study, participants were deceptively told that they had a positive probability of having to purchase the products they selected during their shop. This design feature potentially avoids biases that may be associated with studies using hypothetical shopping exercises (Chang et al., 2009). Despite this, participants' shops were still hypothetical transactions, reflecting their stated preferences as opposed to their revealed preferences. As such the purchasing patterns and effects of the different taxes observed in our study may not be entirely indicative of what would be observed in a real-world shopping environment. Furthermore, our randomized controlled trial design allowed us to directly compare the impact of multiple, different taxing strategies simultaneously in the same population and time-period, which is in contrast to existing studies that rely on observational study designs using real-world data to estimate the effects of a single taxing strategy (Batis et al., 2016; Nakamura et al., 2018; Silver et al., 2017). We also report price elasticities of demand for each of the intervention arms that allow us to confirm the validity of our results, in that our price elasticity of demand estimates are very much in line with existing estimates reported for food and beverage products (Andreyeva et al., 2010; Green et al., 2013).

The primary limitation of our study is that it was underpowered for testing for statistically significant differences across arms for many of the included outcomes given the magnitude of the observed differences were smaller than expected. This is apparent given the wide 95 % CIs observed in Table 2. Our sample size calculation was based on an expected difference of at least 20 kilocalories per serving between any two arms, whereas the largest difference in kilocalories per serving between intervention and control arms (let alone between intervention arms) was 13 kilocalories per serving. Despite this shortcoming, the magnitude and direction of effects in the primary outcome across arms are consistent with theory and given the paucity of evidence on different tax strategies, the results provide important information on the likely effects of these strategies. Future studies with much larger sample sizes will be required to test for differences of this magnitude between the different strategies presented. In addition, participants only had the chance to shop once within NUSMart and therefore we were unable to capture the sustained effects of the different taxes (implicit, fake and explicit). It is possible that the effect of implicit taxes in our study have been underestimated as over multiple shops, participants in the implicit taxes arm might have become more aware of the price increases of the targeted/taxed products and decreased their consumption accordingly, despite the tax not being salient and clearly delineated. It is possible that our imposed spending limits (minimum and maximum spend of S$50 and S$100 respectively) could have also resulted in substitution effects (Fischer, 2014), leading participants to switch to products that were not taxed/labelled in order to meet the imposed limits. However, a minimum spending limit was essential to encourage participants to shop as they would in a real weekly online shopping experience and a maximum was used such that a single shopper did not overly influence the results. Future studies should explore the effects of imposing these limits. Furthermore, our study was not powered to detect differences in sub-groups (supporter versus non-supporters as well as other subgroups tested) within the intervention arms and therefore care must be taken in interpreting the results from our moderator analyses. We attempted to address this issue by combining both the fake and explicit tax arms, but it is likely that we were still underpowered to detect any differences between the subgroups of interest.

## 5. Conclusion

Public health taxes on less healthy food and beverage products can be an effective way to reduce consumption of these products, but the manner in which taxes are implemented can greatly influence any potential beneficial effects. Any messaging concerning the application of the tax should be salient and clearly delineated in order to achieve the desired reduction in consumption of the targeted products. However, even when effective, policymakers should recognize that changes in purchasing patterns may not improve diet quality and that results from one locale should not be expected to generalize to other areas where levels of support differs.

## Contributor and guarantor information

BD extracted, analyzed and interpreted the data; drafted and revised this article; and gave final approval of this version to be published.

FJLA designed the study protocol, oversaw data collection; critically reviewed and edited the draft article; and gave final approval for this version to be published.

EAF conceptualized the study; assisted with its design and the interpretation of data; critically reviewed and edited the draft article; and gave final approval of this version to be published.

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## Data sharing statement

De-identified, individual participant data collected for the study will be made available on the NUSMart website (https://nusmart.duke-nus.edu.sg/welcome) upon publication of this study. The study protocol and other trial related documentation, including the Participant Information Sheet and Online Consent Form are available as supplementary material.

## Declarations of Competing Interest

The authors declare no conflicts of interest, including employment, consultancies, stock ownership, honoraria, paid expert testimony, patients or patent applications and travel grants.

## Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ehb.2020.100860.

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