Statistical method

dCDH estimators

We apply de Chaisemartin and D'Hautefoeuille (2022),[1] thereafter called dCDH, estimators to assess the effects of SSB tax and PPP (our treatment) on the average sugar content of new SSBs (our outcome) in France, the United Kingdom or the Netherlands. We chose this estimation method because dCDH estimators are robust to heterogeneous and dynamics policy/treatment effects, unlike the estimator computed in the commonly-used dynamic two-way fixed effects regression, also known as event-study regression (presented in Appendix G).[1–3] Moreover, they can be used even if the policy/treatment is not binary or the design is not stagerred (i.e. countries have maintained the policy after announcing/implementing it).

Below, we present the method for the SDIL and 2018 French tax to facilitate the reading. Only the notation has to be adapted for the Dutch PPP and 2012 French tax.

The dCDH estimators are difference-in-differences (DID) estimators of intertemporal treatment effects. They have shown that for any country (or group) c, whose treatment changed for the first time at period F_c, the instantaneous and dynamics effects of that change can be unbiaisedly estimated under the parallel trends assumption (i.e. in the absence of the policy, both the United Kingdom or France and the control group countries would have experienced the same evolution of the average sugar content of new SSBs). In our setting, F_{UK}=2016 and $F_{FR} = 2018$ for the United Kingdom and France, respectively. Let $Y_{c,t} = 1/N_{c,t} \sum_{i \in c,t} Y_{i,c,t}$ denote the average sugar content in grams per 100 mL of new SSBs in country c at period t, where $N_{c,t}$ stands for the number of new SSBs in country c at period t. Let N_t^u denote the number of new SSBs in the control group countries at period t. In our binary and staggerred treatment design where all considered countries have no SSB tax implemented in 2010, dCDH estimator is for $l \geq 0$

$$DID_{c,l} = \left(Y_{c,F_c+l} - Y_{c,F_c-1}\right) - \frac{1}{N_{F_c+l}^u} \sum_{c':F_{c'}>F_c+l} N_{c',F_c+l}\left(Y_{c',F_c+l} - Y_{c',F_c-1}\right), \quad (F1)$$

when weighted by the number of new SSBs per country per year.[1] It is a DID estimator comparing the $F_c - 1$-to-$F_c + l$ evolution of the average sugar content of new SSBs in France or the United Kingdom and in the control group countries, for $l \geq 0$. The estimator $DID_{c,l}$ is interpreted as the effect of announcing/implementing the tax rather than not for $l + 1$ years. The estimator $DID_{UK,l}$ of the estimated effect of SDIL is calculated for $l = \{0,1,2,3\}$. The estimator $DID_{FR,l}$ of the estimated effect of the 2018 French SSB tax is calculated for $l = \{0,1\}$. To illustrate, $DID_{UK,l=2}$ is the dCDH DID estimator comparing the evolution of the average sugar content of new SSBs from 2015 to 2018 in the United Kingdom, that announced the tax in 2016, and in Germany, Italy, and Spain.

[1] In contrast to dCDH,[1] we have chosen to define the dCDH DID estimators for $l \geq 0$ to be as close as possible to the event-study regression.

Testing the plausibility of parallel trends hypothesis: Placebo estimators

dCDH propose "long-difference" placebo estimators, computed using pre-policy observations, to test the parallel trends assumption underlying dCDH estimators.[1] Contrary to the standard test used in the dynamic two-way fixed effects regression, the dCDH placebo estimators are robust even if the tax effects vary across countries and over time.[1] In our setting, dCDH placebo estimator is for $l \geq 0$

$$DID_{c,l}^{pl} = \left(Y_{c,F_c-l-2} - Y_{c,F_c-1}\right) - \frac{1}{N_{F_c+l}^{u}} \sum_{c':F_{c'}>F_c+l} N_{c',F_c+l}\left(Y_{c',F_c-l-2} - Y_{c',F_c-1}\right), \quad (F2)$$

$DID_{c,l}^{pl}$ mimiks $DID_{c,l}$. Like $DID_{c,l}$, it compares the evolution of the average sugar content of new SSBs in France or the United Kingdom and in the control group countries. But unlike $DID_{c,l}$, it compares those groups' outcome evolutions from the year $F_c - 1$, namely one year before the United Kingdom or France has announced/implemented the SSB tax for the first time, to the year $F_c - l - 2$. Accordingly, $DID_{c,l}^{pl}$ assesses if the United Kingdom or France, and the control group countries experience the same evolution of the outcome over $l + 1$ years before the first year of the announcement/implementation of the tax, i.e. the number of years over which the parallel trends has to hold for $DID_{c,l}$ to be unbiased. To illustrate, $DID_{UK,l=2}^{pl}$ is the placebo dCDH DID estimator comparing the evolution of the average sugar content of new SSBs from 2015 to 2012 in the United Kingdom, that announced the tax in 2016, and in Germany, Italy, and Spain.

dCDH show that under the parallel trends assumption, $E[DID_{c,l}^{pl}|\boldsymbol{D}] = 0$, where $\boldsymbol{D}$ be a vector stacking the treatments of all countries at every period. dCDH show that finding an estimation of $DID_{c,l}^{pl}$ significantly different from 0 implies that the parallel trends assumption is violated.

Controlling for covariates

It is possible that France or the United Kingdom and the control group countries have experienced different evolutions of the average sugar content of new SSBs over time. However, the dCDH DID approach can still produce unbiased estimators provided that those differential evolutions are accounted for by a linear model in $X_{c,t} - X_{c,t-1}$, the change in country's covariates between t and $t - 1$. Furthermore, it is also possible that each SSB category follows its own linear average sugar content trend, leading to biased dCDH DID estimators. A key specificity of dCDH approach is that it allows to both control for time-and country-varying covariates and group-specific linear trends.

Accordingly, we consider in our analysis time- and country-varying covariates that may affect consumers' preferences and consequently/or companies' strategy regarding SSB sugar content in each country, but uncorrelated to the treatment, i.e. the policy announcement/implementation. Country's variable indicators of health (i.e. childhood obesity rate,[4] share of out-of-pocket medical expenses over total health spending,[5] death rate due to NCDs among populations aged 30--70 years,[6] and dietary and high body mass index risks[7]); the agricultural producer price index of sugar deflated by the GDP deflator;[8] and whether the beverage was manufactured and marketed by a national brand or not were considered. In our estimations, the country's variable indicators of health control for beverage sugar content variations caused by changes in a country's health context. For example, if out-of-pocket medical expenses increase (i.e., the health care system becomes less protective), an individual may be more motivated to adopt healthier food habits such as purchasing healthier food products, which in turn may encourage SSBs companies to remove sugar. Only the share of out-of-pocket medical expenses over total health spending was included in the estimations. For the other health variables, it was difficult to distinguish their effects from those of country fixed effects given their weak variability over time. The agricultural producer price index of sugar controls for the cost of the main raw material in SSBs that might impact the level of the sugar content of new SSBs launched in the market. We also consider the share of national brands for each SSB category per year in each country, as national brands can have different strategy than private label brands,[9] as consumers of retailer brand products tend to be more motivated by price than by quality.

A two-step procedure is used in the dCDH's method to control for $X_{c,t}$. First, they regress the first difference in the average sugar content of new SSBs in country c, $(Y_{c,t} - Y_{c,t-1})$, on $(X_{c,t} - X_{c,t-1})$ and time fixed effects. This regression is estimated for the sample of countries and years for which the tax policy has not (yet) been implemented in year t. The dCDH DID estimators and placebo estimators are then calculated as described in equations (F1) and (F2), respectively, except that the $(Y_{c,t} - Y_{c,t-1})$ is replaced by the residuals of the previous regression.

The statistical method was first published in December, 2021 on the study's githhub webpage. Changes to protocol published since December, 2021 are also detailed in the webpage.

Comparison of the identification methods with analyses already carried out

The "Soft Drinks Industry Levy" (SDIL) has been previously evaluated for its impact on average sugar content. Three studies exist.[9–12] To our knowledge, evaluations of the impact of the Portuguese sugar tax[13,14] and the South African Health Promotion Levy[15] on this outcome (or energy intake) have been descriptive. The former study modelled the impact of the Portuguese tax policy on beverage reformulation and purchases, and assessed its impact on obesity incidence. The latter examined the effect of the tax on the price of SSBs, including those of brands that reduced the sugar content of their beverages.

Only one study[9] provided statistical evidence of reformulation in response to the SDIL. Public Health England's analyses were based on comparisons between average outcomes in 2019 and the baseline year 2015 and did not include a control group,[10] which may have led to bias in results. Bandy and colleagues' analysis[12] used a Kruskal-Wallis test to test for differences between the sales-weighted mean sugar contents of each soft drink category from 2015 to 2016—2018. However, the authors have acknowledged that their analysis did not provide an evaluation of the SDIL partly because they did not *"estimate the specific impact of the SDIL in comparison with the general trend of sugar reduction in soft drinks"*.

In contrast, the quasi-experimental approach used in our study and Scarborough and colleagues' analysis [9] can support an hypothesis that tax is causally associated with sugar reduction. The latter appraisal used a controlled interrupted time series design, in which control group is made up of 100% fruit juices, milk-based drinks and milk alternatives. They built separate logistic regression models for the intervention and control drinks with indicator variables for the announcement and implementation of the SDIL to assess its impact on the average sugar content of soft drinks. In our study, we deployed a dCDH DID approach using the average sugar content of new SSBs marketed in Germany, Italy and Spain as counterfactual trend, and a test of the plausibility of the parallel trends hypothesis. The no violation of the parallel trends assumption found in Table 3 (except for new fruit-flavoured still drinks marketed between 2013 and 2015 and carbonated soft drinks between 2014 and 2015 in the United Kingdom) and Table 4 increases our confidence in inferring a causal relationship between tax and sugar reduction in new SSBs.

However, like other evaluations[9–11] our estimates are vulnerable to co-interventions. The SDIL is part of a wider sugar reduction strategy launched in England in 2016, the childhood obesity plan.[16] The plan is an ambitious private-public partnerships (PPP) policy that challenges all sectors of the food industry to reduce the amount of sugar in the foods that contribute most to children's intakes by 20% by 2020. Although no guideline was published for soft drinks in it, the plan may have indirectly affected drink manufacturers. It may have created an incentive environment that has encouraged SSBs sugar reductions. Although we could not assess whether and to what extent it has strengthened the average sugar content reduction of new SSBs, the childhood obesity plan has been found to have achieved minimal changes in targeted food categories beyond those attributable to the SDIL.[10]

References

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