The Effectiveness of Sin Food Taxes: Evidence from Mexico *

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Abstract

We measure the effect of a large nationwide tax reform on sugar-added drinks and caloric-dense food introduced in Mexico in 2014. Using scanner data containing weekly purchases of 47,973 barcodes by 8,130 households and an RD design, we find that calories purchased from taxed drinks and taxed food decreased respectively by 2.7% and 3%. However, this was compensated by increases from untaxed categories, such that total calories purchased did not change. We find increases in cholesterol (12.6%), sodium (5.8%), saturated fat (3.1%), carbohydrates (2%), and proteins (3.8%).

Keywords: Obesity, Sin Taxes, High Caloric Foods and Drinks, Mexico.
JEL: H20, I18, H31

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1 Introduction

Obesity and its associated chronic illnesses are a growing and costly health problem affecting both developed and developing countries. Since 1980, worldwide obesity rates have almost tripled, while the prevalence of diabetes and hypertension has doubled (Gracner, 2015; WHO, 2002). Mexico and the U.S. rank among the most obese countries in the world, with one third of their adult population being obese.

While the high costs of obesity are undeniable, debate continues over which policies might best combat the problem. Proposals span a wide spectrum (Cawley, 2015), including increasing the availability of drinking water, mandating nutritional labeling, launching media campaigns promoting healthier lifestyles,[1] and limiting the serving sizes of certain high-caloric foods (OECD, 2014). Several international institutions and various policy-makers strongly advocate for taxes on high caloric foods and sugary drinks, but there is still controversy around it.[2] Several countries have already implemented or are discussing such measures (Allcott et al., 2019b).

On January 1st, 2014, the Mexican government introduced two national levies as part of Mexico's Special Tax on Production and Services (*Impuesto Especial de Productos y Servicios –IEPS*). Drinks with added sugar were taxed at one peso (7.64 US cents)[3] per liter, which amounts to approximately 12% of their pre-tax average price. The tax on beverages excludes any drinks without sugar added, like fruit juices. Additionally, the reform stipulated an 8% ad-valorem tax on solid foods with a caloric density greater than or equal to 275 kilocalories per 100 grams, exempting basic staples (*canasta basica*), including high caloric products such as sugar, bread, tortillas, rice, beans, and cooking oil. The taxes are relatively high, at about three times that of the average state-level soda tax in the U.S., apply to thousands of products, and are national. After the reform, IEPS tax collection increased by 51.7% from 2013 to 2014.

Several papers (Allcott et al., 2019a; Gertler et al., 2021) argue that these taxes can be appropriate if consumers are misinformed or have self-control problems. Nonetheless, we still are short on evidence on how they impact the consumption of nutrients, especially in developing countries. Early studies correlated prices and quantities with no causal empirical design and found a wide range of estimates (Andreyeva et al., 2010). Others estimated demand systems, which could account for substitution patterns arising from household preferences (Dubois et al., 2014; Harding and Lovenheim, 2017; Finkelstein et al., 2013) but did not study a tax actually implemented, and instead relied on simulation —with little role for the supply side.

[1] Recent literature has, however, shown that simply informing individuals about their health status, or even giving disease diagnoses, has little effect on their diets (Hut and Oster, 2018; Oster, 2017; Ogden et al., 2010).

[2] Philipson and Posner (2008) argues that "Probably any feasible tax would cost more to enforce than it would be worth in reducing the social costs of obesity", while Gruber (2010) argues that "a simple tax on calories could do more harm than good by deterring low-income people from getting enough nutrition" recommending a gradual approach starting with soda taxes. On the other hand, Brownell and Frieden (2009) argue that "it is difficult to imagine producing behavior change of [the magnitude of a tax] through education alone". Other academics such as Bhattacharya and Sood (2011) suggest there may not be a need for corrective taxation at all, while Larry Summers is advocating for large taxes on sodas.

[3] Using the U.S. dollar-Mexican peso exchange rate at the time of the reform (December 31, 2013).

Cawley et al. (2019) reviews the existing studies that quantify the effectiveness of taxes on sugary drinks in a variety of settings and finds a wide range of potential impacts, both on prices (pass-through ranges from 50 to 100 percent) and consumption.[4] Some papers conclude that while successful at reducing the consumption of taxed goods, the introduction of taxes on sugar-sweetened beverages has not translated into large changes in the intake of calories and sugar, due to substitution patterns (e.g. Restrepo and Cantor (2020); Fletcher et al. (2010)). Allcott et al. (2019b) also highlight the importance of understanding substitution patterns for optimal tax design.

Our paper focuses on how substitution worked against the tax's intended effects of reducing calorie and sugar consumption to fight obesity. The fact that Mexico introduced the tax on sugar-sweetened beverages together with a tax on high caloric foods, and that it excluded a large segment of high caloric products, makes it a particularly interesting setting to study substitution patterns. It is interesting to delve deeper into its impact on nutrients given that it is often cited as a success to fight obesity, and we document that its results are much more modest.

Using weekly scanner data information gathered from the purchases of 8,130 households and an event study design we find a 9.7% increase in prices and a 2.7% decrease in the purchase of calories from taxed drinks (TD) as a result of the tax reform. Similarly, we estimate a 6% increase in prices and a 3% decrease in the purchase of calories from taxed foods (TFs). Importantly, there was substantial substitution towards untaxed goods: when we sum calories from all categories in our dataset (taxed and untaxed), we find a small and statistically insignificant 0.3% reduction in the purchase of *total* calories (70 calories per week per household). Increased calorie consumption in the non-taxed drinks (NTD) category compensates for 13% of the decrease of TD calorie consumption, while substitution to non-taxed foods (NTF) calories more than compensates the decrease in calories in TFs by about 30%. While we do not find an effect on total calories, we do find statistically significant increases in purchased cholesterol (12.6%), sodium (5.8%), saturated fat (3.1%), carbohydrates (2%), and protein (3.8%).

Further exploring substitution mechanisms, we find that the tax reform design also implied changes in relative prices inside both the TD and TF categories, leading to different substitution patterns *within* these groups. Within TD, barcodes with higher caloric content saw larger price increases thus creating incentives to reduce the consumption of such high caloric content products. However, the opposite was true for TF: the ad-valorem tax on high caloric foods generated greater price increases for barcodes with fewer calories shifting relative prices in favor of goods with *more* calories within the TF group.

Previous papers have analyzed the impact of the Mexican tax reform. Grogger (2017) finds that the tax generated more than proportional increase in prices of taxed drinks, and a smaller increase in that of non-taxed drinks, which he interprets as evidence of substitution towards untaxed drinks. In an often cited paper, Colchero et al. (2016) investigate the impact of the same tax, but

[4]Many of the existing papers analyze soda taxes in U.S. cities: the Berkeley tax has been studied by Cawley and Frisvold (2017) looking at pass-through, Taylor et al. (2019) argue that publicity rather than the tax itself decreased sales of sodas, and Rojas and Wang (2017) show that the Berkeley tax did *not* decrease volume of sodas sold. Stephan Seiler (2019) studies a soda tax in Philadelphia and find that consumers avoid the tax by shopping in neighboring cities –hence the importance of taxing at the national level– and estimate zero effects on nutrients purchased.

with important limitations. First, they study the volume purchase of taxed and untaxed drinks only, overseeing the food categories. Ignoring the tax on food could bias their estimated effect, as this other major tax occurred simultaneously. Also, the omission of food categories overlooks the potential impacts due to substitution across categories. This omission is serious, as we find that once we take substitution into account the tax did not decrease total calories consumed. Second, they do not measure the purchase of calories or nutrients, which is what ultimately we care about around obesity: volumes of liquid are not the same as calories. Finally, they use a before/after design that linearly extrapolates the growth rates from 2012-2013 trends, which is more problematic the further in the future they extrapolate. Batis et al. (2016) studies the taxes' impact on kilos of food purchased but again lack an empirical design. Neither of these studies measure the impact of the tax on total consumption and total nutrients, which is critically important for assessing the success of the tax. We show that failing to take substitution into account leads to wrong conclusions about the effectiveness of the tax.

Our paper contributes to the literature in the Mexican tax in at least two respects. First, it estimates causal impacts con consumption of sugary drink rigorously within a causal empirical framework. Second, we focus on a broader consumption basket, rather than just taxed products. We contribute to the broader international literature by (a) estimating the effects of the taxes on a large battery of nutrients, including sugar, fats, sodium, cholesterol, among others; (b) by documenting not only substitution across taxed and non-taxed drinks and food categories, but also within taxed categories; and (c) by estimating the effects of a nationwide tax, which by its nature limits geographical substitution found in some of the cited papers.

The paper has two main weaknesses. First, the event-study methodology we use is suitable for estimating the short run effects of the taxes, not the long run effects. We show however that there is no trend break in the growth of consumption of taxed drinks before and after the tax, and provide a causal estimate of the tax 1 year after the tax using a synthetic control methodology, reaching a similar conclusion. Some papers have shown that short term responses are larger than longer-term ones (Hut and Oster, 2018), but others have argued that dietary changes may take long (Hut, 2020; Gertler et al., 2021). Second, while we exploit a dataset that includes thousands of products, we do not observe all purchases. To mend this we show our dataset does capture a large share of packaged products, and that using total national production when possible –instead of supermarket purchases– results in similar estimates.

The paper proceeds as follows. Section 2 reviews the obesity outlook in Mexico and provides details on the taxes we evaluate. Section 3 describes our data sources. Section 4 outlines our empirical strategy. Section 5 presents the main results, while section 6 adds robustness checks. The last section concludes.

2 Context and tax reform

Over the past decades, worldwide obesity rates have risen at an alarming pace. In Mexico, the proportion of overweight population has increased from 30% to 70% over the past 25 years (Gracner, 2015). This has large health implications: obesity is a major cause of chronic diseases like diabetes and hypertension (Kahn et al., 2006; Eckel et al., 2011), which account for more than one third of the costs of health care in Mexico. The direct and indirect costs of obesity in Mexico increased from 35 billion pesos in 2000 to 67 billion in 2008. According to the Mexican Ministry of Health, 3 out of 4 hospital beds are devoted to patients with obesity-related diseases.[5] The cost is also high in terms of lives: the mortality rate due to type 2 diabetes increased from 77.9 to 89.2 per 100,000 inhabitants between 2000 and 2007, making it the number one cause of death in the country (Sánchez-Barriga, 2010) (for the US case, see and Bhattacharya and Sood (2011)).

In an effort to fight widespread obesity, on January 1, 2014, the Mexican government introduced two levies as part of Mexico's Special Tax on Production and Services (*Impuesto Especial de Productos y Servicios –IEPS* for its acronym in Spanish): a tax on drinks with added sugar, and another tax on high calorie foods.[6] The nominal incidence of the tax falls on producers and importers, who pay the taxes on a monthly basis to Mexico's tax authority. The 2014 IEPS reform established that drinks with *added sugar* were to be taxed at one peso (7.64 US cents) per liter, which amounts to approximately 12% of their average price. Taxed drinks include sodas, some nectars, concentrates with added sugar, and powdered drink mixes, among others described in detail in the appendix.[7] Dairy products are exempt, as are alcoholic beverages, although the latter are subject to another tax rate defined in the IEPS law. Drinks sweetened with non-caloric sugar substitutes are also excluded. The reform also stipulates a separate tax on food, which consists of an 8% tax on products with a caloric content greater than or equal to 275 kilocalories per 100 grams, with some exceptions considered as part of the basic Mexican diet, i.e the "canasta basica", which contains about 80 goods. Products subject to this tax include snacks, candies, chocolate, pudding, marmalade, peanut butter, and cereals (among others). Caloric density (calories per 100 grams) is determined using the information on the product's nutritional content label. If a product lacks this information, it is automatically taxed.

The taxes are relatively high (about three times that of the average state-level soda tax in the

[5]Similarly, Finkelstein et al. (2009) note that "The estimated annual medical cost of obesity in the U.S. was $147 billion in 2008; the medical costs for people who are obese were $1,429 higher than those of normal weight.". The U.N. (2011) predicts that the cost of diabetes, hypertension, and related chronic diseases in low-and middle-income countries will surpass $7 trillion by 2030.

[6]IEPS was originally established in 1980, and it imposed specific tax rates on the acquisition or import of products such as alcoholic drinks, tobacco, and fuel and on activities such as lotteries and gambling. The 1980 tax did include some drinks with added sugar but was later modified in 1987 to exclude them. Before 2014, the government only taxed drinks with added sugars as part of a 16% VAT, while high caloric foods were VAT exempt. The tax instituted in 2014 is applied in addition to the VAT for drinks with added sugar.

[7]See Section Appendix A. in the appendix. The law establishes that sugars include monosaccharides, disaccharides, and polysaccharides employed as sugar substitutes with caloric content. Partial liters are proportionately taxed. For example, a 355ml soda is charged a tax of 35.5 Mexican cents. According to the law (Article 8 section I(e)), any sales in restaurants or other food service establishments are not charged with the tax.

U.S.) and have a fairly broad base: they apply to 39.4% of food products and 46.3% of beverage products in our data. Taxed products account for about 23% of expenditures captured in our data, 33% of total calories from packaged goods, and 39% of total food expenditures. The introduction of these taxes resulted in 31,945 million pesos of tax revenues in 2014, 18,280 from TDs and 13,666 from TFs. This represents a significant fraction of the total revenue from IEPS, which totaled 124,061 million pesos in 2014, an increase of 51.7 percent with respect to 2013.

3 Data Sources and Main Variables

3.1 Kantar World Panel Household Panel

The main dataset employed is from Kantar World Panel (KWP). With 60 years of experience, KWP specializes in the collection of high quality household purchase data in more than 50 countries. The data is aimed at satisfying companies' needs for marketing and sales strategies. KWP recruits and provides incentives to households to participate in the panel for up to four years, during which they are required to keep ticket receipts for all purchases made in formal and informal establishments. They are visited weekly by surveyors, who scan and save all collected receipts. The scanned information records each product's barcode, and the transaction's date, price, number of units purchased, and the store's location, type and name. KWP also registers precise information for each barcode: brand, content size (in liters or grams), and a detailed classification using broad categories (e.g., carbonated flavored beverages, coffee, snacks, soup, yogurt, cereal, etc.), and more specific details depending on the category (e.g. flavor, whether it is branded as sugar-free or sugar-added, and some of its ingredients).[8]

We exploit the information in this dataset for all weeks in 2013 and 2014, restricting to households that were interviewed at least once in both 2013 and 2014. This amounts to 8,130 households in 93 cities and 727,397 household-week observations. Our data includes 2,560 barcodes for sugary drinks and 3,663 barcodes of high caloric food products. KWP also carries out a yearly questionnaire that captures a useful set of socioeconomic and demographic characteristics, including household assets and BMI, which we use to study heterogeneous impact of the taxes. Table 1 shows that the KWP information matches important data from Mexico's 2014 Income and Expenditure Survey (ENIGH) and the 2012 Health and Nutrition Survey (ENSANUT), the country's main reference surveys for consumption and health.

While extraordinarily detailed, the data has some limitations. First, it measures purchases, which do not necessarily correspond perfectly to consumption. We argue that as long as waste is unaffected by the tax, our estimates should approximate changes in consumption well. Second, it only contains information of processed packaged foods, and does not include fresh foods like fruits and meat. Because taxes are levied on packaged products and not on fresh food, as long as the degree of substitutability between packaged and fresh foods is low, our estimates of the change

[8] Sections B.1 and B.2 in the appendix provide more detail about KWP and give specific examples of the dataset's level of detail.

in consumption of nutrients from the set of products included in the KWP will be informative. Moreover, given that the existing literature argues that the availability of *packaged* foods and drinks is one of the important forces behind increasing obesity rates (Cutler et al., 2003; Brownell and Frieden, 2009), our focus on these goods is appropriate.[9] Finally, the KWP records only in-home consumption. According to the 2014 ENIGH, 19.5% of all food expenditure corresponds to out-of-home consumption in Mexico. The working paper version of this document explores potential bias in our estimates driven by partial observation of consumption and concludes that it is unlikely that we are substantially underestimating the taxes' impact. To tackle this issue further, we use with total industry *production* as a dependent variable and find similar results.

3.2 Barcodes' Nutritional Content

We systematically collected nutrient information of the barcodes contained in the KWP data since packaged products must display it by law. Our enumerator team gathered information for 6,071 barcodes representing 81.6% of all purchase events, which correspond to 83.1% of expenditures in our data from direct observation of product labels in supermarkets and convenience stores (see Tables OA-8 for details of the collected information by product type). We impute calories for the remaining barcodes (see detail in subsections B.3 and B.4 of the Appendix). To ensure that our calorie data has good quality we did double inputting, placebo checks, and an audit by an international auditing firm.

3.3 Classification of taxed and untaxed products

We classify all barcodes into four categories: taxed drinks (TD), non-taxted drinks (NTD), taxed foods (TF), and non-taxed foods (NTF). To this end, we use the two main official regulations and resolutions issued by the Mexican tax authority (SAT) –the IEPS law and the Miscellaneous Fiscal Resolution.[10] Specifically, we first gather all food and drink barcodes in the data. Then we identify, based on the caloric content (for TFs) or the sugar added (for TDs), which barcodes qualify for a tax exemption according to the law. For barcodes in the drinks category, we consider all dairy products and all items with no added-sugar as tax-exempt. Taxed drinks include sodas, nectars, concentrates, and powdered drink mixes with added sugar (monosaccharides, disaccharides, and polysaccharides). For food, we classify all product categories included in the Basic Consumption Basket and all barcodes with less than 275 calories per 100 grams as exempt from the tax. Products subject to the 8% ad-valorem tax include snacks, candies, chocolate, desserts, marmalade, peanut butter, and cereals. The taxes apply to a broad base: 39.4% of food products and 46.3% of beverage products in our data. They account for about 33% of total calories from packaged products, 23%

[9] According to the ENIGH, the average Mexican household's monthly food expenditure amounts to 2,415 pesos, while KWP's products amounts to 1,085 pesos. Yet the ENIGH captures virtually the same level of expenditures on the goods included in KWP.

[10] These regulations can be accessed at (IEPS law): https://goo.gl/K44kp5 and here (Miscelanea Fiscal): https://goo.gl/uJBCya. The Stata code for the classification is publicly available at http://www.aguilaresteva.com/do-files/.

of total expenditures, and 39% of food expenditures. Appendix A. provides more detail about the classification of products into taxed and untaxed.

Given that our findings on substitution rely on the correct classification of products as taxed or untaxed, we asked an independent internationally renowned company to audit it. They concluded that our procedure adequately interpreted the tax regulation and was highly accurate.[11] Moreover, three additional pieces of evidence support our classification: first, prices jump sharply for taxed goods right around the tax implementation date, whereas they change only slightly or not at all for untaxed products. Second, we obtain similar quantitative results as other papers on the Mexican tax for the common outcomes we study. Third, classification error would most likely bias our results against finding substitution across taxed and untaxed categories, but we find a substantial amount of it. Finally, it is important to highlight that our main result on *total* calories and nutrients is *not* affected by tax classification.

3.4 Quantity variables

Our main outcome variables are the total calories contained in all purchased products from each category by each household. We aggregate detailed weekly household $\times$ barcode level information in the KWP data as follows. For each household i in week t of year y, we calculate a measure of calories from taxed drinks purchased (C_{ity}^{TD}) by first multiplying the units of barcode b purchased, u_{bity}^{TD}, by their calories, c_b, and then summing across b for all barcodes in the TD category. Formally, $C_{ity}^{TD} = \sum_{b \in TD} u_{bity}^{TD} c_b$. We do this separately for untaxed drinks, taxed foods, untaxed foods, and for all food and drink products together. Besides calories we also use cholesterol, sodium, saturated fat, carbohydrates, and proteins.

3.5 Price variables

To analyze the impact of the taxes on prices, we generate a Laspeyres-type index keeping each household's 2013 consumption ($u_{bi,2013}$) fixed throughout all of 2013 and 2014. We avoid using 2014 observed purchases for the construction of this consumption bundle, since the 2014 quantities purchased may have been affected by the tax. For each household we calculate how much it would have spent had it kept its average 2013 consumption constant across time, but using the current period's prices. This means that for both 2013 and 2014 the index is an imputed expenditure. We normalize the index to 100 in December 2013. Formally, our household-level price index can be expressed as:

$$P_{ity}^{J} = \sum_{b \in J} (u_{bi,2013}^{J} \, p_{bity}^{J}) * \frac{100}{A_i} \tag{1}$$

where $A_i = \sum_{b \in J} (u_{bi,2013}^{J} \, p_{bi,52,2013}^{J})$ is household's i 2013 consumption basket value in Decem-

[11] As part of the audit, the firm selected a sample of 200 products that they thought the classification could be controversial. In this "controversial sample" they disagreed with only 6.5% of our classifications. In the appendix Table OA-13 presents a robustness test using their classification instead of ours where we virtually find the same results.

ber of that year, $u^J_{bi,2013}$ measures the total units of barcode b (restricted to group J) purchased by household i in 2013, and p^J_{bity} is the price of barcode b that household i incurs in week t of year $y = \{2013, 2014\}$. We calculate price indices for the four subsets of barcodes $J \in$ {TD, NTD, TF, NTF}. Note that p^J_{bity} is not always observed, as household i may not have purchased item b in week t. In such cases, prices are imputed. Appendix C. explains the procedure and shows quality is high and results robust.

4 Empirical Strategy

Our empirical strategy exploits the sharp change in prices observed on the date when the taxes came into effect. It can thus be considered as an event study or as a regression discontinuity design that uses time as a running variable, with the date after which the taxes were introduced (January 1st, 2014) as the treatment of interest.[12] The main identification assumption is that absent the tax change, prices and quantities of food consumed would have followed a smooth trend after controlling for seasonality, and so any sharp change in prices in January 2014 can be attributed to the tax reform.

In a potential outcomes framework let $Y_{hwt}(1)$ and $Y_{hwt}(0)$ denote potential outcomes with and without the tax. Let $\bar{t}$ denote January 1st 2014. A consumer i is then treated at week t when $t \geq \bar{t}$.

$$\widetilde{Y}_{hwt} = \begin{cases} \widetilde{Y}_{hwt}(0) & \text{if} \quad t < \bar{t} \\ \widetilde{Y}_{hwt}(1) & \text{if} \quad t \geq \bar{t} \end{cases}$$

We are interested in estimating the average treatment effect of the tax close to the enactment date $\tau := E\{\widetilde{Y}_{hwt}(1) - \widetilde{Y}_{hwt}(0)|t = \bar{t}\}$. We construct the estimator of τ by using kernel-based local polynomials on either side of the threshold.

$$\hat{\tau}_p(h_n) = \hat{\mu}_{+,p}(h_n) - \hat{\mu}_{-,p}(h_n) \tag{2}$$

where $\hat{\mu}_{+,p}(h_n)$ and $\hat{\mu}_{-,p}(h_n)$ represent the intercept (at $\bar{t}$) of a weighted pth-order polynomial regression for only treated and only control units, respectively, and h_n is a positive bandwidth sequence. Following Calonico et al. (2014) we use local regression with a second order local polynomial and triangular kernel with a 52 week bandwidth.[13] We implement this estimation after partialling out week-of-the-year (γ_w) and household fixed effects (η_h) from our main outcomes to remove seasonality and household-specific components as suggested by (Calonico et al. (2018), Hausman and Rapson (2018)). More concretely, in the first stage we estimate equation 3 by OLS, and then use the residuals in equation 2:

$$Y_{hwt} = \eta_h + \gamma_w + \widetilde{Y}_{hwt} \tag{3}$$

[12]A number of recent papers have profitably used an analogous empirical design (Byker, 2016; Chetty et al., 2014), but it has a tradition in economics and finance (MacKinlay, 1997).

[13]We employ the Calonico et al. (2017) *rdrobust* Stata command for our estimations.

By residualizing this way we are removing seasonality at the week level. Note that given the nature of the RD design, we can only identify the effect locally, which means that we estimate short run responses to the tax. Appendix G. plots time trends and uses a synthetic control method to look at longer horizons.

5 The Impact of the Taxes

5.1 Prices

An increase in price due to the tax is a necessary condition for its effectiveness in reducing consumption. Price incidence depends on the supply and demand (own and cross price) elasticities for the thousands of products that were taxed and their substitutes[14], which is why it is difficult to predict ex-ante the effects of such levies. Here we concentrate on estimating reduced form causal effects.

Graphical evidence for prices: We begin with graphical evidence. Figure 1 presents the weekly evolution of the price indices constructed using equation 1 for different baskets of goods. We show the demeaned and seasonally adjusted index obtained from an OLS regression of the price index in equation 1 on household fixed effects and 51 calendar week dummies. We then graph a binscatter plot and a quadratic polynomial prediction on the residuals. Since quantities are kept constant at their 2013 level, the jump observed in January 2014 is only attributable to changes in prices, not to changes in consumer behavior. The large jump in TDs and TFs contrasts with their non-taxed equivalents, which display much smaller changes.

Statistical evidence for prices: We now discuss the quantitative effect separately for the four categories of products in light of the results in Panel A of Table 2. We observe that prices of taxed drinks increased by 9.7%, which is roughly an average pass through of 80%. Similarly, the prices of taxed foods increased by 6%. Given that these foods were subject to an ad-valorem tax of 8%, average pass through was about 75%, lower than that for taxed drinks. For NTF, we detect a slight 0.7% increase in the price, and for NTD a 2.7% increase. These later results could be interpreted as evidence of substitution towards these categories. In the following sections we directly document that such substitution did indeed occur by looking at quantities. Importantly, we find similar price incidence for obese, overweight and normal weight households, and no differential incidence by household wealth (see working paper version).

5.2 Calories and Nutrients

Ultimately, we are interested in the impact of the taxes on the nutritional content of households' consumption baskets.

[14]Throughout the text we avoid talking about *a* demand elasticity, since many products were taxed. Our aim is not to estimate demand elasticities but rather only the reduced form effect of the tax on the nutrients of the consumption basket.

Graphical evidence for calories: Figure 2 shows RD graphs for calories. They show that calories from taxed drinks and taxed foods sharply declined in the weeks following the implementation of the tax. But calories from untaxed foods, and to a lesser extent from untaxed drinks increased. The evidence thus points toward a substitution of calories from taxed to untaxed products, particularly for food. Aggregating across all categories, subfigure (e) shows that there is virtually no change in total calories purchased.

Statistical evidence for calories: Quantitatively the results in Table 2 show that calories from taxed drinks decreased by 2.7% (112 calories per week per household), and calories from taxed foods decreased by 3% (84.7 calories per week per household). Calories from NTD and NTF change *in the opposite direction*. In 2013, 65% of calories came from foods and drinks in our dataset that were not in these taxes' tax base. This includes milk, juice, beer and alcoholic drinks, bread tortillas, etc. Substitution towards non-taxed drinks (NTD) compensates 13% of the decrease of TD, while substitution to non-taxed foods (NTF) more than compensates the decrease in calories in TFs by about 30%. Aggregating these effects, we find that the change in total calories is not statistically different from zero: a small and statistically insignificant decrease of 70 total calories per week per household (0.3% of the mean).

Evidence for nutrients: Figure 3 and panel C of Table 2 shows results for nutrients. Since nutrients have different units and baseline values, we use the log of sugar, saturated fat, carbohydrates, cholesterol, sodium and proteins as dependent variables. We find no significant effect on sugar, a 3.1% increase in saturated fat, a 2% increase in carbohydrates, a 12.6% increase in cholesterol, a 5.8% increase in sodium, and a 3.8% increase in proteins.

We conclude this section by reviewing our methodology. Our main identification assumption is that once we control for week dummies and smooth time trends, the sharp increase in prices in January are due to the new taxes. We argue that the following aspects provide strong evidence for the validity of this RD assumption: (a) the prices changes are overwhelming concentrated in taxed foods and drinks compared to untaxed items, even though many of untaxed food and drinks are highly caloric; (b) Section E.2 of the appendix documents a discontinuous jump right at the caloric density threshold of 275cal/100gr state in the tax law; and (c) we observe jumps in 2014 only for Mexico and not other similar Latin American countries.[15]

5.3 Incidence by socioeconomic status

KWP carries out a yearly questionnaire that captures a useful set of socioeconomic and demographic characteristics, including household assets, the number of rooms, type of floor, number of bathrooms, whether the dwelling has a gas stove, number of light bulbs, number of cars, and household head's education. Using these variables they classify households into socioeconomic status (SES) categories —(A,B,C+,C,D+,D,E)— using a proprietary methodology. We group these

[15] See working paper version for evidence on this last point.

into 3 categories A/B/C+, C/D+ and D/E to have similar-sized groups of households: 21, 52 and 27 percent of households respectively. We estimate equation 2 separately for these three groups in Table OA-18 of the Appendix.

We find that price incidence is the same across SES. There is slightly a bigger increase in prices for the lower SES group for TF and NTF but the difference is not significant. It is important to remember that the results on prices hold each household's 2013 consumption basket constant. Table OA-17 shows that, before the tax, the proportion of household expenditures (as a percentage of their food consumption) is similar across SES groups. As for calories, we find non-significant change in calories purchased for every SES group.

The last column of Table OA-18 uses *actual* expenditures (i.e. allowing both prices and quantities to change– recall that the tax induced changes in quantities) as a dependent variable. We find that actual expenditures increased by 5.5% for the high SES group, 5% for the medium SES, and 4.4% for the low one. We view these as small differences across SES groups. As a final exercise, we calculate the tax paid by each SES group as a proportion of their food expenditures. We find that the all income groups contribute similarly as a proportion of their food expenditure to the new tax (low, medium and high SES groups contribute with 3.6%, 3.6% and 3.4% of their food expenditures).

5.4 Substitution within Taxed Drinks and Taxed Foods

The richness of the data allows us not only to study responses across taxed and untaxed categories, but also to observe shifts *within* both the TD and TF categories. A useful way to organize this analysis is by comparing price changes for barcodes with more calories versus those with less calories. We could look for substitutions across all products in our sample but this quickly runs into a dimensionality problem as there are thousands of items. It also raises a statistical issue of multiple testing.

Instead, we model the relationship between prices of barcodes p_b and calories per barcode c_b using a polynomial of degree q (set as 2) with parameters β: $h_q(c_b, \beta)$. We then allow this whole function to change after the tax is implemented. For practicality, we estimate the following regression by OLS:

$$\begin{aligned} y_{bity} = \alpha_i + \gamma_{w(t)} + f(t, g(b)) + \eta I(t \geq 2014) + f(t, b) \times I(t \geq 2014) + \\ h_q(c_b, \beta) + \mathbf{I(t \geq 2014)} \times \mathbf{h_q(c_b}, \theta) + \nu_{bity} \end{aligned} \tag{4}$$

The regression is estimated at the barcode b, household i, week t level of year y. We weight each barcode by the number of units of that barcode sold in the 2013-2014 period. Note that by controlling for smooth time trends in prices of groups of barcodes $f(t, g(b))$[16], *we use variation given by the discontinuity at the moment of the taxes' implementation for identification*, this is important since it

[16]We allow for flexible time trends $f(t, g(b))$, where $g(b)$ indicates deciles of calories – each decile has its own quadratic time trend before and after the tax.

makes our variation transparent and strong. We are interested in the term $I(t \geq 2014) \times h_q(c_b, \theta)$ which measures discontinuous changes in prices and consumption before versus after the tax across barcode's caloric content (c_b). We also control for household fixed effects α_i, seasonality with 51 week dummies ($\gamma_{w(t)}$), and dummies for product groups —$f(t, g(b))$— like cookies, chips, cereals, etc. This regression is estimated for the log prices and for the log number of units purchased. Having estimated the coefficients of regression 4, one can calculate the heterogeneous effect of the tax for barcodes with different calories as $\Delta(c_b) = [\hat{y}_+(c_b)] - [\hat{y}_-(c_b)]$. This will be a polynomial of order two that is a function of barcode caloric content (c_b) evaluated at the estimated parameters $\hat{\theta}$ at week 1 of 2014.[17]

Figure 4 plots $\Delta(c_b)$ as a red line separately for taxed foods and for taxed drinks, where the dependent variable is either prices or quantities. The figures also display in the background a histogram of calories per barcode to show that barcodes are very heterogeneous in their calorie content. Panel (a) shows that prices increased proportionately more for units with higher calories within the TD category: from a negligible price change for units with less than 200 calories, up to an increase of almost 14% for units with 1000 calories. The implied *relative price* change should discourage consumption of the more caloric units, and indeed this seems to be the case: Panel (c) shows higher calorie barcodes experience a larger decrease in purchases. Interestingly, the opposite relative price change occurs within TF: barcodes with *less* calories experienced *higher* price increases (Panel b). The difference is almost 15 percentage points between units with 2500 calories versus those with close to 100 calories. This means that for TF the price-substitution effect associated with the relative price changes is pushing consumers towards buying barcodes with *more* calories, and this is what we observe in Panel (d). In the working paper version we also find substitution toward smaller TD package sizes, and towards products with cheaper calories which we interpret as lower quality products.

These complex substitution patterns across and within taxed categories underscore the difficulty of predicting the effects of taxes on total nutrient consumption ex-ante. In our case it turned out that TF suppliers passed through the tax to prices in such a way that the resulting relative prices created substitution effects towards more caloric foods.

There could be many reasons why the tax on foods was less effective that the tax on drinks. One is the type of tax: while taxes on foods were ad-valorem, those for drinks were unit prices, and we know from the literature that unit prices have larger pass through under fairly general assumptions (Delipalla and Keen, 1992; Suits and Musgrave, 1953). Second, the tax on sugary drinks maps closely to a tax on sugar, as variation in the per liter caloric content of products in this category is small (see our working paper version); this is not the case for the ad-valorem tax on foods, it was levied on prices and not closely on calories. Third, the price per liter of large products tend to be smaller than those of small products[18], so the tax on drinks was proportionately higher for larger

[17] $\hat{y}_+(c_b)$ and $\hat{y}_-(c_b)$ stand for the limits of the outcome variable when approaching the discontinuity (January 1, 2014) from the right and left, respectively. Given the interaction with $h_q(c_b, \theta)$, this is a function of c_b.

[18] For example, Figure OA-6 in the appendix shows that the price per liter of a 600 ml. bottle of Coca-Cola is 14 pesos

drink sizes. Finally, the market structure and consumer demand are likely different for TF and TD categories, implying different supplier pass through and consumer responses.

5.5 Discussion

Will the tax as implemented reduce obesity in Mexico? We think this is highly unlikely, even if there were no substitution towards untaxed food and drink categories. One obvious way to start thinking about the potential for taxes on sodas and sugary drinks to combat obesity is by asking how many calories of sodas are actually consumed by Mexicans. Using Mexico's official National Health Survey —ENSANUT— Stern et al. (2014) find that children 1 to 4 years old consume only 20 calories from soda per day, while they consume close to 100 from milk, another 75 from flavored milk, and 25 from juice drinks (milk and juice with no added sugar are untaxed). "Aguas frescas" —fruit drinks sold informally and therefore not subject to the sugary drinks tax— supply as many calories to children as sodas do. Regarding adults, the same study finds they consume less than 100 daily calories from sodas per day per adult on average. These numbers already showcase the limitations of soda taxes. According Butte and Ellis (2003) in the prestigious journal Science, to *prevent* weight gains calorie intake has to decrease by 200 calories per day; even larger reductions would be needed to decrease weight. With these numbers, evidently, even a complete ban of sodas will not achieve the required reduction, complementary policies are needed.

The much advertised success of a 6% reduction in sugary drinks purchases observed by Colchero et al. (2016) is tiny in comparison; even *without* taking substitution into account it translates into an average reduction of only about 6 calories per day for adults (less than that for children). Even if all calorie reduction was concentrated among the overweight comprising 1/3 of the population, the reduction would amount to only about an 18 calorie per day, an order of magnitude smaller than what is needed even with this very conservative assumptions. To make matters worse, there *is* substitution, as many economists expected, rendering the tax almost completely ineffective.[19]

The results are also discouraging because we find an *increase* in sodium and saturated fats. There seems to be strong agreement in the health literature around the adverse impacts of saturated fat on cardiovascular disease (Clifton and Keogh, 2017), and of sodium on high blood pressure (Karppanen and Mervaala, 2006). As economists we are not well positioned to take a stance in terms of the health consequences and trade-offs involved in the nutritional changes we document. Medical research would have to determine whether the shifts we document are important. To benchmark these changes, we estimated a regression of BMI against nutrients $BMI_i = \alpha + \beta' N_i + \nu_i$, using the cross-section of households in 2013 (pre-reform), where BMI_i is the body mass index of the household head, and N_i is the vector of measured nutrients consumed on average for an average week in household i in year 2013. Table OA-20 in the Appendix presents the estimation

while the price per liter of a 2 liter bottle is only 7 pesos.

[19] Gary Becker was one of the skeptics regarding the effectiveness of these taxes: "The result of this tax on beverages would be at most a very small reduction in the intake of calories and sugar. Indeed, it is quite possible that since consumers do not only buy products on the basis of their sugar and calorie content, these substitutions away from beverages and toward sweets and other drinks induced by a tax on beverages could actually increase calorie and sugar consumption." https://www.becker-posner-blog.com/2009/05/a-tax-on-sodas-becker.html

and maps the nutritional changes to predicted BMI by multiplying the estimated β's by the effects documented in Table 2. We find that predicted BMI decreases by -0.016, with 95% confidence interval lower bound of -0.041, a tiny number compared to BMIs close to 25. Appendix H. shows no changes in measured BMI in our panel of respondents 1 year after the tax came into effect. Being a short-run analysis, one must be cautious with the results of BMI since, being a stock variable, effects on BMI may take longer than one year to materialize.

As we said above, our main results are short term results. Section 6.6 uses different methodologies to shed light on longer-run outcomes, which are of course relevant in the assessment of this policy.

6 Robustness

6.1 Anticipatory effects

If consumers anticipate a price increase due to the tax, they may build up stocks of food and drinks before the tax is active and save some money. If in 2013 consumers indeed increased their inventories before the tax was imposed, we would be *over*estimating the effect of the tax, as we would observe higher than normal purchases before its introduction and fewer purchases right after its implementation. If this is the case, this bias would go against our argument that changes in total calories were minuscule.

To explore this further, we performed a simple exercise. We recalculate our estimates by excluding one, two, and three weeks before and after the introduction of the tax. We find almost identical effects (see Table 3). Additional evidence for the lack of inventory stocking is given in the appendix section D.4, where we show that there is not any atypical hoarding (higher purchases of TD) just before the tax came into effect.

6.2 Industry Level Production

A final potential caveat to consider is that of in-home versus out-of-home consumption. As described in Section 3, KWP measures only the former, such that our results apply only to in-home consumption.[20] We address this question by analyzing changes in total *production* of sodas in Mexico as a function of the tax. Given that (a) less than 2% of sodas sold in Mexico are imported/exported, (b) neither exports nor imports of sodas changed with the introduction of the taxes (see Appendix D.5) and (c) that inventories likely do not vary considerably over a period of several months, *total* domestic production should be a good proxy of *total* domestic consumption. Estimating a drop in production of a similar magnitude as that reported above would provide strong evidence that changes in total out-of-home consumption are at most small.

[20]According to the the National Survey of Household Income and Expenditure (ENIGH), about 20% of food expenditure corresponds to out-of-home consumption.

To estimate the effect of the tax on the production of soda, we use public data from Mexico's National Institute of Statistics and Geography (INEGI). Concretely, for prices we use Mexico's Consumer Price Index (INPC), and for quantities we use the Monthly Survey of Manufacturing Industry (EMIM). The INPC data is gathered from more than 16,000 stores in 46 cities countrywide, while EMIM includes more than 1,200 food and beverage manufacturing plants. The EMIM survey is designed to cover, on average, more than 80% of production in every product category, although in the specific case of sodas all producing plants are surveyed. Soda production is measured in thousands of liters and is classified into five packaging and flavor categories. For the analysis, we sum these to get total production. An added advantage of this analysis is that since the information is public, it is easy to replicate. A disadvantage is that these are aggregate national time series data with no cross-section.

To conduct this test, we follow an empirical strategy that is as close as possible to that used before, except that here we are forced to use aggregate time series information on national prices and production and, given the paucity of data, estimate a parametric RD. We run the following specification:

$$log(Y_{ty}) = \alpha_t + \theta I(y \geq 2014) + f(ty) + \epsilon_{ty} \tag{5}$$

where Y_{ty} refers to prices and volume produced, $f(.)$ is a second order polynomial in time, α_t are monthly dummies, and $I(y \geq 2014)$ is our variable of interest. We have monthly data from 2007 to 2015 on soda prices and quantities.[21]

Columns 1 and 2 of Table 4 present the estimated θ coefficient when the dependent variable is the soda price index and thousands of liters respectively. The main takeaway is that the results are quantitatively close to our previous results: we find an increase of 12% in price of sodas and a decrease of 6.9% in liters of sodas produced. To assess whether these results are spurious, we also estimate *placebo* regressions, where instead of using January 2014 as the start of the tax regime we use January 2012 and 2013. Columns 3 and 4 present placebo results for 2013 for price and quantity, while columns 5 and 6 do the same for 2012. Placebos show no changes in quantities and small decreases in prices. This suggests that we are not reaching erroneous aggregate conclusions by not observing out-of-home consumption in the KWP data.

6.3 Falsification test

An additional robustness check is a set of falsification tests following the logic of a Fisher Exact Test. Our aim is to show that the effect captured with the tax variable in our main estimations is indeed a quite an unusual event in terms of size. This test consists in replicating our main specification several times and using in each replication a different *placebo* date to generate the tax variable. In total 53 replications were done, and in each replication a different week between July

[21] Figure OA-14 in the online appendix plots the log of seasonally adjusted liters produced, revealing both a sharp jump in the price of sodas and a slowdown in the growth of soda production, thus qualitatively replicating our main finding using the KWP data.

2013 and June 2014 was employed to create the tax variable. In particular, the replication that uses the first week of 2014 is exactly our main specification. The other replications establish artificially the tax at dates where it did not happen and as such are placebo estimates. If say, end of quarter months were particularly good at TDs sales, this would show up in their respective month effects.

Figures OA-12 and OA-13 use the set of 53 coefficients and plot an empirical cumulative distribution function (CDF) for prices and calories, respectively. We find that for the price estimates, our true tax effect is in the top 95 percent of coefficients. For calories of taxed products, it is below the 5th percentile (strongly indicating a negative effect), while for non-taxed calories and aggregate calories are above the 85th percentile.

6.4 Seasonality

A potential concern for interpreting our findings as the impact of the taxes on purchases is that they incorrectly attribute to the tax changes in consumption that are mechanically due to the start of the year. While our main estimates are computed after accounting for week-of-the-year fixed effects and therefore flexibly control for seasonality, it is possible that two years of data, 2013 and 2014, are insufficient to correctly account for seasonality in consumption. Note also that if consumption is higher in Christmas and New Years Eve, then we would be *overestimating* the effect of the tax, as calories would decline in January, just as the tax is implemented. However we find that calories do *not* decrease. This subsection describes three exercises we implemented to assess the potential seasonality confound.

Donut estimation: Following the recommendation of Hausman and Rapson (2018) Table 3 performs a "donut estimation", removing some weeks close to the discontinuity. The results still hold.

Residualizing with more months of data: Table OA-15 replicates our main non-parametric specification, this time residualizing using equation 3, but with 2012 as an additional year, together with 2013, and 2014.[22] We reach virtually identical conclusions to those shown in Table 2.

Directly controlling for January effects common across years: Table OA-16 turns to a parametric RD specification using data from 2012-2014. The key new variable is a "2013-year dummy" that takes the value of zero for year 2012, and of 1 for years 2013 and 2014. This variable accounts for the average increase/decrease in prices/calories each year. Controlling for this variable should remove from our main *Tax* variable any effect that is common to all year beginnings. Because we also control for a cubic time trend, and household and week-of-the-year fixed effects, our estimates are identified out of jumps at the beginning of the years. We find that the impacts on prices are very similar to those presented in our main specification. Our *tax effect* is 3 times larger for TD and 2.8 times larger for TF, compared to the placebo "2013-year dummy". Analogously, we find null

[22] There is a cost of adding data from 2012 since this means that our use of a balanced panel of barcodes results in a smaller set of barcodes in the intersection. The same is true of households since we keep households that appear in all years.

effects on calories in 2013, and that controlling for the average Januaries jump does not change our conclusions for calories.

We conclude that seasonality is not driving our results.

6.5 Measurement error in calories?

One may be concerned with measurement error in the construction of the calories and nutrients data. Yet the fact that we *do* find calorie reductions for taxed drinks and foods, increases in calories from untaxed categories, and effects on other nutrients makes it unlikely that our results are spurious. Another concern may be that calories do decrease but only for products outside the KWP dataset. While we cannot fully address this concern, we believe it is unlikely. First, our data contains most of the goods to which the new taxes applied. For substitution patterns to overturn the positive effect, households would have had to *decrease* their consumption of *untaxed* goods not included in our dataset in a significant way. Section 6.2 shows that results are quantitatively close –if anything bigger– when we look at total *production*, which captures out-of-home consumption.

6.6 Longer Run Effects

Thus far we have focused on short-term results given that the RD methodology we rely on is local in nature. Longer run effects are, however, certainly of interest. Unfortunately these are harder to estimate, both because the time span in our data is not long, and because the policy we study was national, making it difficult to identify a control group that was unaffected by the tax. In an attempt to shed some light on long-term outcomes, in this section we plot time trends for the production of drinks and for tax revenues from TD and TF as a proxy measure of consumption of TD and TF. In the Appendix we make an effort to estimate causal effect by employing a synthetic control method.[23]

Panels (a) and (b) of Figure 5 use two independent data sources to assess the evolution of the consumption of TDs. They have the advantage of plotting longer-term results –3 years after the tax– and of using easily accessible public data, but the disadvantage of not presenting causal effects. Panel (a) uses data from Mexico's tax authority (SAT)[24] to plot tax revenue from taxed drinks and taxed food categories, which correspond exactly to the categories studied in the paper and comprehensively cover all taxed foods and drinks from the universe of Mexicans. Recall that for taxed drinks one peso is collected for each liter, so tax revenue tracks taxed liters exactly. For comparison, we also plot revenue from beer and liquor, which were taxed from before and did not experience tax changes in 2014. We also plot VAT collected for all categories of consumption. We normalize the series to equal 1 in 2014. Two results stand out from this graph. First, there does not seem to be a trend break in 2014 on the consumption of TD and TF in yearly averages. Second, the consumption of TD and TF continues to increase at high rates, even 4 years after the

[23] The appendix also presents a differences in differences strategy to compare trends of households with high TD and TF consumption vs those with low consumption pre-reform.

[24] http://presto.hacienda.gob.mx/EstoporLayout/estadisticas.jsp

tax: consumption of TD and TF is about 30% *higher* in 2017 than in 2014. In fact, consumption grew faster in TD and TF than in VAT and beer, although slower than liquor.

Panel (b) uses INEGI data on liters of drinks produced in Mexico by year. Unfortunately INEGI reports volumes for sodas without separating sodas with no sugar vs those with sugar, and it does not report production from all categories taxed drinks categories, making panels (a) and (b) not directly comparable. Again we find no flattening of trends after the tax. We do observe an increasing trend in water production since 2007 that accelerated after the tax, but the increase for juice production is much larger, increasing by almost 40% in the 3 years following the tax.

Mexico's GDP grew at less than 3% per year on average from 2014 to 2017. In comparison consumption of taxed drinks grew close to 10% per year! This of course does not mean that the tax did not work in the long run since the counterfactual consumption might have been even higher. But it does mean that consumption growth has not stopped, suggesting that obesity will continue to grow with the tax.

Figure OA-16 in the Appendix presents causal estimate from a synthetic control methodology. We estimate a decline of about 0.2 standard deviations in the consumption of liters of sodas Immediately after the tax came into effect. This is equivalent to 0.8 liters per household-week (close in magnitude to the RD estimate), but it is short lived, reverting to a an effect of zero 3 months after. The effect becomes less precise with time, but there is no downward trend. This suggest that there is no long run decline in soda consumption.

7 Conclusions

Governments and organizations alike are advocating for the introduction of special taxes on food and beverages in order to combat obesity. However, the effectiveness of these policies is still not well understood. Analyzing the impact of the introduction of two taxes in Mexico, one on sugary beverages and another one on high caloric foods, we find there was substantial substitution across taxed and untaxed categories and within those categories, resulting in no statistically significant decreases in the purchase of total calories, nor on economically sizeable changes.

Our results on the effect on calories from taxed drinks replicates Colchero et al. (2016)'s result that the tax resulted in lower consumption of sugary drinks (we estimate a 3% decrease in calories and they estimate a 6% decrease in liters), even though they use a different dataset (Nielsen), focus only on larger cities (we have 93 cities including small ones while they have 53), and rely on extrapolation. We go further than them documenting effect on overall nutrients and showing there is no decrease in calories when looking at a broad basket of foods and drinks. Fletcher et al. (2010) finds that a 1 pp increase in the soda tax in US States implies a reduction of only 6 soda-calories per day, while we find that a 1pp increase in the tax on TD translates into a reduction of 1-2 calories per day per household from TD. Both small effects. In consonance with our results Fletcher et al. (2010) finds no change in total calories.[25]

[25]Comparison with papers that study city level taxes on drinks in the US is harder however due to less comprehensive

More positively, our paper provides evidence that may be informative for improving the design of these taxes in the future: substitution patterns play an important role in explaining the taxes' overall impact. It may be difficult to have it both ways: exempting important caloric foods (e.g. tortillas, bread, oil, milk like in Mexico) from the tax in an effort to avoid harming the poor can severely weaken the effectiveness of the tax to decrease calorie consumption by facilitating substitution. We therefore think the tax base should be broader if the government seeks to reduce caloric intake. In Mexico —and we suspect many developing countries– it is very common to consume food and drinks prepared at home or at street vendors locations, as we discussed in Section 5.5. Most of these foods are not covered by the tax. Taxing sugar and oil directly will cover a larger share of calories. Supporting our opinion, Grummon et al. (2019) argue that a sugar tax would be much more effective than a soda tax, and Dubois et al. (2020) show that soda taxes are not very successful at targeting the sugar intake of those with high total dietary sugar.

But policy should also look beyond taxes. Taxes on sodas alone are likely insufficient to fight obesity, as we discussed in Section 5.5. Complementary public policies should be tried and evaluated: from detecting obesity early at schools and warning parents, to increasing the availability of drinkable water and vegetables (fighting food deserts). A promising often overlooked anti-obesity policy is nutrition during pregnancy. The emerging scientific consensus around "the thrifty phenotype" —Barker (1990); Gluckman and Hanson (2004); McCance (1962); Painter et al. (2005); Hoynes et al. (2016)— strongly suggest that promoting good nutrition of pregnant mothers reduces obesity and metabolic disease.[26] Obesity is a complex problem and many measures will be needed to limit its advance.

Our study's limitations point to directions for further research. First, we have refrained from discussing whether there is an economic rationale for government intervention. Further research should quantify externalities and internalities of obesity; Allcott et al. (2019a) is a first step but we need studies with stronger identification to document that internalities indeed exist and are large enough to warrant the introduction of taxes. Second, this paper estimates short run effects on consumption of nutrients. Recent papers Allcott et al. (2019b); Hut (2020) however have shown that changes in diet may take a long time, and more research is needed to determine the long run effects of these type of taxes in the health of people. Third, the potential differences in the adverse effects of these taxes across contexts should receive additional attention. (Gutierrez and

data sources, substitution across cities and stores, and taxes of a different magnitude. Cawley et al. (2018) find that while the tax in Philadelphia reduced soda consumption for adults, although they can't reject a zero effect on sugar consumption for adults and children on average. Stephan Seiler (2019) also study the Philadelphia tax. They find that a 34% increase in price led to a 16% decrease in calories from drinks, while we find that a 9% increase in prices led to a 1-2% decrease, a smaller effect. One advantage of our study is that we observe household purchases in *all* stores for a weekly panel of more than 8000 households. Failure to observe all purchases in all stores may result in over or under estimation of the effect size depending on the price set by the unmeasured stores. Stephan Seiler (2019) also emphasize the importance of substitution, saying that "the tax's effectiveness at reducing consumption of unhealthy products is hindered by tax avoidance through cross-shopping and compositional changes in demand toward relatively less healthy products."

[26]The metabolic system seems to adapt to a low nutrient environment in utero to allow the individual to survive in an environment with chronic food shortages. Therefore, if the environment in adulthood is not short on calories, obesity results from a metabolisms unsuited to the environment.

Rubli, 2020) for instance found that the SD tax in Mexico seems to have led to an increases in gastrointestinal morbidity due to low water quality.

Tables

Table 1: Summary Statistics

Variable	KWP	ENIGH	ENSANUT
Household's Head Characteristics			
Age	46.7 [13.93]	48 [13.9]	49.4 [33.49]
Male (percentage)	0.78 [0.42]	0.72 [0.45]	0.75 [0.43]
Schooling Level			
Primary (percentage)	0.56 [0.5]	0.49 [0.5]	0.67 [0.47]
Secondary (percentage)	0.13 [0.33]	0.16 [0.37]	0.11 [0.31]
More than Secondary (percentage)	0.27 [0.44]	0.35 [0.48]	0.22 [0.42]
Body Mass Index (BMI)	27.5 [4.12]	-	28.34 [5.49]
Overweight (percentage)	0.48 [0.5]	-	0.39 [0.48]
Obese (percentage)	0.28 [0.45]	-	0.33 [0.33]
Household Assets			
TV (percentage)	0.91 [0.29]	0.96 [0.19]	0.93 [0.26]
Computer (percentage)	0.42 [0.49]	0.39 [0.49]	0.24 [0.42]
Car (percentage)	0.43 [0.49]	0.49 [0.5]	0.41 [0.49]
Expenditure[a]			
Total Expenditure	-	8835.59	-
Food at home	-	2414.99	-
KWP goods[b]	1085.33 [673.63]	1193.84	-
Sugary Drinks	256.37 [234.15]	198.71	-

Notes: This table compares summary statistics of the main database use in the analysis (Kantar World Panel), in Column 1, against the official expenditure survey (ENIGH 2014), Column 2, and official health survey (ENSANUT, 2012) in Column 3. ENIGH provides the national reference values for household demographics, expenditures and income. ENSANUT provides the national reference values for health and nutrition statistics. We apply the same filters in all the samples for comparative purposes (urban areas only, female household head for BMI measures, and dropped where household head was above 70 years old). The table has three panels: the first has descriptive characteristics of the household head; the second shows household assets; the third panel describes different me Total expenditures are measured in Mexican pesos per household per month. [a] ENIGH figures for expenditures come from the official figures, which can be consulted at `https://goo.gl/HpXMPu`. [b] KWP goods and sugary drinks cannot be perfectly matched to ENIGH's classification. Using the official figures classification, the authors selected those categories of food and beverages that most closely relate to KWP products.

Table 2: Impact of the Tax on Prices, Calories, and Nutrients.

Panel A. Dependent Variable: Price Index (Dec 2013=100)

	Total	Total Drinks	Taxed Drinks (TD)	Untaxed Drinks (NTD)	Total Food	Taxed Food (TF)	Untaxed Food (NTF)
Tax	4.403***	5.702***	9.684***	2.673***	2.552***	6.020***	0.778***
	(0.0262)	(0.0382)	(0.0413)	(0.0564)	(0.0300)	(0.0805)	(0.0337)
Mean (control)	100	100	100	100	100	100	100
Observations	721213	721213	721089	721213	721213	720980	721213
Bias corrected effect	4.731	6.224	9.812	3.466	2.631	5.992	0.892
Robust Std. Error	0.0327	0.0476	0.0519	0.0705	0.0380	0.0977	0.0426

Panel B. Dependent Variable: Calories

	Total	Total Drinks	Taxed Drinks (TD)	Untaxed Drinks (NTD)	Total Food	Taxed Food (TF)	Untaxed Food (NTF)
Tax	-69.89	-97.02**	-112.10***	15.08	27.13	-84.69***	111.80*
	(97.39)	(39.17)	(29.18)	(22.73)	(78.52)	(24.44)	(67.68)
Mean (control)	20,058	7,383	4,099	3,283	12,675	2,815	9,860
Observations	721,213	721,213	721,213	721,213	721,213	721,213	721,213
Bias corrected effect	15.15	-91.44	-113.80	22.37	106.60	-65.59	172.20
Robust Std. Error	131.70	52.88	39.48	30.31	105.80	32.63	91.18

Panel C. Dependent Variable: Log(1 + Nutrients)

	Sugar	Saturated Fat	Carbs	Cholesterol	Sodium	Proteins
Tax	0.00978	0.0313***	0.0198**	0.126***	0.0577***	0.0383***
	(0.00905)	(0.00913)	(0.00865)	(0.0132)	(0.0100)	(0.00912)
Mean (control)	1,775	275	2,441	400	25,488	301
Observations	721,213	721,213	721,213	721,213	721,213	721,213
Bias corrected effect	0.0089	0.0281	0.0197	0.1160	0.0564	0.0430
Robust Std. Error	0.0122	0.0123	0.0117	0.0175	0.0136	0.0122

Notes: This table estimates the effect of the tax on prices (Panel A), calories (Panel B), and nutrients (Panel C) using a RD methodology with time as running variable and Tax as the treatment dummy. Data employed for this estimation comes from the weekly KWP Mexico chapter for 2013 and 2014. The unit of observation is the household-week. In Panel A the dependent variable is a price index (P^k_{ity}) at the household i week t year y level. The price index is defined in equation 1, for our four baskets of goods: k ∈ {TD, NTD, TF, NTF} , and the sum of beverages, food and all products. The price index is representative of the Mexican consumption basket in 2013 and normalized to 100 at December 2013. Since quantities are kept constant at their 2013 level, the jump observed in January 2014 is only attributable to changes in prices, not changes in consumer behavior. In Panel B the dependent variable is total calories purchased by household i in week t year y (C^k_{ity}), described in section 3.2. Each column corresponds to a separate regression. Column 1 shows the result for the aggregate consumption basket, columns 2 and 5 show beverage and food aggregates, while the remaining columns show the effect for subgroups (TD, NTD, TF, NTF). In Panel C the dependent variable is the log of one plus total calories purchased by household i in week t year y. Each column corresponds to a separate regression, which shows the results for total purchases of sugar, saturated fat, carbohydrates, cholesterol, sodium and proteins. Residuals of all the outcome variables are used as dependent variables and are obtained after partialling out household and week of the year fixed effects. The *Tax* variable indicates that the purchase was done after January 1st 2014. All estimations consist of a local linear regression of a second degree polynomial with triangular kernel weights and a 52 week bandwidth, estimated using *rdrobust* in Stata.

Table 3: Robustness to Inventory (donut estimation)

Robustness: Anticipatory Behavior in Purchase								
	Price Index (Dec2013=100)				Calories			
Ommited weeks	None	One	Two	Three	None	One	Two	Three
Panel A. Total Purchases								
Tax	4.403***	4.298***	4.240***	4.105***	-69.89	-137.71	-193.48**	-177.73*
	(0.0262)	(0.0451)	(0.0502)	(0.0560)	(97.39)	(84.93)	(92.71)	(103.45)
Panel B. Taxed Drinks (TD)								
Tax	9.684***	9.720***	9.711***	9.698***	-112.10***	-125.20***	-129.51***	-122.40***
	(0.0413)	(0.0604)	(0.0653)	(0.0715)	(29.18)	(29.76)	(32.62)	(36.53)
Panel C. Taxed Food (TF)								
Tax	6.020***	6.006***	6.020***	5.883***	-84.69***	-100.86***	-110.27***	-107.24***
	(0.0805)	(0.1004)	(0.1124)	(0.0906)	(24.44)	(23.95)	(26.17)	(29.06)
Observations	719,615	704,584	689,474	674,229	719,844	704,805	689,687	674,434

Notes: The *Tax* variable indicates if the observation is captured after January 1st 2014. All estimations consist of a parametric second order polynomial estimation. The outcomes of each regression correspond to the residuals of the price index (columns 1-3) or the level of calories of products purchased (columns 4-6) after partialling out for household and week of the year fixed effects. The price index results from keeping constant each household's 2013 consumption and for 2014 inputting the price of such consumption using the most geographically disaggregated information available for each product. Then, the consumption cost is normalized to 100 using the December 2013 level. The caloric purchase is calculated using the observed or imputed level of calories per each product as described in section 3.2. Each column shows the result of aggregating the purchase of each product's corresponding type as indicated by each panel. The column classification *None*, *One*, *Two* and *Three* refers to the number of weeks that were omitted before and after the introduction of the taxes (i.e. January 1st 2014). Data employed for this estimation comes from the weekly KWP Mexico chapter for 2013 and 2014. The unit of observation is the household-week pair. Errors are clustered at the household level.

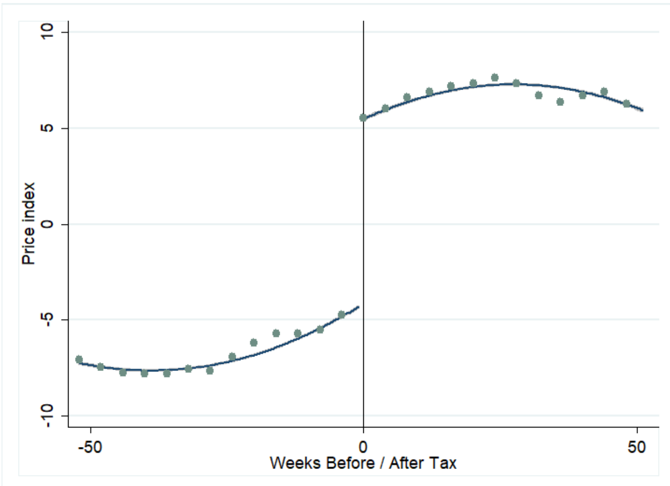
Table 4: Effect of Tax on Industry Production and National Soda Prices

Effects and Placebos						
	2014		2013		2012	
	Price	Liters	Price	Liters	Price	Liters
Tax	0.12	-0.069	-0.04	-0.01	-0.03	-0.02
	[0.006]	[0.026]	[0.01]	[0.02]	[0.015]	[0.015]
Month FE	yes	yes	yes	yes	yes	yes
Deg. Polynomial	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Observations	107	107	107	107	107	107
R-squared	0.99	0.89	0.98	0.91	0.98	0.92

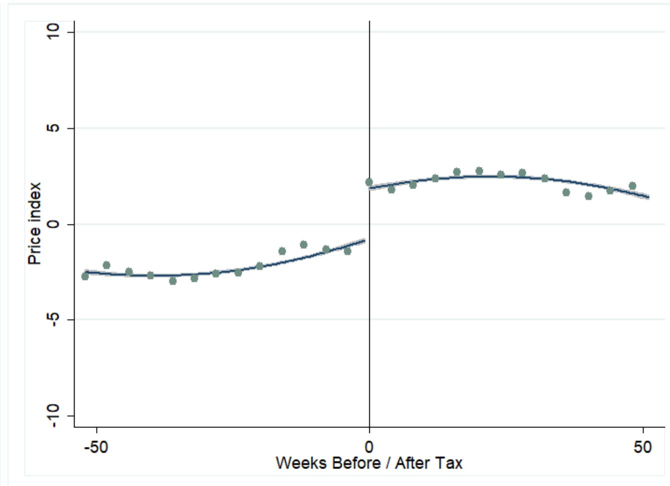
Notes: This table presents estimates of the effect of taxes using industry level *production* using survey data from the EMIM industry data, from INEGI. The data have the advantage that they constitute a good proxy for all sales in the country, not only in-home consumption, and that they are publicly available. They have the limitation that they are time series and have no cross-sectional element. Using monthly data from 2007 to 2015 on soda prices and quantities, we estimate by OLS the regression $log(Y_{ty}) = \alpha_t + \theta I(y \geq 2014) + f(ty) + \epsilon_{ty}$, where Y_{ty} refers to prices or volume produced, $f(.)$ is a second order polynomial in time, α_t are monthly dummies, and $I(y \geq 2014)$ is our variable of interest. The tax variable reports the θ coefficient from equation 5. Columns 1, 3 and 5 use the log of the price index as dependent variable. Columns 2, 4 and 6 present use log liters produced in the month as a dependent variable. Robust standard errors clustered at the date level in brackets.

Figures

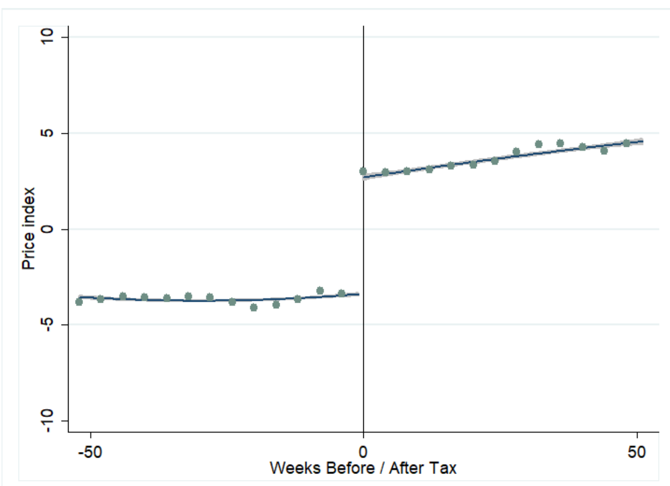
Figure 1: Tax Effect on Prices, by category



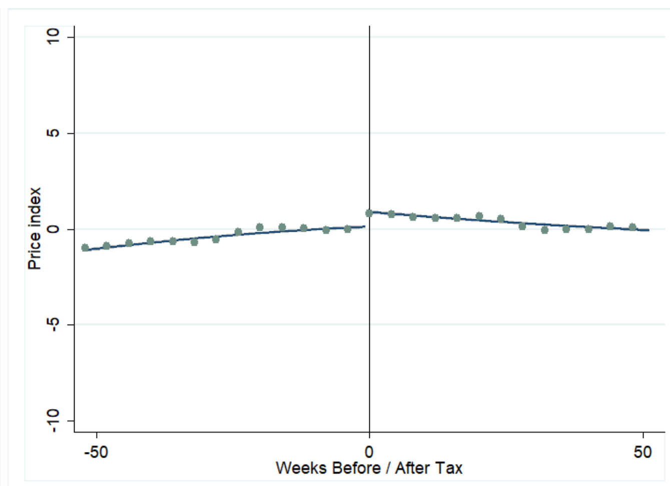
(a) Taxed Drinks



(b) Non-Taxed Drinks



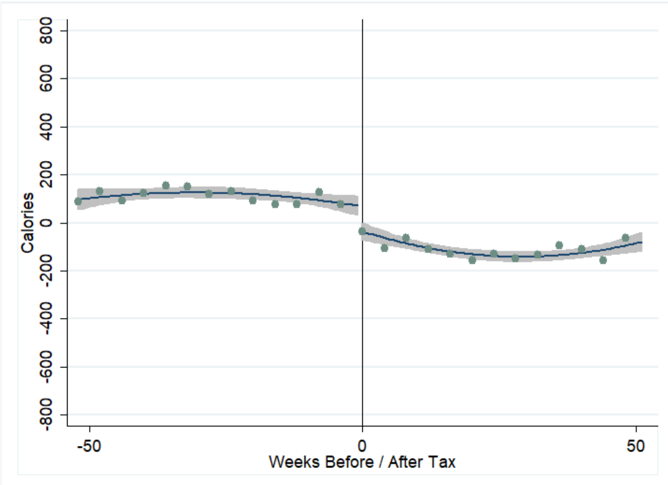
(c) Taxed Food



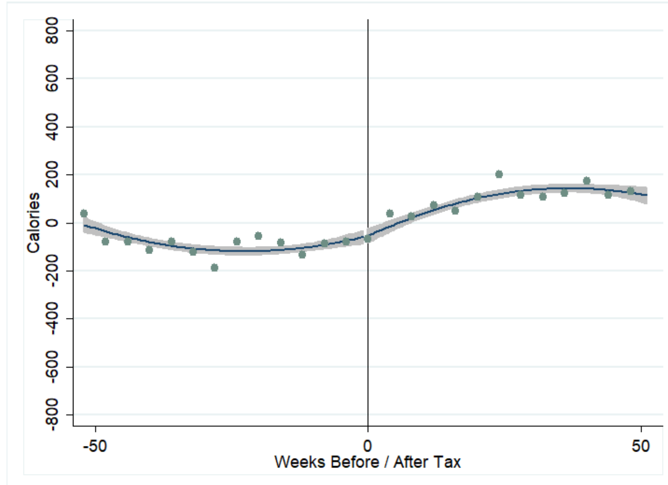
(d) Non-Taxed Food

Notes: This Figure show the weekly evolution of the prices indices P^k_{ity} defined in equation 1 for our four baskets of goods: $k \in \{TD, NTD, TF, NTF\}$. Each graph's horizontal axis covers all 2013 and all 2014. Week 1 corresponds to the first week of January 2014, when the tax started being collected. The price index is representative of our sample households consumption basket in 2013 and normalized to 100 at December 2013. Since quantities are kept constant at their 2013 level, the jump observed in January 2014 is only attributable to changes in prices, not changes in consumer behavior. Graphs show RD plots on de-meaned and seasonally adjusted residuals. These residuals were obtained from an OLS regression of the respective price index P^k_{ity} on household fixed effects and 51 week of the year dummies. We then use these residuals at the household week level to plot a month bin scatterplot, and fit a separate quadratic polynomial prediction to weeks corresponding to 2013 and those corresponding to 2014, along with a 95% confidence interval. The level change at the discontinuity corresponds to the inferred effect of the tax. Graphs were produced using the qfitci Stata command.

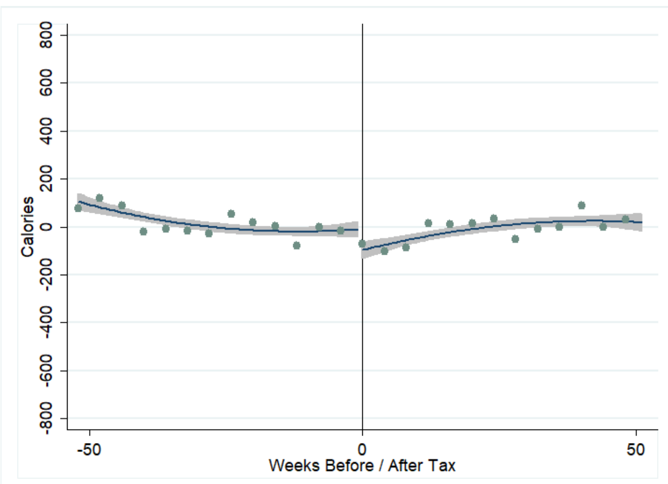
Figure 2: Tax effect on calories purchased



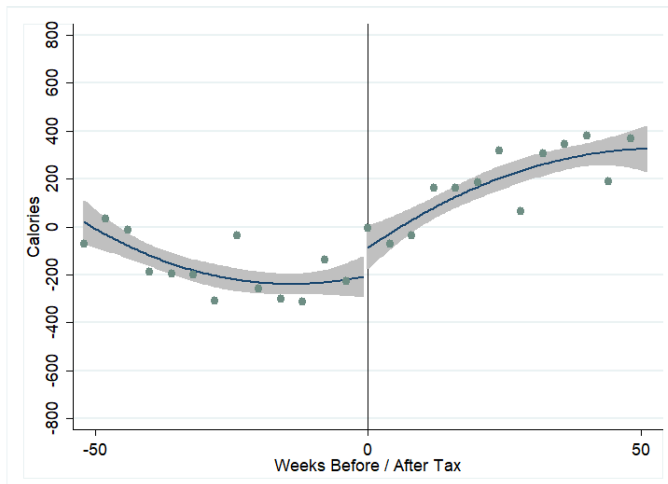
(a) Taxed Drinks



(b) Non-Taxed Drinks



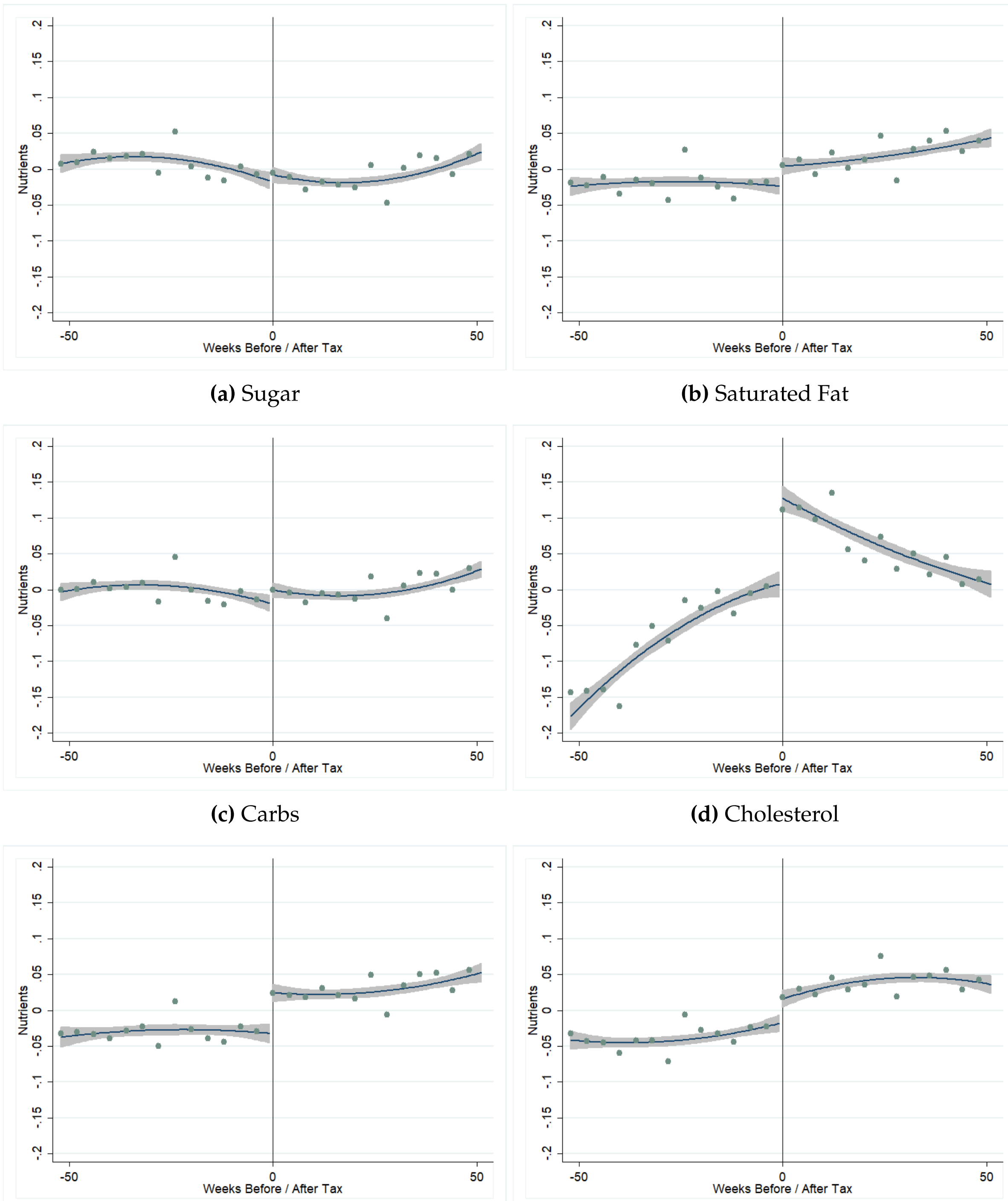
(c) Taxed Food



(d) Non-Taxed Food

Notes: This Figure show the weekly evolution of the calories purchased by Mexicans in the KWP for our four baskets of goods (TD, NTD, TF, NTF) and the sum total across all foods. Each graph's horizontal axis covers all 2013 and all 2014. Week 1 corresponds to the first week of January 2014, when the tax started being collected. We sum calories purchased of food basket type $k \in \{TD, NTD, TF, NTF\}$ by each household i at the week level t, and therefore obtain C^k_{ity}. We then calculate de-meaned and seasonally adjusted residuals from an OLS regression of C^k_{ity} on household fixed effects and 51 week of the year dummies. We use these residuals to plot a month bin scatterplot, and fit a separate quadratic polynomial prediction to weeks corresponding to 2013 and those corresponding to 2014, along with a 95% confidence interval. The level change at the discontinuity corresponds to the inferred effect of the tax. Graphs were produced using the qfitci Stata command.

Figure 3: Tax effect on log nutrients purchased



(a) Sugar

(b) Saturated Fat

(c) Carbs

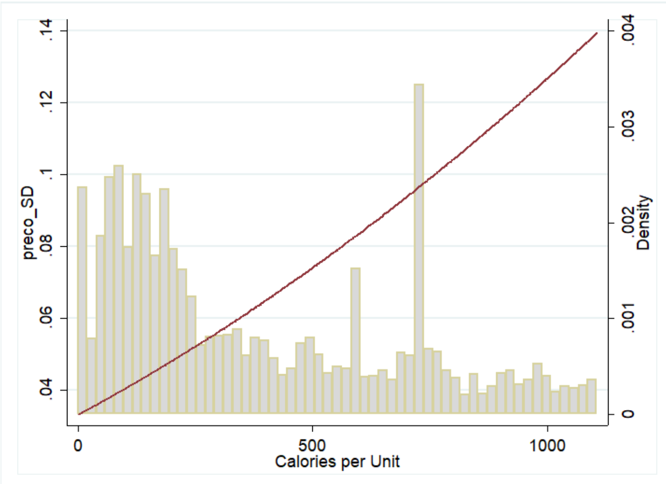
(d) Cholesterol

(e) Sodium

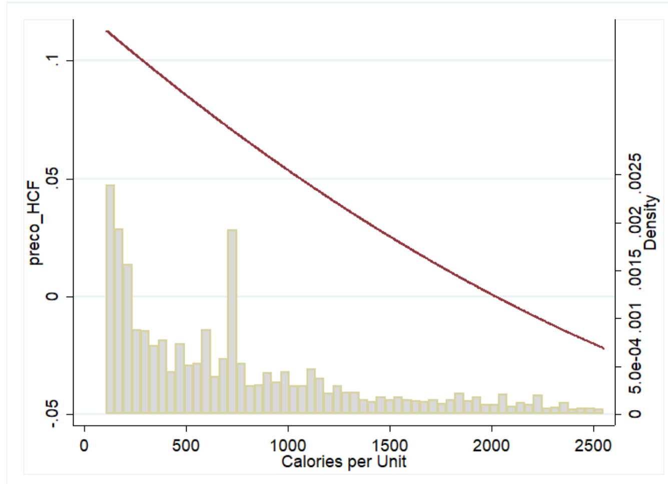
(f) Proteins

Notes: This Figure show the weekly evolution of several nutrients purchased by Mexicans in the KWP. These correspond to totals, summing across TDs, NTDs, TFs, and NTFs. Each graph's horizontal axis covers all 2013 and all 2014. Week 1 corresponds to the first week of January 2014, when the tax started being collected. For each nutrient $N \in \{Sugar, SaturatedFat, Carbs, Cholesterol, Sodium, Proteins\}$, we sum the nutrient purchased by each household i at the week level t, and therefore obtain N^k_{ity}. We then compute $ln(N)_{ity} + 1)$ and calculate de-meaned and seasonally adjusted residuals from an OLS regression of $ln(N_{ity} + 1)$ on household fixed effects, 11 calendar month dummies (February, March,..., December), and a quadratic polynomial in weeks. We then use these residuals at the household week level to plot a month bin scatterplot, and fit a separate quadratic polynomial prediction to weeks corresponding to 2013 and those corresponding to 2014, along with a 95% confidence interval for the mean. The level change at the discontinuity corresponds to the inferred effect of the tax. Graphs were produced using the qfitci Stata command.

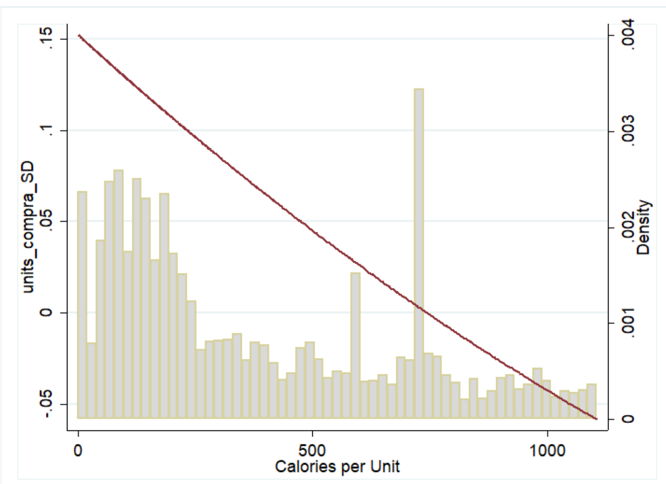
Figure 4: Price and Quantity changes by Calories of Barcode



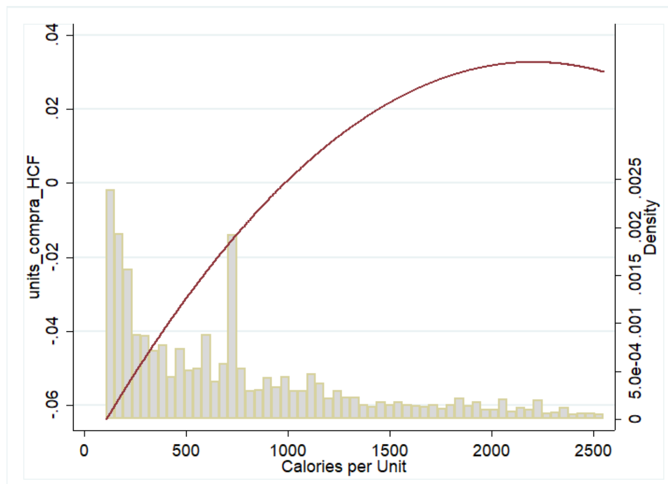
(a) ΔPrice vs Calories, TD



(b) ΔPrice vs Calories, TF



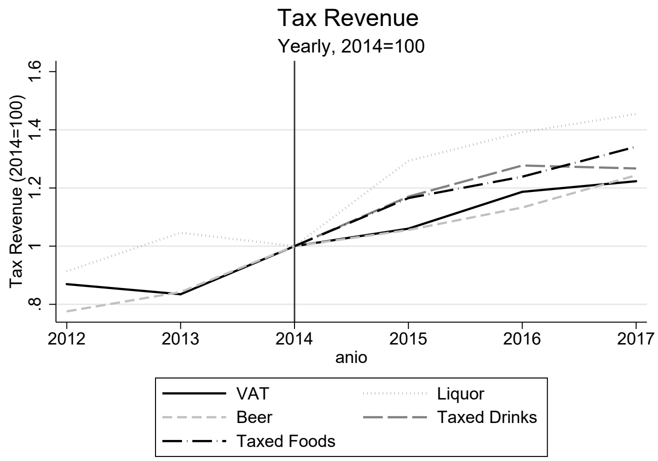
(c) ΔQ vs Calories, TD



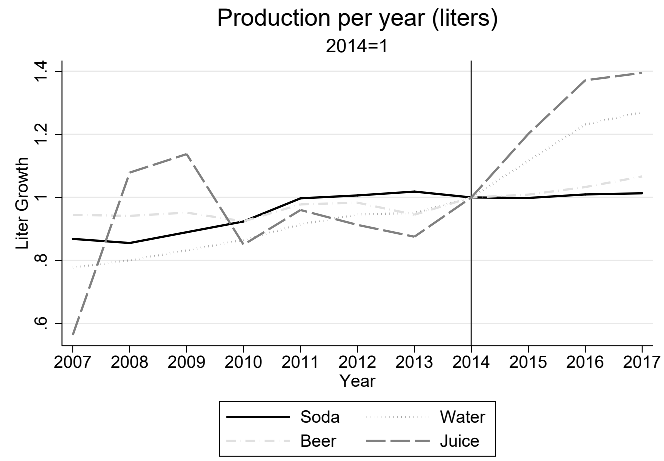
(d) ΔQ vs Calories, TF

Notes: These graphs illustrate the heterogeneous effect of the tax on price and quantities by the caloric content of each product. This is done separately for TD in Panels (a) and (c) or TF in Panels (b) and (d). We model the relationship between prices of barcodes p_b and calories per barcode c_b using a polynomial of degree q and parameters β: $h_q(c_b, \beta)$. We then allow this relationship to change after the tax is implemented. Equation 4 in the paper estimates this relationship. Having estimated the coefficients of regression 4, one can calculate the effect of the tax for barcodes with different calories as $\Delta(c_b) = [\hat{y}(c_b)|I(t > 2014) = 1] - [\hat{y}(c_b)|I(t > 2014) = 0]$, which will be a polynomial that is a function of barcode calories evaluated at the estimated parameters $\hat{\theta}$. This Figure plots $\Delta(c_b)$ as a red line separately for taxed foods and for taxed drinks, where the dependent variable is either prices or quantities. The figures also display a in the background a histogram of calories to show that barcodes cover the whole support. Panel (a) shows that prices increased proportionately more for units with more calories within the taxed drinks category. Panel (c) shows that higher calorie barcodes experience a decrease in purchases. The opposite happens for taxed foods: barcodes with *less* calories experienced *higher* price increases. Panel (d) shows that within TF consumers buy barcodes with *more* calories after the tax

Figure 5: Longer Run Trends



(a) Tax revenue by drink category



(b) Production of Drinks (taxed and untaxed)

Notes: This Figure presents outcomes 3 years after enactment of the tax. Panel (a) uses public data from Mexico's tax authority (SAT). Recall that for taxed drinks one peso is collected for each liter, so tax revenue tracks taxed liters. While what we call Taxed Drinks and Taxed Foods began being taxed on January 2014, beer, alcoholic drinks and Energy drinks have been taxed for many years before that. We also include total VAT collected as a comparison. For comparability we normalized revenues and production so that they equal 100 in 2014. Panel (b) uses public INEGI data on liters drinks produced in Mexico.

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For Online Publication

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Contents

Appendix A. Taxed products classification

This is one of the most important constructed variables since mis-classifications could induce bias in our estimates. We were therefore very careful in the classification of products as taxed or untaxed, and went to great length to convince ourselves and the referees that our classification is accurate. Let us describe the steps and checks we did.

As described in the main text, two different tax designs were implemented beginning on January 1st, 2014: (i) one peso per liter of sugar added drinks, and (ii) an 8 percent ad-valorem tax for non-basic food items with a caloric density above 275 kilocalories per 100 grams. We used the two main official regulations and resolutions issued by the Mexican tax authority (SAT): the IEPS law and the Miscelanea Fiscal. Importantly, for political reasons and to limit the regressivity of the tax, items from the Basic Consumption Basket ("Canasta Basica')'[27] were excluded. Interestingly, several high calorie items like oil, tortillas, bread, etc. are in the Canasta Basica, and were thus excluded from the Tax.

The procedure to define our tax variable is implemented separately for drinks and food.

Step 1a: For drinks, it starts by assigning all drinks as taxed, and then using the information in the KWP data to exempt from the tax milk based drinks as well as those whose classification indicate that they do not have added sugar (e.g. diet, light, zero sugar) since these categories are explicitly excluded by the law. KWP classification was very useful in this exercise as one of the variables codifies whether the product is "diet, light" or "non-sugar added". For drinks for instance, the exempt products include bottled water, sparkling water, beer, milk, powdered milk, evaporated milk, and atole, among others. We were very careful to exclude items from the "Canasta Basica" as these are also excluded by law. In this first pass we used only variables from the KWP data.

Step 1b: Similarly, for food, we start by assigning all food products as taxed and then we exclude products that are part of the canasta basica (e.g. cooking oil, bread, etc.), those not included in the listed products to be taxed in the law, and those with less than 275 calories per 100 grams. For instance, we classified as tax eligible: cereal bars, snacks, condensed milk candy (cajeta), cereal, chocolate, sweet spreads (e.g. hazelnut, peanut butter), cookies, ice creams and popsicles, industrialized bread, refrigerated and powdered dessert (e.g. jello). Again, we were very careful to exclude items from the "Canasta Basica".

Step 2: we searched by hand those products that seemed problematic. In particular, for drinks we verified the label of the product, using the data collected by our enumerators, and checked that the included categories had added sugars, and therefore should be also exempted.

Step 3: Using the data on calories –that was collected by us independently– we searched for outliers: drinks that had many calories but that we classified as tax exempt. We found almost none, confirming that our classification is reasonable. Thus, for drinks we classified as taxable drinks powdered drinks, energy drinks, carbonated and non-carbonated soft drinks, sports drinks, flavored milk, and non-diet iced-tea, among others.

Step 4: For those products where the law/regulations were not completely clear, we contacted an association of food producers (Conmexico) and asked for help to verify with the producer if the product pays the tax.

Step 5: We hired an internationally renowned auditing company, Deloitte, to audit our data and tax classification. They had access to our list of products and classification, as well as complete independence as to methodology they used. Importantly these methodology included taking a sample and going to supermarkets

[27] The "Canasta Basica" contains about 80 articles, mostly food products, but also a few like transport. It is designed using Mexico's income-expenditure survey ENIGH.

to verify our data collection on calories, so it could be seen as a dual check: a check on our interpretation of the regulation, but also on the data collection on calories. Deloite chose to use a methodology where they "searched for mistakes" by looking at our classification and drawing a sample of 200 products where they though it was more likely that we made mistakes. This makes their sample non-representative, but likely generates an upper bound of mistakes. Their final classification disagreed with ours for 6.5% of the products, and indicated that in 4.5% of the cases the law is not specific enough to be able to clearly classify the product. Deloitte provided a letter to the editor of this journal summarizing the results of their audit. To give reassurance to us and the reader, we show robustness by reestimating the table of main results with an alternative tax classification. There we assumed as taxed the products for which Deloitte considered that the law was not specific enough. Table OA-13 shows these results in comparison to the main estimate. Given the small set of goods where there was doubt, we were not surprised to learn that results are almost unchanged.

Tables OA-5 and OA-6 show, by product-group, the percentage of items classified as being subject to either the sugary drink (*tax_beverage*) or the high caloric-dense food tax (*tax_food*).

Table OA-5: Tax variable: sugary drinks

Product type	Barcodes with tax (percent)
Bottled water	0
Sparkling water	0
Powdered drinks	84
Energy drink	98
Carbonated soft drink	90
Sports drink	100
Non-carbonated soft drink	68
Coffee	0
Cornflour drink (atole)	0
Powdered Milk	0
Evaporated Milk	0
Drinking Milk	0
Flavored Milk	0
Iced-tea	87

Table OA-6: Tax variable: caloric dense food

Product type	Barcodes with tax (percent)
Cooking oil	0
Baby food	0
Canned tuna	0
Cereal bar	100
Snacks	100
Condensed milk candy	98
Seasonings and broths	0
Cereal	96
Chocolate	99
Tomato puree	0
Liquid seasoning	0
Creamer/Substitutes of cream	0
Sour cream	0
Sweet spreads	100
Breadcrumbs	0
Cookies	100
Ice creams and popsicles	0
Condensed Milk	0
Margarine	0
Mayonnaise	0
Jams	0
Honey	0
Flavored Milk Powder	87
Vegetable Juice	0
Industrialized bread	53
Pastas	0
Refrigerated Dessert	7
Powdered Desserts	8
Tomato puree	0
Ketchup	0
Snack sauce	0
Homemade bottled sauce	0
Pasta Sauce	0
Instant Soups	0
Yogurt	0

Appendix B. Data

B.1 Kantar World Panel: some examples

Section 3 in the main paper describes our data sources. Our main source comes from Kantar World Panel (KWP), a company with more than 50 years of experience measuring consumption of households in dozens of countries. Together with Nielsen they are the most important companies specializing in household scanner data collection worldwide.

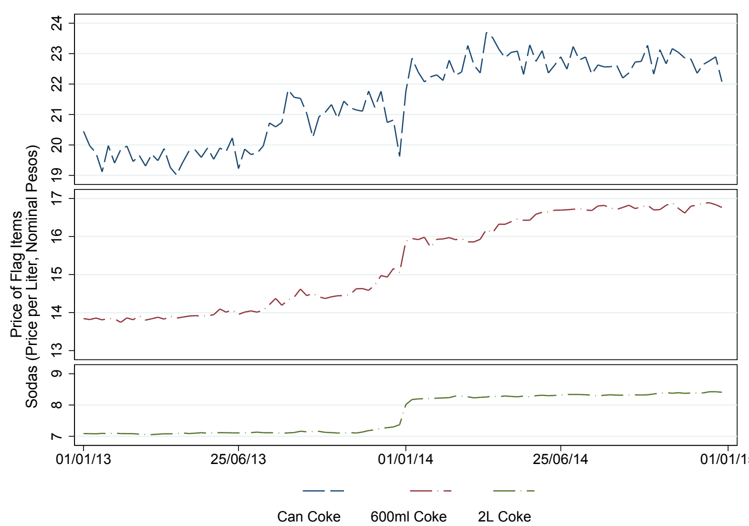
One remarkable characteristic from the KWP data is its high frequency (weekly) and the the high level of disaggregation, which allows us to make a detailed statistical analysis from different perspectives. KWP's product catalogue comprises a total of 47,973 barcodes (SKUs); 24,796 for foods and drinks. It classifies barcodes along ten variables. The categories used to classify products include: basic ingredient, flavor, size, brand, product's characteristics (e.g. light, lactose-free, caffeine-free, etc.), among others. Table OA-7 below shows an example of how five products are classified along these dimensions.

Table OA-7: Product classification example

id	product	subproduct	brand	clas01	clas02	clas03	clas04	clas05	content
3510	Cereals	No subproduct	Kelloggs	Corn Flakes	.	Apple w cinnamon	.	.	750 gr
105944	Cookies	Sweet	Marinela	Principe	.	Strawberry-filled	Chocolate	.	44 gr
43379	Carbonated drinks	Regular	Lift	Red apple	.	.	.	.	1000 ml
72523	Milk	Pasterurized	Alpura	.	Regular	Non lactose-free	.	.	1000 ml
133285	Mayonnaise	Regular	Kraft	Mayo	Regular	.	.	Light	443 gr

We used the above information to detect which barcodes were subject to the tax and which were exempt and to impute nutritional content as we detail in this Appendix. Before proceeding with this detail however, we would like to exemplify the richness of our data by plotting prices for some selected products. Figure OA-6 shows the price per liter through time for three Coca-Cola package sizes: the 355 ml. can, the 600 ml. bottle and the 2 liter bottle. We could potentially plot these graphs by storebrand, by city or by type of household.

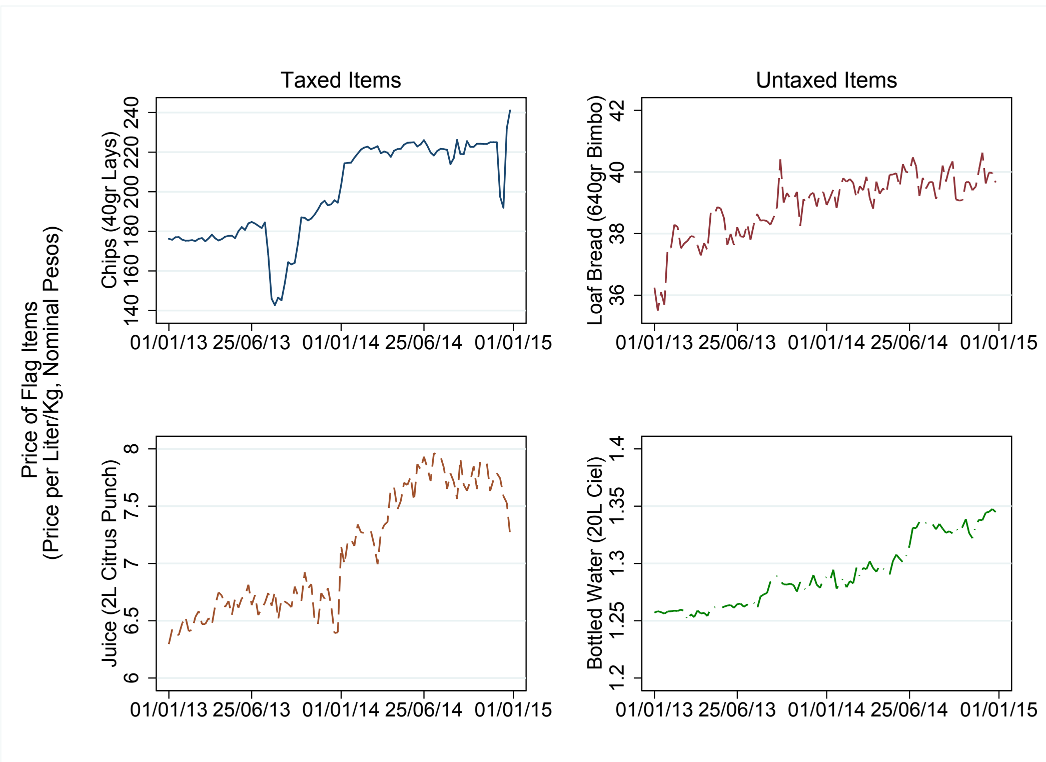
Figure OA-6: Price per liter of Coca Cola by Package Size



Source: KWP data

Figure OA-7 gives another example. It plots the price liter or kilogram (depending on the product) for the following products: (i) a 40 gram bag of Lays chips (a taxable food product), (ii) a 640 gram of Bimbo bread (a not taxable food), (iii) a 2 liter bottle of Citrus Punch juice (a taxable drink), and (iv) a 20 liter bottle of Ciel natural water (a non-taxable drink).

Figure OA-7: Four products example, prices



Source: KWP data

B.2 Yearly questionnaire

KWP also carries out a yearly questionnaire that captures a useful set of socioeconomic and demographic characteristics, including household assets and both the male and female household head's age, weight, and height, from which we compute their body mass index (BMI).[28] We classify households as having a normal weight if the reported BMI of the female head is lower than 25, over-weight if it lies between 25 and 30, and obese if above 30.[29] We use KWP's classification for our socioeconomic status (SES) categories, which gathers households into three groups (ABC+, CD+, and DE) as a function of household assets, where ABC+ refers to the highest SES level. SES categories are derived using standard methodologies. SES categories are derived from different measures of household assets: number of rooms, type of floor, number of bathrooms, whether the dwelling has a gas stove, number of light bulbs, number of cars, and household head's education. Following the procedure, about 21, 52 and 27 percent of households in the data are classified in the A/B/C+, C/D+ and D/E SES categories, respectively.

B.3 Collection of Nutritional Data

We start with 24,796 barcodes for foods and drinks. However some of these are exactly the same product in the sense they have exactly the same substance in it, and just vary in the quantity (milliliters of milligrams) per unit. For example a can of 355ml coke has the same substance as a 500ml coke. Once we remove these size differences we end up with 14,723 barcodes, of which 10,518 are consumed every single year. Our goal in this section is to describe how we recorded or imputed caloric and nutritional content for each of these 14,723 barcodes.

The first step consisted of recruiting a team of more than 20 enumerators and train them to search for the items in supermarkets (physically and through their internet website[30]), manufacturer's website, and local grocery stores. This work involved several months of work. Enumerators took pictures of the nutritional label and then coded such label on a predetermined format. This enabled us to do double coding for a sample of barcodes and verify that the enumerators actually went to the supermarket and found the appropriate product. Each enumerator was given a list of barcodes by the researchers an a format to fill out and enter the nutritional content available in the product's label: serving size, calories, sugar, fat, saturated fat, iron, carbohydrates, cholesterol, and sodium. In the selection of barcodes to be given to the enumerators, the researchers prioritized those with the largest percentage of purchase events. Finally, we performed quality check which consisted of selecting a random sample of 5 percent of the barcodes that had been captured and asking a second enumerator to repeat the process. In less than 1 percent of the cases, the enumerator captured different values.

Using this process we managed to collect direct information for 6,071 barcodes which cover 81.6 percent of purchase events and 83.1 percent of household's expenditure. Table OA-8 shows the proportion of events and expenditures that were collected for each product-category that covers all of KWP data.[31] Enumerators were quite successful finding the assigned barcodes: more than 95 percent of the assigned barcodes were found and captured. Products that were very local, but comprised a low fraction of purchase events and expenditures, are

[28]See online appendix for more details. BMI measures are self-reported, which may impose limitations on our analysis. Nonetheless, data checks (see working paper version) suggest they are good indications of individuals' body weight.

[29]We find a large within household correlation, above 0.5, for the BMIs of the male and female heads of the same household. Because strong positive correlations of BMI across members of a household are typical, we take the liberty of referring to household BMI, even if we are using the female household head BMI only.

[30]Mainly Walmart's website was used: [www.walmart.com.mx]

[31]Product category is a variable in KWP data.

underrepresented. In these instances, enumerators seek the manufacturers contact information and attempted to reach them in order to ask for the nutritional information.

Table OA-8: Coverage of Caloric information as a fraction of Expense and Purchases

Product	Expenditure (percent)	Purchase events (percent)
Cooking oil	85	84
Bottled water	37	35
Sparkling water	88	85
Baby food	48	56
Canned tuna	84	81
Cereal bar	92	92
Powdered drinks	93	92
Energy drink	95	95
Carbonated soft drink	97	97
Sports drink	91	91
Non-carbonated soft drink	73	71
Snacks	94	95
Coffee	80	83
Condensed milk candy	44	30
Seasonings and broths	77	81
Cereal	93	90
Chocolate	92	92
Tomato puree	87	86
Liquid seasoning	58	55
Creamer/Substitutes of cream	62	76
Sour cream	63	60
Cream Spreads	71	62
Breadcrumbs	93	92
Cookies	42	44
Cornflour drink (atole)	72	65
Ice creams and popsicles	32	34
Vegetable Juice	94	95
Condensed Milk	95	95
Powdered Milk	34	38
Evaporated Milk	93	93
Milk	59	59
Flavored Milk	87	85
Margarine	69	71
Mayonnaise	80	81
Jams	72	70
Honey	53	54
Flavored Milk Powder	93	93
Industrialized bread	90	89
Pastas	65	62
Refrigerated Dessert	98	98
Powdered Desserts	78	77
Tomato puree	83	82
Ketchup	85	88
Snack sauce	68	70
Homemade bottled sauce	83	84
Pasta Sauce	52	35
Instant Soups	91	89
Iced-tea	33	30
Yogurt	81	81

For each product category, this table shows what fraction of the category would we find caloric information. For many categories we found more than 80% in terms of purchase events, and in terms of expense.

B.4 Caloric and nutrient imputations

After collecting the nutritional information for a very large fraction of purchase events, we had to impute the nutritional characteristics of the remaining products that appear in KWP's dataset. In this subsection, we describe the steps followed to perform such imputation:

1. Convert sizes to the same units: We begin by using serving sizes along with calories and nutrients of the products that we gathered to generate a variable that shows the amount of calories or nutrients per 100 grams (or per 100 ml. for drinks). We will refer to this variable as our *density measure*.

2. We explored by hand each product-group[32] using the variables shown in Table OA-7), and within each product-group we imputed the nutrient/caloric density to the closest groups of products. In other words, for each article with missing caloric and nutrient information, we search for the most similar product with information available based on the *matching variables*[33]. We seek to establish such match with the highest level of disaggregation possible. If an exact match was not possible for a given level of disaggregation, we used a lower level of disaggregation, that is, we use a subset of the *matching variables*. The following table exemplifies this procedure. In this case, *subproduct* and *clas01* were chosen as the matching variables. As can be seen, there are 4 products with $subproduct = REGULAR$[34] and $clas01 = COLA$ with missing information for calories. In this case, these products are matched to those with the same *subproduct* and *clas01* for which information is non missing. The average value of the *density measure* of those products with available information is imputed to those with missing information. The same process is followed with the two missing values for the $subproduct = REGULAR$ and $clas01 = LEMON\_LIME$ products. However, we can see that we have in the first line a cherry-flavored drink which cannot be matched to other drink with the same *subproduct* and *clas01* values. In this case, a lower level of disaggregation is used and that product is imputed with the average *density measure* value from all drinks that have $subproduct = REGULAR$.

3. For barcodes for which we were not reasonably sure about the quality of the imputation we send enumerators to get the information on the supermarket.

[32]The different types of products-groups available are: cooking oil, bottled water, sparkling water, baby food, canned tuna, cereal bars, powdered drinks, energy drinks, carbonated soft drinks, sport drinks, non-carbonated soft drinks, snacks, coffee, condensed milk candy (cajeta), seasonings and broths, cereal, beer, chocolate, tomato puree, liquid seasoning, creamer, sour cream, sweet spreads, breadcrumbs, cookies, cornflour drink (atole), ice creams and popsicles, vegetable juice, condensed milk, powdered milk, evaporated milk, regular milk, milk-based flavored drinks, margarine, mayonnaise, jams, honey, milk-based flavored powder, industrialized bread, pastas, refrigerated dessert, powdered desserts (e.g. jello), ketchup, salsas, homemade bottled salsas, pasta sauce, instant soups, iced-tea, yogurt.

[33]The matching variables are: product,subproduct,brand,clas01, clas02,clas03, clas04,clas05} exemplified in Table OA-7.

[34]DIET/LIGHT is the other possible value for *subproduct*

Table OA-9: Imputation example

num	product	subproduct	brand	clas01	kcal_100ml
124	CARB. DRINK	REGULAR	GARCI CRESPO	CHERRY	
48	CARB. DRINK	REGULAR	CABALLITOS	VANILLA / ROOT BEER	29
2	CARB. DRINK	REGULAR	PEPSI	COLA	45.3
7	CARB. DRINK	REGULAR	BIG COLA	COLA	42
4	CARB. DRINK	REGULAR	RED COLA	COLA	
90	CARB. DRINK	REGULAR	CHIVA	COLA	
133	CARB. DRINK	REGULAR	SMART	COLA	
39	CARB. DRINK	REGULAR	BIG COLA DOBLE	COLA	43
1	CARB. DRINK	REGULAR	COCA COLA	COLA	42
52	CARB. DRINK	REGULAR	AURRERA	COLA	
3	CARB. DRINK	REGULAR	BIG COLA MEGA	COLA	42
115	CARB. DRINK	REGULAR	COCA COLA LIFE	COLA	18
11	CARB. DRINK	REGULAR	7 UP	LEMON-LIME	34
8	CARB. DRINK	REGULAR	SPRITE	LEMON-LIME	36
81	CARB. DRINK	REGULAR	BIG FRESH	LEMON-LIME	
97	CARB. DRINK	REGULAR	AURRERA	LEMON-LIME	

B.4.1 Quality of the Imputation

One way to asses the quality of the imputation is to check that the variance within the "matching variables cell" is low before the imputation. That is, the cells identify products that are very similar in terms of calories. We ran an exploratory analysis to measure the variance of caloric density for different aggregations, using the variables {product,subproduct,brand,clas01, clas02,clas03, clas04,clas05}. The highest level of disaggregation is when we use all these 8 variables to create cells. At this level which we call L8 we find tiny variances within the group. This just means for instance that Alpura Milk has the same amount of calories per liter across its package sizes. The intraclass correlation in L8 cells is 0.995 using captured calories of products. If we go all the way to the lowest level of aggregation (i.e. L1 cells), the ICC is still quite large: 0.96.

We also followed another way to assess the quality of the imputation, in the spirit of a cross validation exercise.

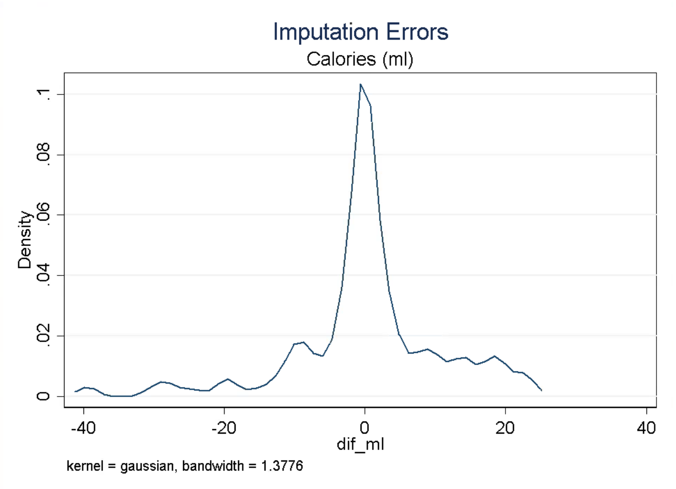
1. We randomly drop the *observed* values for 10 percent of the products for which we *have* available caloric and nutrient information.

2. We implement the imputation algorithm described above for the product whose information was deleted in the previous step. We compare the imputed versus the observed values.

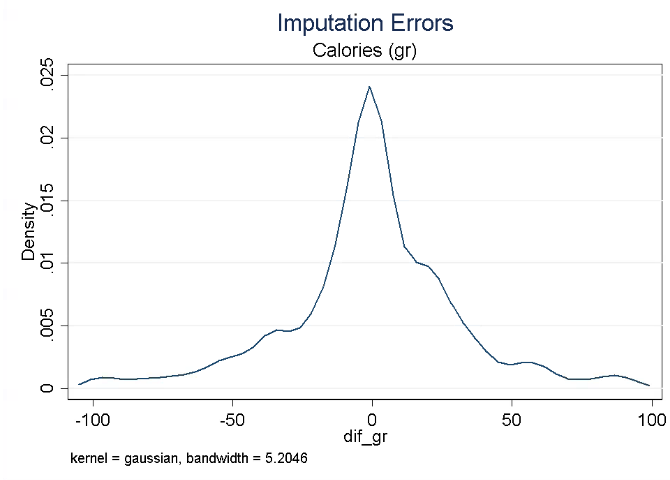
3. We repeated this exercise 5 times.

4. Figure OA-8 plots the density of difference between the observed and imputed values for calories, sugar and fat. Similar graphs for the rest of the nutrients are available upon request. As the graphs display, there is a big concentration in zero which speaks of the adequacy of the process implemented to input the missing information. The imputation errors for calories are relatively small: for drinks we obtain from this out of sample exercise that the absolute value of the imputation error is 9.5 calories per 100 ml on average, while the average caloric density is 127.5 calories per 100ml. For solid foods, the corresponding average value of the imputation error is 49.5 calories per 100 gr, while on average caloric density is 267.4 calories per 100 gr.

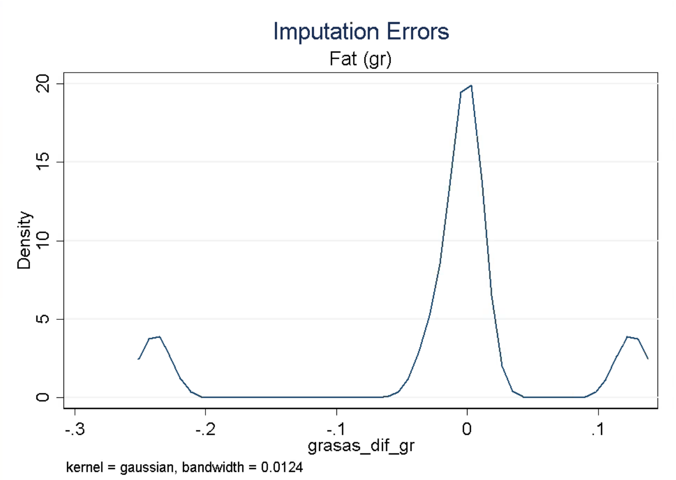
Figure OA-8: Outsample imputation errors for Calories, Fats and Sugars



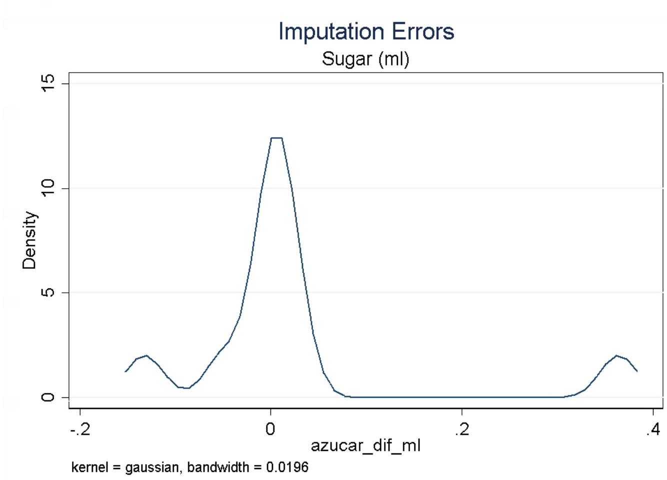
(a) Calories Liquids



(b) Calories Solids



(c) Fat



(d) Sugar

Notes: Gaussian kernel density estimations shown

Appendix C. Price Imputation

The problem of missing values: One problem faced by many studies like ours, that have access to information on "personalized" prices paid by individuals, is that we only observe the price that the particular household faced – p_{bity} – when the good is actually purchased. This gives rise to two problems. The first is missing data on prices for barcodes that are not purchased by a particular household in a particular week. The second is a selection problem, as prices may be observed by the econometrician only when they are low enough to lead to a purchase. We address both problems by imputation, perform several robustness tests to evaluate if the procedures are reasonable, and show that they are not driving our results.

The missing prices problem is not as grave as it may seem given our procedure. Recall that our main interest is in estimating quantities of calories, and we don't face this missing data problem there. Recall further that when we study prices for each household we fix the basket of goods they consumed in 2013, and focus on the cost of purchasing this fixed basket in 2014 and how this cost changed as a result of the tax. This means that we do not have to impute prices for all barcodes for all household, only for those that the household bought in 2013 and not in each given week in 2014.

The problem of selection is also not severe, since the paper is mostly concerned with measuring how the prices *changed* as a result of the tax. We are not directly concerned with the exact price level, but only on price changes for a given consumption basket.[35]

Roughly, the way the imputation method works is as follows. If barcode b was in household's i 2013 consumption basket, then we have to keep track of the price of that barcode throughout all week in 2013 and 2014, regardless of whether household i actually bought it. If household i bought barcode b in week $t \in \{1, ..., 52\}$ in year $y \in \{2013, 2014\}$ then we know the price and we use this price. But if not, then we need to impute it. We use a sequential procedure to do the imputation: inputing the missing price using observed prices of purchases of that barcode in the same city, district, and store-brand[36] where household i bought the barcode in 2013, but in the respective week of interest. If no household in our data bought the barcode b in that week, city, district, and type of store-brand, then we impute at a higher level of aggregation: week, city, district, at *any* type of store. If that is not enough to impute all prices, then we go to an even higher level of aggregation, and so on. The table below lists the sequence of imputations and the fraction of prices imputed in each step.[37]

[35] We re-estimated the results for prices not using households personalized prices, but instead prices per city-week and results were virtually unchanged.

[36] Types of store are for example Wallmart, 7 eleven, Oxxo, Superama, etc.

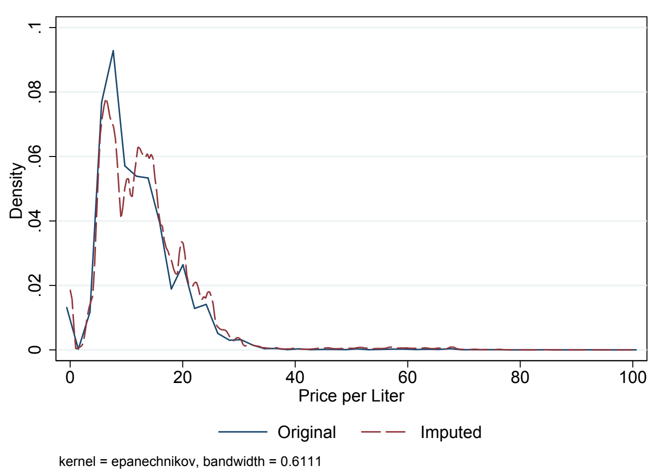
[37] R^2 corresponds to a regression of observed price in our full dataset against fixed effects of the categorical variables of each level of aggregation (i.e. imputation level column).

Table OA-10: Sequential price imputation

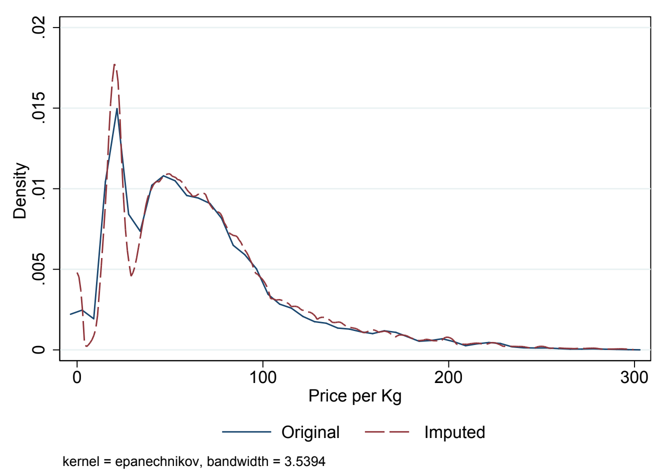
	Imputation of Prices		
Step	Imputation level	R^2	Imp. Prices. (Percent.)
1	Week, store, household	0.99	4.0
2	Week, city, district, store	0.92	25.9
3	Week, city, district	0.90	17.2
4	Week, city, store	0.91	6.1
5	Week, city	0.89	3.0
6	Week, region, store	0.88	18.0
7	Week, region	0.84	5.1
8	Week, store	0.87	11.4
9	Week	0.83	2.3
10	Quarter, store	0.86	3.4
11	Quarter	0.78	1.8
12	Year, store	0.84	2.1
13	Year	0.75	0.2

The second is that the distribution of prices before and after imputing is very similar, as shown in Figure OA-9. Third, note that we follow the same imputation protocol for all years. Since our strategy is to compare across years, the imputation should not have important influence on our estimates.

Figure OA-9: Price distributions before and after imputations



(a) SDs



(b) HCFs

Notes: Price densities in KWP before and after imputation.

Appendix D. Robustness

D.1 Bandwidths and parametric specifications

The usual robustness checks for RD analysis were implemented for our identification. Table OA-11 below shows the sensitivity of our main specification to changes in the bandwidth employed while Table OA-12 shows the sensitivity to the use of different parametric specifications instead of the non-parametric estimation done for the main specification.

Table OA-11: Robustness: Sensitivity to different bandwidths

	Total	Total Drinks	Taxed Drinks (TD)	Untaxed Drinks (NTD)	Total Food	Taxed Food (TF)	Untaxed Food (NTF)
Panel A. Dependent Variable: Price Index (Dec 2013=100)							
Tax (BW=6 months)	4.843***	6.395***	9.721***	3.820***	2.659***	6.111***	0.869***
	(0.0339)	(0.0493)	(0.0539)	(0.0727)	(0.0396)	(0.0978)	(0.0442)
Tax (BW=9 months)	4.605***	6.017***	9.769***	3.143***	2.608***	6.010***	0.857***
	(0.0292)	(0.0423)	(0.0463)	(0.0625)	(0.0339)	(0.0899)	(0.0380)
Tax (BW=12 months)	4.403***	5.702***	9.684***	2.673***	2.552***	6.020***	0.778***
	(0.0262)	(0.0382)	(0.0413)	(0.0564)	(0.0300)	(0.0805)	(0.0337)
Tax (BW=15 months)	4.381***	5.662***	9.643***	2.635***	2.553***	6.050***	0.768***
	(0.0255)	(0.0374)	(0.0400)	(0.0554)	(0.0289)	(0.0776)	(0.0326)
Tax (BW=18 months)	4.375***	5.651***	9.633***	2.624***	2.554***	6.057***	0.766***
	(0.0255)	(0.0375)	(0.0398)	(0.0556)	(0.0288)	(0.0769)	(0.0324)
Panel B. Dependent Variable: Calories							
	Total	Total Drinks	Taxed Drinks (TD)	Untaxed Drinks (NTD)	Total Food	Taxed Food (TF)	Untaxed Food (NTF)
Tax (BW=6 months)	-21.67	-112.1*	-102.0**	-10.08	90.41	-78.79**	169.2*
	(143.6)	(57.60)	(43.08)	(32.77)	(115.1)	(35.17)	(99.32)
Tax (BW=9 months)	-32.86	-97.38**	-116.9***	19.56	64.53	-76.17***	140.7*
	(113.8)	(45.67)	(34.01)	(26.37)	(91.51)	(28.34)	(78.86)
Tax (BW=12 months)	-69.89	-97.02**	-112.10***	15.08	27.13	-84.69***	111.80*
	(97.39)	(39.17)	(29.18)	(22.73)	(78.52)	(24.44)	(67.68)
Tax (BW=15 months)	-40.67	-114.0***	-116.5***	2.521	73.31	-82.03***	155.3**
	(89.43)	(35.99)	(26.79)	(20.99)	(72.26)	(22.59)	(62.32)
Tax (BW=18 months)	33.18	-109.9***	-111.4***	1.428	143.1**	-60.19***	203.3***
	(84.51)	(34.01)	(25.28)	(19.92)	(68.39)	(21.47)	(59.02)

The *Tax* variable indicates if the observation is captured after January 1st 2014. All estimations consist of a local linear regression of a second degree polynomial with triangular kernel weights and different bandwidths depending on the line. The outcomes of each regression correspond to the residuals of the price index (panel A) or the level of calories of products purchased (panel B) after partialling out for household and week of the year fixed effects. To perform the partial out, we keep constant the week and household dummies coefficients that result from our baseline results. The price index results from keeping constant each household's 2013 consumption and for 2014 inputting the price of such consumption using the most geographically disaggregated information available for each product. Then, the consumption cost is normalized to 100 using the December 2013 level. The caloric purchase is calculated using the observed or imputed level of calories per each product as described in section 3.2. Each column shows the result of aggregating the purchase of each product's corresponding type. Data employed for this estimation comes from the weekly KWP Mexico chapter for 2013 and 2014. The unit of observation is the household-week pair.

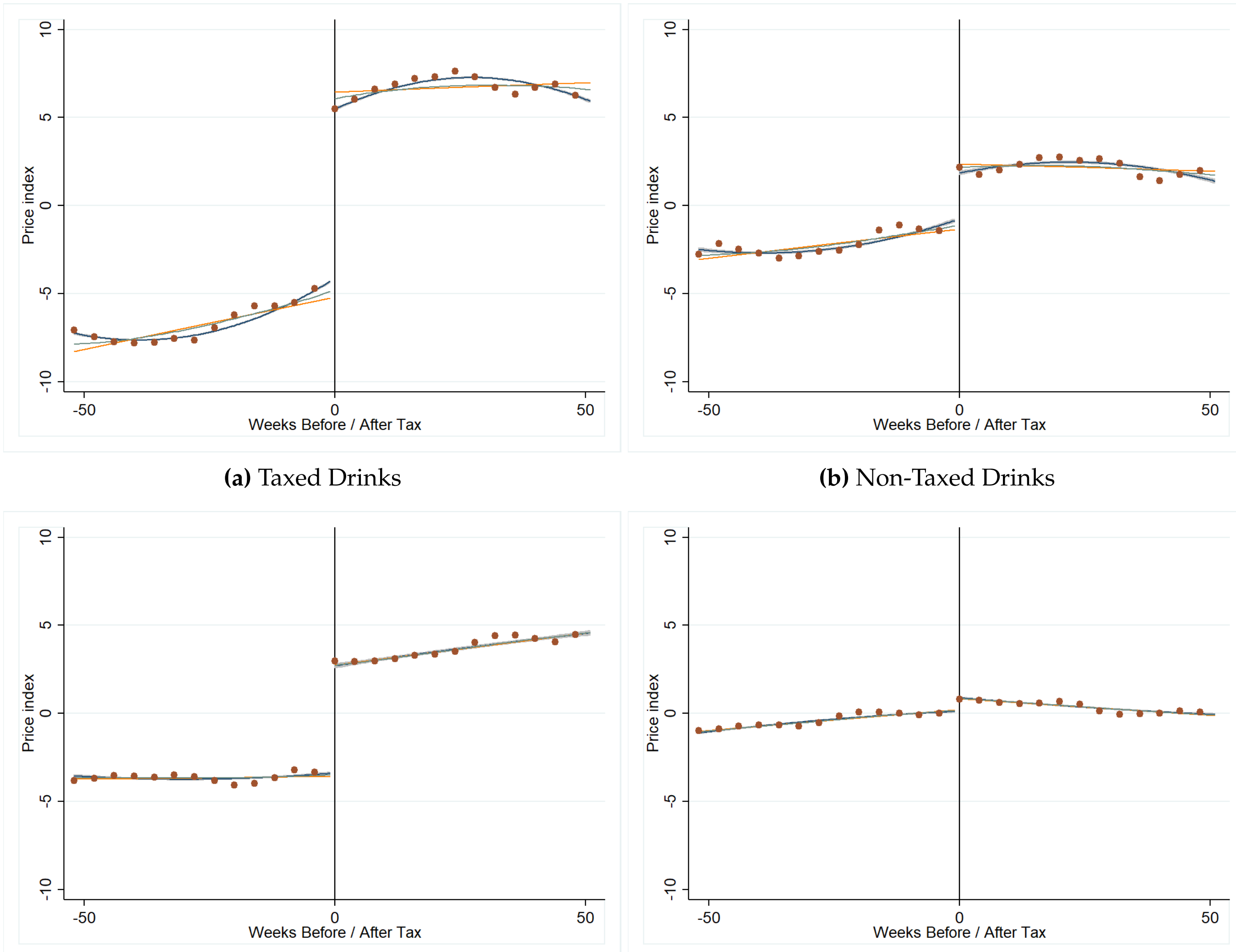
Table OA-12: Robustness: Sensitivity to parametric estimations

Panel A. Dependent Variable: Price Index (Dec 2013=100)							
	Total	Total Drinks	Taxed Drinks (TD)	Untaxed Drinks (NTD)	Total Food	Taxed Food (TF)	Untaxed Food (NTF)
Tax (Non-parametric)	4.403***	5.702***	9.684***	2.673***	2.552***	6.020***	0.778***
	(0.0262)	(0.0382)	(0.0413)	(0.0564)	(0.0300)	(0.0805)	(0.0337)
Tax (Parametric Deg 2)	4.359***	5.621***	9.607***	2.596***	2.556***	6.075***	0.762***
	(0.0392)	(0.0622)	(0.0554)	(0.0861)	(0.0311)	(0.0854)	(0.0335)
Tax (Parametric Deg 3)	4.462***	5.812***	9.790***	2.778***	2.547***	5.946***	0.798***
	(0.0382)	(0.0594)	(0.0563)	(0.0868)	(0.0376)	(0.0810)	(0.0415)
Tax (Parametric Deg 4)	5.069***	6.741***	9.840***	4.329***	2.736***	6.050***	1.008***
	(0.0466)	(0.0749)	(0.0607)	(0.1135)	(0.0411)	(0.0942)	(0.0457)

Panel B. Dependent Variable: Calories							
	Total	Total Drinks	Taxed Drinks (TD)	Untaxed Drinks (NTD)	Total Food	Taxed Food (TF)	Untaxed Food (NTF)
Tax (Non-parametric)	-69.89	-97.02**	-112.10***	15.08	27.13	-84.69***	111.80*
	(97.39)	(39.17)	(29.18)	(22.73)	(78.52)	(24.44)	(67.68)
Tax (Parametric Deg 2)	-74.83	-103.82***	-102.31***	-1.51	28.99	-87.85***	116.84**
	(76.07)	(33.32)	(25.73)	(18.72)	(61.00)	(20.76)	(53.51)
Tax (Parametric Deg 3)	-63.22	-87.82**	-125.29***	37.47	24.61	-80.40***	105.01
	(104.12)	(42.10)	(31.89)	(23.55)	(84.45)	(27.39)	(73.91)
Tax (Parametric Deg 4)	113.31	-96.01*	-99.43**	3.42	209.32*	-47.03	256.35***
	(133.65)	(53.28)	(41.06)	(28.40)	(108.86)	(34.62)	(95.37)
Observations	727,397	727,273	727,397	727,164	727,397	727,397	727,273

The *Tax* variable indicates if the observation is captured after January 1st 2014. The non-parametric estimation corresponds to our baseline estimate which consist of a local linear regression of a second degree polynomial with triangular kernel weights and a 52 week bandwidth. The other estimations are parametric with different degrees for the polynomial with different parametric estimates to the right and left of the discontinuity. The outcomes of each regression correspond to the residuals of the price index (panel A) or the level of calories of products purchased (panel B) after partialling out for household and week of the year fixed effects. The price index results from keeping constant each household's 2013 consumption and for 2014 inputting the price of such consumption using the most geographically disaggregated information available for each product. Then, the consumption cost is normalized to 100 using the December 2013 level. The caloric purchase is calculated using the observed or imputed level of calories per each product as described in section 3.2. Each column shows the result of aggregating the purchase of each product's corresponding type. Data employed for this estimation comes from the weekly KWP Mexico chapter for 2013 and 2014. The unit of observation is the household-week pair. The parametric estimates use clustered errors at the household level.

Figure OA-10: Tax Effect on Prices, sensitivity to different specifications



(a) Taxed Drinks

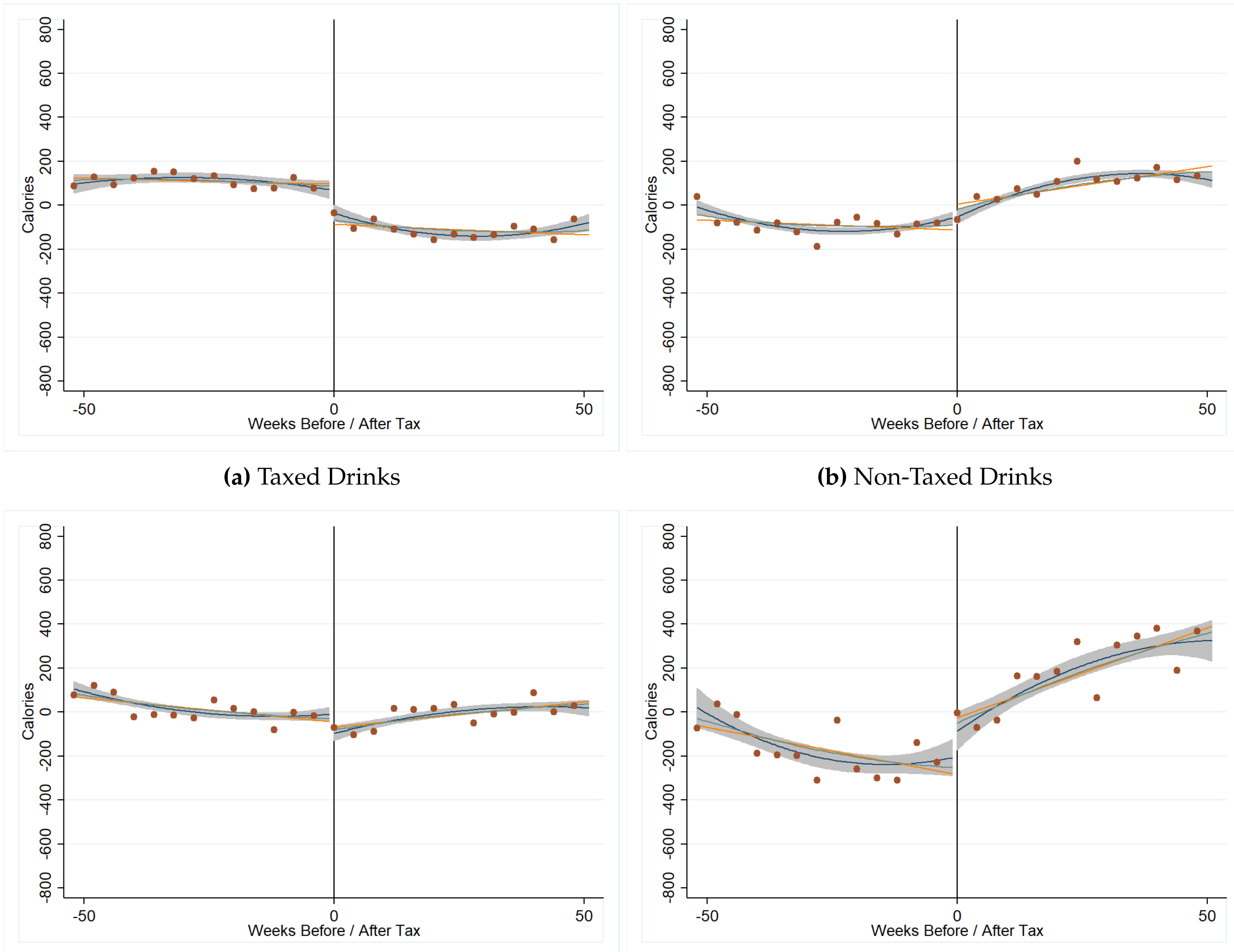
(b) Non-Taxed Drinks

(c) Taxed Food

(d) Non-Taxed Food

Notes: This Figure shows the sensitivity of our main results depicted in Figure 1 to the use of different specifications. We contrast our main result (blue line) with a linear (orange line) and a local linear regression (green line), which are separately specified before and after January 2014. In every case the price index is normalized to 100 at December 2013. Our dependent variables are de-meaned and seasonally adjusted residuals that were obtained from an OLS regression of the respective price index P^k_{ity} on household fixed effects and 51 week of the year dummies.

Figure OA-11: Tax effect on calories purchased, sensitivity to different specifications



(a) Taxed Drinks

(b) Non-Taxed Drinks

(c) Taxed Food

(d) Non-Taxed Food

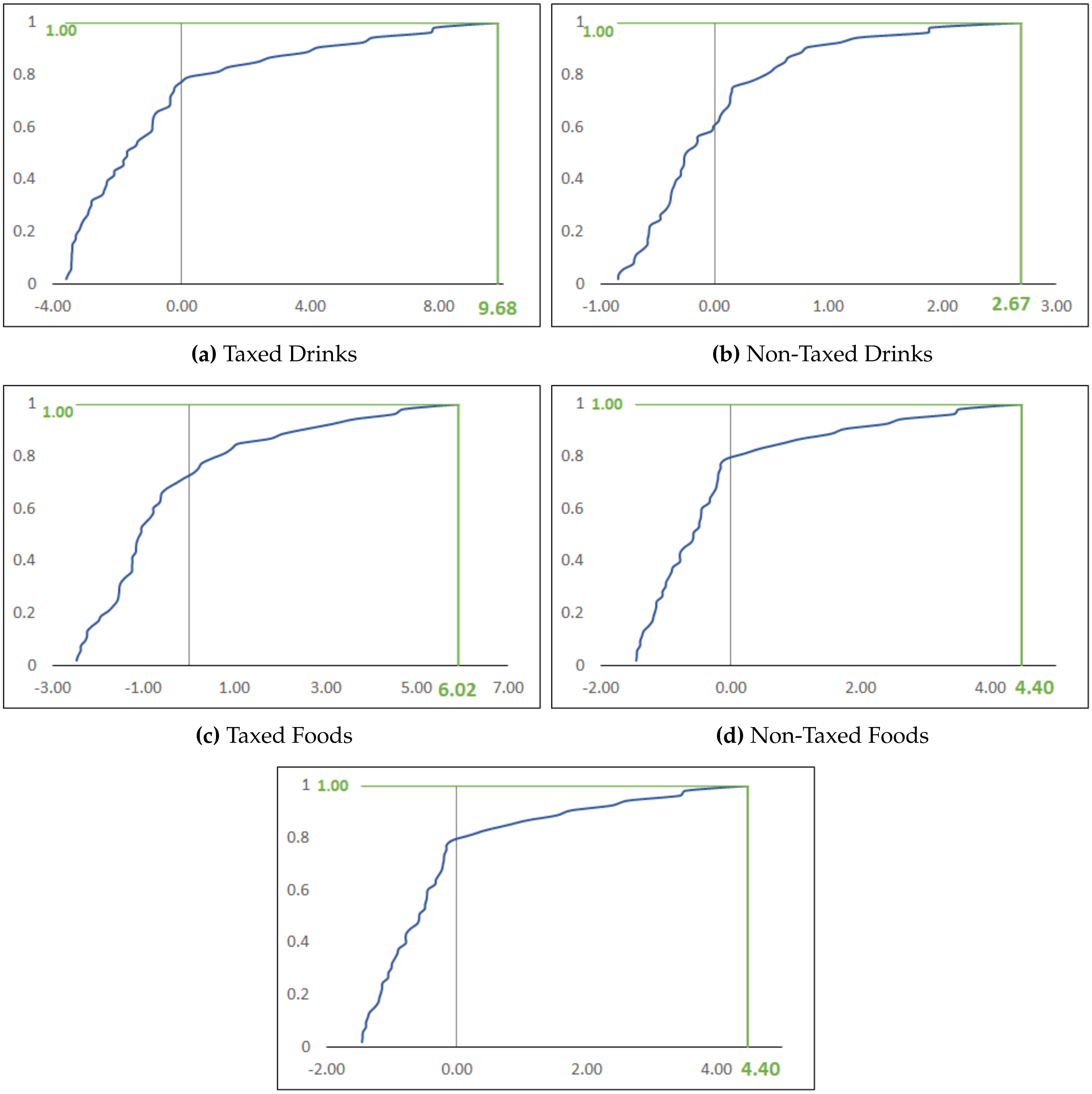
Notes: This Figure shows the sensitivity of our main results depicted in Figure 2 to the use of different specifications. We contrast our main result (blue line) with a linear (orange line) and a local linear regression (green line), which are separately specified before and after January 2014. In every case We sum calories purchased of food basket type $k \in \{TD, NTD, TF, NTF\}$ by each household i at the week level t, and therefore obtain C^k_{ity}. To form the dependent variable we then calculate de-meaned and seasonally adjusted residuals that were obtained from an OLS regression of C^k_{ity} on household fixed effects and 51 week of the year dummies.

D.2 Fisher tests

We proceeded to estimate the 53 regressions and collected the resulting $\{\beta^1, \ldots, \beta^{53}\}$ from our estimations. We do this for each dependent variable separately. If our equation is correctly specified and if in reality the tax in January 2014 did have an effect, we would expect all betas other than the one for the first week of 2014 to be statistically zero, except perhaps for sampling variance. With 90 percent confidence we should therefore observe that the coefficient for January 2014 is either in the top 10 percent of the distribution when the effect is positive (e.g. price) or the lowest 10 percent when the effect is negative (e.g. quantities), and to be outside this range when there is no effect of the tax (e.g. calories).

Figures OA-12 and OA-13 use the set of 53 coefficients and plot an empirical cumulative distribution function (CDF) for prices and calories, respectively. We add a vertical green line to indicate the position of the first week of 2014 coefficient (the true tax). We find that for the price estimates, our true tax effect is in the top 95 percent of coefficients. For calories of taxed products, it is below the 5th percentile (strongly indicating a negative effect), while for non-taxed calories and aggregate calories are above the 85th percentile. The results of these tests are consistent wit the results of statistical significance we found in the paper.

Figure OA-12: Fisher Exact Placebo Test: Prices



(a) Taxed Drinks

(b) Non-Taxed Drinks

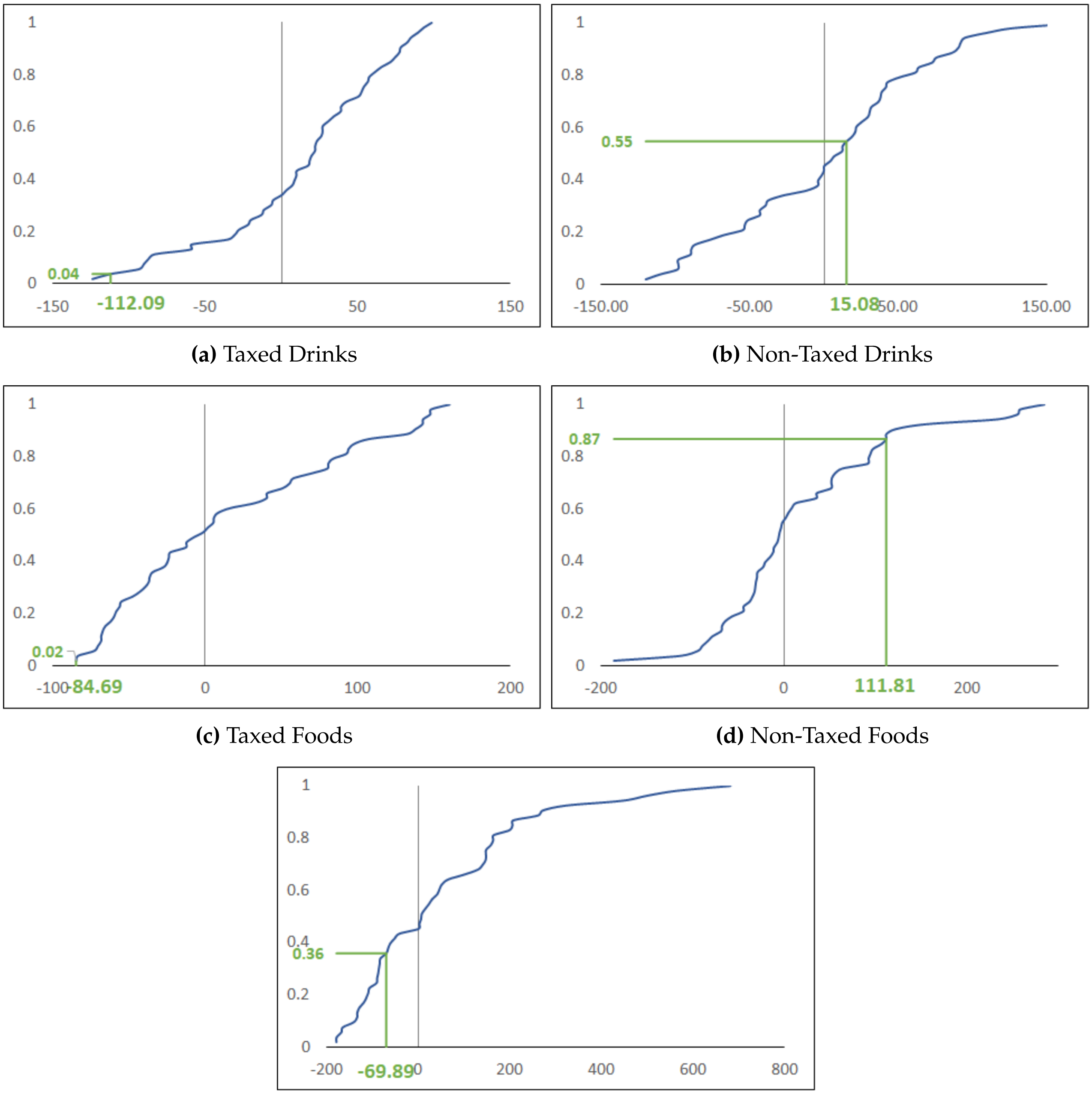
(c) Taxed Foods

(d) Non-Taxed Foods

(e) Total Calories

Notes: This figure estimates 53 regressions with placebo weeks to mimic the moment in which the tax came to effect. Each regression simulates the tax becoming in effect at each week between July 2013 and June 2014. It then ranks the estimated RD coefficient (x-axis) and plots the cumulative density (y-axis) of these, i.e. the fraction that fall below a particular value. The dependent variable used in these specifications is the Price index (Dec 2013=100). The vertical green line shows where the coefficient for the January 2014 lies. We expect true effects to lie at the extremes of the distribution whenever effects are evident. This is akin to a Fisher exact test.

Figure OA-13: Fisher Exact Placebo Test: Calories



(a) Taxed Drinks

(b) Non-Taxed Drinks

(c) Taxed Foods

(d) Non-Taxed Foods

(e) Total Calories

Notes: This figure estimates 53 regressions with placebo weeks to mimic the moment in which the tax came to effect. Each regression simulates the tax becoming in effect at each week between July 2013 and June 2014. It then ranks the estimated RD coefficient (x-axis) and plots the cumulative density (y-axis) of these, i.e. the fraction that fall below a particular value. The dependent variable used in these specifications is Calories. The vertical green line shows where the coefficient for the January 2014 lies. We expect true effects to lie at the extremes of the distribution whenever effects are evident. This is akin to a Fisher exact test.

D.3 Robustness to Tax Classification

As we described in the definition of the tax variable, we consulted with Deloitte to ensure that our tax definition was accurate. As part of the discussions with Deloitte, we reached the conclusion that some products have an unclear definition of whether they are subject to the tax or not. This is the case in two specific products:

ice creams and creamers. In the case of ice creams, the difficulty relies in the fact that this product is typically measured in liters rather than grams, but it is considered a food products for tax purposes. The law indicates that to be subject to the tax, the product should surpass the 275 kilocalories per 100 gram cutoff. This makes necessary to convert liters of ice cream to grams, however, the tax code does not provide a specific conversion to be used, leaving it as responsibility of each company. Secondly, in the case of creamers, we originally considered them as a food product following discussion with industry authorities. Deloitte considered this as a product potentially subject to the tax since it is a product consumed as part of a drink. We believe that even being a drink, most of the cases that we revised do not have added sugar as part of their ingredients and it is a milk-based product, making it exempt to the tax.

In both cases, to avoid any potential mistake that could result from our classification, we decided to carry out a sensitivity analysis in which we changed the tax classification of these products and considered them as subject to the tax. Then, we replicate the strategy described in the main results and show the results below in Table OA-13. As can be seen, the conclusions remain unmoved.

Table OA-13: Robustness: Sensitivity to tax classification of products with unclear definition

	Total	Total Drinks	Taxed Drinks (TD)	Untaxed Drinks (NTD)	Total Food	Taxed Food (TF)	Untaxed Food (NTF)
Panel A. Dependent Variable: Price Index (Dec 2013=100)							
Main specification	4.403***	5.702***	9.684***	2.673***	2.552***	6.020***	0.778***
	(0.0262)	(0.0382)	(0.0413)	(0.0564)	(0.0300)	(0.0805)	(0.0337)
Sensitivity test	4.403***	5.702***	9.566***	2.673***	2.552***	5.955***	0.730***
	(0.0262)	(0.0382)	(0.0412)	(0.0564)	(0.0300)	(0.111)	(0.0337)
Panel B. Dependent Variable: Calories							
	Total	Total Drinks	Taxed Drinks (TD)	Untaxed Drinks (NTD)	Total Food	Taxed Food (TF)	Untaxed Food (NTF)
Main specification	-69.89	-97.02**	-112.10***	15.08	27.13	-84.69***	111.80*
	(97.39)	(39.17)	(29.18)	(22.73)	(78.52)	(24.44)	(67.68)
Sensitivity test	-69.89	-94.19**	-109.30***	15.08	27.13	-84.81***	111.90*
	(97.39)	(39.51)	(29.52)	(22.73)	(78.52)	(24.61)	(67.58)
Observations	721,213	721,213	721,213	721,213	721,213	721,213	721,213

In this table we compare two alternative definitions of the taxed products: (a) main specification, refers to our tax definition employed throughout the paper and (b) sensitivity test, refers to an alternative scenario in which we assume that all the products where the tax definition is unclear are assumed to be taxed. According to the revision of our methodology done by Deloitte, the products with an unclear definition of the *tax* variable include: ice creams (possible taxed food) and milk substitutes (possible taxed drink). Each line in the table presents an independent estimation of the *Tax* variable, which indicates if the observation is captured after January 1st 2014. The same procedure as in our main estimates was followed. Each column shows the result of aggregating the purchase of each product's corresponding type. Data employed for this estimation comes from the weekly KWP Mexico chapter for 2013 and 2014. The unit of observation is the household-week pair. Standard errors are clustered at the household level.

D.4 Anticipation

Another way to shed light into the issue of anticipation is to estimate if there was inventory buildup after the tax was announced but before it came into effect. In particular we estimate the "December effect" on the quantity purchases of TD and TF by estimating the following regression by OLS:

$$\log\left(q_{ty}\right) = \alpha_i + \gamma_m + \beta_1 I(t = Dec2013) + \beta_2 I(t = Dec2012) + f(ty) + \epsilon_{ty} \tag{6}$$

where q_{ty} refers to liters of TD or kilograms of TF, $f(.)$ is a second order polynomial in weeks, α_i are household fixed effects, $I(t = Dec2013)$ and $I(t = Dec2014)$ are dummies for the months indicated, and $gamma_m$ are 11 dummies indicating January, February,..., November; we omit December so that the coefficients β_1 and β_2 are measured with respect to December 2014.

Table OA-14 shows the results. That β_1 is smaller than β_2 means that December 2013 had *less* purchases than December 2012 on average, i.e. less inventory build up. That β_1 is not statistically different from zero means that December 2013 did *not* have more inventory buildup than December 2014. Moreover, despite having a positive effect for sugary drinks, the size of the effect is lower than the negative effect found for January on the main specification.

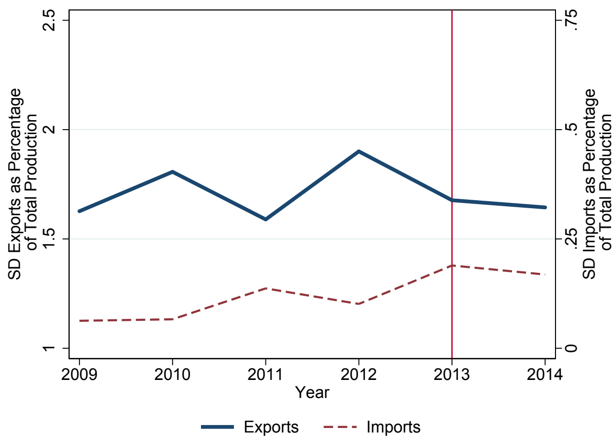
Table OA-14: Evidence of Inventory Behavior

	Log Liters TD	**Log Kilos TF**
Dec 2013	0.021***	0.002
	(0.0055)	(0.0020)
Dec 2012	0.083***	0.035***
	(0.0063)	(0.0023)
Observations	1,004,209	1,004,209

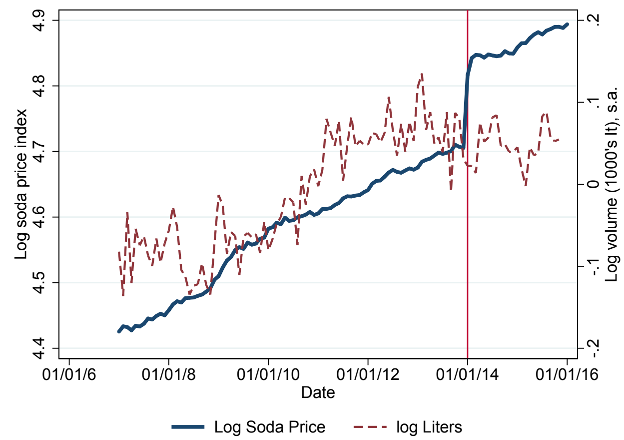
This table estimates the "December effect" on the quantity purchases of TD or TF. Data employed for this estimation comes from the weekly KWP Mexico chapter for 2012, 2013 and 2014. The unit of observation is the household-week. In particular we estimate the following regression by OLS: $log(q_{ty}) = \alpha_i + \gamma_m + \beta_1 I(t = Dec2013) + \beta_2 I(t = Dec2012) + f(ty) + \epsilon_{ty}$, where q_{ty} refers to liters of TD or kilograms of TF, $f(.)$ is a second order polynomial in months, α_i are household fixed effects, $I(t = Dec2013)$ and $I(t = Dec2014)$ are dummies for the months indicated, and $gamma_m$ are 11 dummies indicating January, February,..., November; we omit December so that the coefficients β_1 and β_2 are measured with respect to December 2014. Errors are clustered standard errors at the week level in brackets. That β_1 is smaller than β_2 means that December 2013 had *less* purchases than December 2012 on average, i.e. less inventory build up. That β_1 is not statistically different from zero means that December 2013 did *not* have more inventory buildup than December 2014.

D.5 Trade

Figure OA-14: Commerce and National Production of Soda



(a) International Commerce



(b) National Production

Notes: Source: INEGI.

Appendix E. More on identification

E.1 Are the Changes Attributable to the Taxes?

A potential concern for interpreting our findings as the impact of the taxes on purchases is that they could incorrectly attribute changes in consumption that arise naturally each start of the year to changes due to the implementation of the taxes in 2014. More precisely, while our main estimates are computed accounting for week of the year fixed effects, it is possible that one year of data, 2013, is insufficient to correctly account for seasonality in consumption.

In this sub-section, we include an extra year of data (2012) and show that our main estimates remain similar in magnitude and significance level when we account for seasonality after including this information, and that the change in the purchase of calories around the introduction of the taxes is not observed at the start of 2013; 2014 is a unique year in this regard.[38]

Table OA-15 replicates our main non-parametric specification, this time using the residuals of a regression with data from **2012**, 2013, and 2014 when we control for household and **week of the year** fixed effects. The estimates are close in magnitude and significance level to those presented in the main text.

Table OA-15: Robustness: Seasonality

Panel A. Dependent Variable: Price Index (Dec 2013=100)			
	Total	Taxed Drinks (TD)	Taxed Food (TF)
Taxes' impact (main specification)	4.403***	9.684***	6.020***
	(0.0262)	(0.0413)	(0.0805)
Taxes' impact (New 12-14 specification)	4.763***	9.897***	6.143***
	(0.0273)	(0.0435)	(0.0825)
Observations	721,213	721,089	720,980
Panel B. Dependent Variable: Calories			
	Total	Taxed Drinks (TD)	Taxed Food (TF)
Taxes' impact (main specification)	-69.89	-112.10***	-84.69***
	(97.39)	(29.18)	(24.44)
Taxes' impact (New 12-14 specification)	16.35	-111.3***	-24.96
	(97.39)	(29.18)	(24.44)
Observations	721,213	721,089	720,980

The first row in each panel reproduces the results in the main text, for ease of comparison. The second row presents results where we the partialling-out uses one more year (2012) of the same specification. Results are very similar when we estimate seasonality adding one extra year.

Table OA-16 turns to a parametric RD specification using data from 2012-2014. The key new variable is a

[38] Let us note however that there is a cost of adding data from 2012 in our estimations because our focuses on a balanced sample of barcodes in order to calculate the price indices. Because there is some entry and exit of products, adding 2012 reduces the number of barcodes in the intersection. The same is true of households. Our strategy uses households in the panel in all years, and therefore including more years implies less households in the panel. We incurred in these sample size costs and included two tables of the main results that add the 2012 consumption information.

"2013-year dummy" that takes the value of zero for year 2012, and of 1 for years 2013 and 2014. This variable accounts for the average increase/decrease in prices/calories in year 2013. We also keep our main "Tax" variable equal to zero before 2014 and to 1 in 2014. Concretely, we control for a cubic time trend $P(tw)$, and week-of-the-year-household fixed effects γ_{iw}, and estimate the following regression: $y_{itw} = \gamma_{iw} + \beta_{2013} Year(2013)_t + \beta_{2014} Year(2014)_t + P(tw) + \epsilon_{itw}$.

The "2013-year dummy" serves two purposes: first, its coefficient measures a placebo effect, or the "effect" of the change of year from December 2012 to January 2013; but second, we subtract this coefficient from the coefficient on the "Tax" variable, thus purging our tax estimate from common January's changes. Table OA-16 reports "Tax [Year(2014)-Year(2013)]" which corresponds to $\beta_{2014} - \beta_{2013}$, as well as Year(2013) which corresponds to β_{2013}. Errors are clustered at the household level.

We find that the impacts on prices are very similar to those presented in our main specification. Our *tax effect* is 3 times larger for TD and 2.8 times larger for TF, compared to the placebo "2013-year dummy". As for the changes in the purchases of calories at the start of 2013, these are small and not significantly different from zero, and subtracting them has only negligible effects in our Tax coefficient: we again conclude there is no effect on calories.

Table OA-16: Robustness: Start of the Year Effects

Panel A. Dependent Variable: Price Index (Dec 2013=100)			
	Total	Taxed Drinks (TD)	Taxed Food (TF)
Tax [Year(2014)-Year(2013)]	4.09***	11.12***	4.71***
	(0.0597)	(0.0721)	(0.0862)
Year(2013)	2.735***	3.653***	1.663***
	(0.0646)	(0.0688)	(0.1014)
Household-week FE	Yes	Yes	Yes
Cubic time trend	Yes	Yes	Yes
R-squared	0.813	0.890	0.844
Observations	1,004,209	1,004,209	1,004,209
Panel B. Dependent Variable: Calories			
	Total	Taxed Drinks (TD)	Taxed Food (TF)
Tax [Year(2014)-Year(2013)]	83.39	-173.8***	-69.58**
	(109.81)	(37.81)	(29.49)
Year(2013)	-12.192	18.784	-5.671
	(105.60)	(34.18)	(26.34)
Household-week FE	Yes	Yes	Yes
Cubic time trend	Yes	Yes	Yes
R-squared	0.537	0.577	0.516
Observations	1,004,209	1,004,209	1,004,209

This table implements a parametric RD specification using data from 2012-2014. The key new variable "Year(2013)", is a dummy that takes the value of zero for year 2012, and of 1 for years 2013 and 2014. This variable accounts for the average increase/decrease in prices/calories in 2013. We also keep our main "Tax" variable –Year(2014)– equal to zero before 2014 and to 1 in 2014. We control for a cubic time trend $P(tw)$, and week-of-the-year-household fixed effects γ_{iw}, our estimates are identified out of jumps at the beginning of the years. Concretely, we estimate $y_{itw} = \gamma_{iw} + \beta_{2013} Year(2013)_t + \beta_{2014} Year(2014)_t + P(tw) + \epsilon_{itw}$ The table reports "Tax [Year(2014)-Year(2013)]" which corresponds to $\beta_{2014} - \beta_{2013}$, as well as Year(2013) which corresponds to β_{2013}. Errors are clustered at the household level.

E.2 RD analysis using calories as a running variable

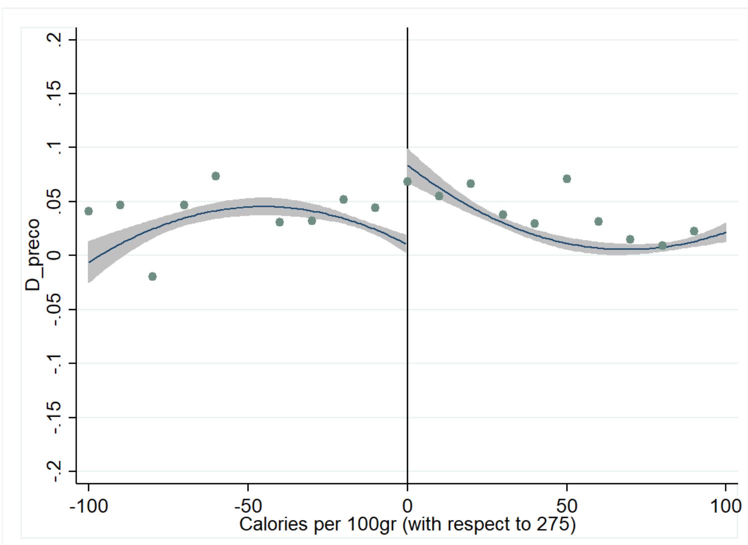
Figure OA-15 below shows the result from using a regression discontinuity design employing the 275 kilocalories per 100 gram cutoff in the definition of the food tax. The estimated figure corresponds to estimating the following specification:

$$\ln\left(P_b^{SD}\right) = \beta_0 + \beta_1\, I(Den_b > 275) + f(Den_b) + \epsilon_b \tag{7}$$

where b denotes barcode and Den_b is the caloric density of barcode b. In the estimates presented, we use a non-parametric estimation in the case of column 1 and a linear trend with different slopes before and after the cutoff in column 2. To make the results comparable to those presented with the household-week as unit of observation, each observation used (which corresponds to a barcode) is weighted by the number of transactions done with that barcode.[39]

The results found with this specification give a 7.3 percent change in prices, which is close to the 8 percent tax rate, meaning something close to a 100 percent pass through. The results of using this specification are slightly larger than the 5.3 percent estimated in the main regressions. It should be indicated though that as a traditional RD result, the estimate is valid for the value of density at the cutoff. Also, it is important to recall that in the paper, no evidence of strategic decisions around the discontinuity is found (see working paper version).

Figure OA-15: RD estimate of change in prices



This graph corresponds to a RD estimation of change in prices with respect to the 275 cal/100gr cutoff specified in the law to implement the 8% VAT on TF. The dependent variable is the change in prices with respect to the same week of the previous year. Each observation is a barcode of food products. The running variable is the amount of calories per 100gr recentered in 275 (the cutoff of the tax). Each dot corresponds to a conditional mean of change in prices of barcodes grouped in intervals of 5 units. The corresponding RD estimate using a bandwidth of 100 units, a local polynomial with a triangular kernel results in an increase of 7.3% in the price.

[39]The purpose of this is to represent that a product with very high demand should capture more importance that a product that is seldom consumed.

Appendix F. Additional estimations

F.1 Heterogeneous effects by SES

Table OA-17: Baseline (2013) Expenditures by socioeconomic status and food-drink categories

	Socio-economic status High	Medium	Low
Food Expenditure	302.44	269.64	232.86
Expenditure on:			
Taxed Drinks (TD)	64.01	63.43	56.78
Non-taxed drinks (NTD)	110.12	93.83	80.73
Taxed Food (TF)	43.13	38.38	32.74
Non-taxed food (NTF)	85.18	74.00	62.61
Percent spent on TD	21%	24%	24%
Percent spent on TF	14%	14%	14%

Expenditure in Mexican pesos spent per week on average. SEs levels are classified using household's socioeconomic and demographic characteristics (num. of rooms, type of floor, num. of bathrooms, gas stove ownership, num. of light bulbs, num. of cars, and household head's education). Three groups are formed (high, medium, low), which correspond to 21, 52 and 27 percent of households, respectively.

Table OA-18: Heterogeneity by socioeconomic status

Panel A. Dependent Variable: Price Index (Dec 2013=100)						
	Total	Taxed Drinks (TD)	Untaxed Drinks (NTD)	Taxed Food (TF)	Untaxed Food (NTF)	Log Expenditure
Tax (main specification)	4.403***	9.684***	2.673***	6.020***	0.778***	0.049***
	(0.0262)	(0.0413)	(0.0564)	(0.0805)	(0.0337)	(0.0059)
Tax (SES High)	4.237***	9.740***	2.822***	5.548***	0.688***	0.055***
	(0.0591)	(0.0972)	(0.147)	(0.112)	(0.0749)	(0.0155)
Tax (SES Medium)	4.455***	9.753***	2.664***	5.958***	0.763***	0.050***
	(0.0341)	(0.0559)	(0.0770)	(0.0609)	(0.0422)	(0.0083)
Tax (SES Low)	4.407***	9.562***	2.616***	6.325***	0.844***	0.044***
	(0.0511)	(0.0765)	(0.0990)	(0.211)	(0.0685)	(0.0101)
Panel B. Dependent Variable: Calories						
	Total	Taxed Drinks (TD)	Untaxed Drinks (NTD)	Taxed Food (TF)	Untaxed Food (NTF)	
Tax (main specification)	-69.89	-112.10***	15.08	-84.69***	111.80*	
	(97.39)	(29.18)	(22.73)	(24.44)	(67.68)	
Tax (SES High)	-42.76	-158.7*	2.888	-23.84	136.9	
	(275.1)	(94.06)	(61.63)	(71.16)	(183.6)	
Tax (SES Medium)	-111.9	-113.9***	-3.493	-106.7***	112.2	
	(141.1)	(41.52)	(32.85)	(35.32)	(98.31)	
Tax (SES Low)	-34.18	-90.16**	43.59	-85.35**	97.73	
	(148.0)	(40.79)	(35.66)	(36.48)	(106.2)	

This table estimates the effect of the tax on prices and calories separately for different populations.The methodology and definitions are as before. For ease of comparison first we show the main results from Table 2. Then we split the sample by socio-economic status (which is classified by asset ownership). All estimations consist of a local linear regression of a second degree polynomial with triangular kernel weights and a 52 week bandwidth, estimated using *rdrobust* in Stata.

F.2 Correcting for autocorrelation

Table OA-19: Correcting for autocorrelation

Panel A. Dependent Variable: Price Index (Dec 2013=100)					
	Total	Taxed Drinks (TD)	Untaxed Drinks (NTD)	Taxed Food (TF)	Untaxed Food (NTF)
Tax (main specification)	4.403***	9.684***	2.673***	6.020***	0.778***
	(0.0262)	(0.0413)	(0.0564)	(0.0805)	(0.0337)
Tax (accumulated)	4.044***	9.136***	2.438***	5.565***	0.682***
	(0.108)	(0.213)	(0.152)	(0.111)	(0.0425)
Panel B. Dependent Variable: Calories					
	Total	Taxed Drinks (TD)	Untaxed Drinks (NTD)	Taxed Food (TF)	Untaxed Food (NTF)
Tax (main specification)	-69.89	-112.10***	15.08	-84.69***	111.80*
	(97.39)	(29.18)	(22.73)	(24.44)	(67.68)
Tax (accumulated)	-39.13	-103.4***	32.84	-72.97***	108*
	(92.89)	(30.68)	(24.18)	(24.26)	(62.39)

This table estimates the effect of the tax on prices and calories by adding a one-period lagged variable as control. The methodology and definitions are as before. For ease of comparison first we show the main results from Table 2, and what Hausman and Rapson (2018)) call the accumulated tax effect ($\frac{\tau}{1-\alpha}$), which corresponds to the immediate tax effect divided by one minus the lagged y-variable coefficient and shows the result of adding the dynamic effect to the tax effect. The coefficient on the lagged variable was estimated separately. All estimations consist of a local linear regression of a second degree polynomial with triangular kernel weights and a 52 week bandwidth, estimated using *rdrobust* in Stata. We added the lagged variable as part of the partial-out and for the estimation of the accumulated tax effect. All errors are clustered at the household level.

F.3 BMI estimations

Table OA-20: BMI estimates

VARIABLES	BMI regression: Single	BMI regression: Joint	Tax effect	Impact on BMI
$\log(calories)$	0.973***	0.811*	-0.0035	-0.003
	(0.123)	(0.418)		(0.0004)
$\log(sugar)$	0.803***	1.506***	0.00978	0.008
	(0.0872)	(0.329)		(0.009)
$\log(saturated\ fat)$	0.563***	0.113	0.0313***	0.018
	(0.107)	(0.346)		(0.0033)
$\log(carbs)$	0.836***	-1.345***	0.0198**	0.0166
	(0.101)	(0.513)		(0.0020)
$\log(cholesterol)$	0.252***	-0.0365	0.126***	0.032
	(0.0594)	(0.0827)		(0.0075)
$\log(sodium)$	0.564***	0.437***	0.0577***	0.033
	(0.0733)	(0.110)		(0.0042)
$\log(proteins)$	0.308***	-0.671***	0.0383***	0.012
	(0.0929)	(0.229)		(0.0035)
Joint effect				-.0163
(IC 95%)				(-0.041 , 0.009)
Observations	8,074	8,074		

The first and second column show the result of estimations using household level observations of the household's head BMI versus the different nutrients. The *single* column corresponds to individual regressions of BMI versus each nutrient separately. Therefore, each line reflects a separate regression. The *joint* column is the result of a single regression of BMI versus all the nutrients. The tax effect column corresponds to the tax estimates on each nutrient's consumption and correspond to the RD estimates shown in Table 2. Finally, the last column shows the result that the tax effect on nutrients would have on BMI by combining the effects of columns (1) and (3). The last line indicated as the *Joint effect* does the same calculation, but combining the results from columns (2) and (3).

Appendix G. Longer Run Effects

G.1 Synthetic Controls Exercises

Throughout the main paper, we focused on short-term results given that the RD methodology we rely on is local in nature. Longer run effects are, however, certainly of interest. Unfortunately, these are harder to estimate, both because the time span in our data is not long and because the policy we study was national, making it difficult to identify a control group that was unaffected by the tax. Figure 2 shows that although there was an immediate decrease in calories from TDs consumed, afterwards there is an upward trend, reaching a level that is close to the pre-tax one. That said, many things may have changed after the tax, and the event study methodology is less credible if we extrapolate for months after the event. In an attempt to shed some light on long-term outcomes, we employ a synthetic control method (SCM) to compare the consumption of sodas for households in Mexico with that of households in six Central American (CAM) countries (Costa Rica, Guatemala, Honduras, Nicaragua, Panama and Salvador) for which we also have scanner data for the same period of time. We additionally present results from a difference-in-differences estimation, comparing households with high versus low pre-taxes consumption of taxed products as the treatment and control groups.

Figure OA-16 uses a synthetic control method to try to get at causality. We focused on CAM countries because their obesity patterns and diet are similar to those in Mexico (see our working paper version of this paper), and because we were able to obtain consumption data for them, covering the same dates (2013-2014) also collected also by KWP using the same methodology as for Mexico. For the estimation, we use all of our Mexican households and 1,954 households for the CAM. An observation in the data is a month of consumption of liters of sodas for a given household. We also observe their monthly expenditure (converted to Mexican pesos) on drinks and food, as well as total liters and kilos of drinks and food purchased (i.e., we observe 5 variables). Unfortunately, neither data on calories purchased or information on food by category is available to us.

We are interested in estimating the effect of the tax on the purchase of sodas for Mexican households. Our dependent variable is the liters of soda purchased in a month by a household. We standardize each observation by subtracting its household specific 2013 mean and dividing it by its household specific 2013 standard deviation. In contrast to Abadie and Gardeazabal (2003) and Abadie et al. (2010) we have multiple treated units. We define a household as treated if it resides in Mexico and the year is 2014. All households in the CAM are potential controls.[40] Several recent papers have shown how to apply SCM methods for multiple treatment units (e.g Acemoglu et al. (2016), Cavallo et al. (2013), Firpo and Possebom (2018), Xu (2016)). Roughly speaking, for each Mexican household, the SCM selects a set of control households in CAM and applies weights to each of them in order to minimize the pre-treatment period distance between that Mexican household and its synthetic control on the five variables we mentioned above. It then calculates the treatment effect in 2014 for *each* Mexican household by comparing soda consumption to that of *its* synthetic control. We then average the treatment effects across the multiple treated units. We obtain confidence intervals by bootstrapping.

For this purpose, we start by describing how we calculated clusters of households using k-means clustering. We first chose the number of clusters we wanted (arbitrarily 400 clusters of households in Mexico and 100 for CAM).[41] The method's objective is to allocate n households across a partition $S := \{S_1, S_2, \dots S_k\}$ if

[40] Once we have multiple treatment units and resampling confidence intervals, the SCM is computationally demanding. As a dimension reduction strategy, we formed 400 clusters of households in Mexico and 100 for CAM using k-means clustering, and keep in the dataset only the median household in each cluster.

[41] Results were similar with other number of clusters.

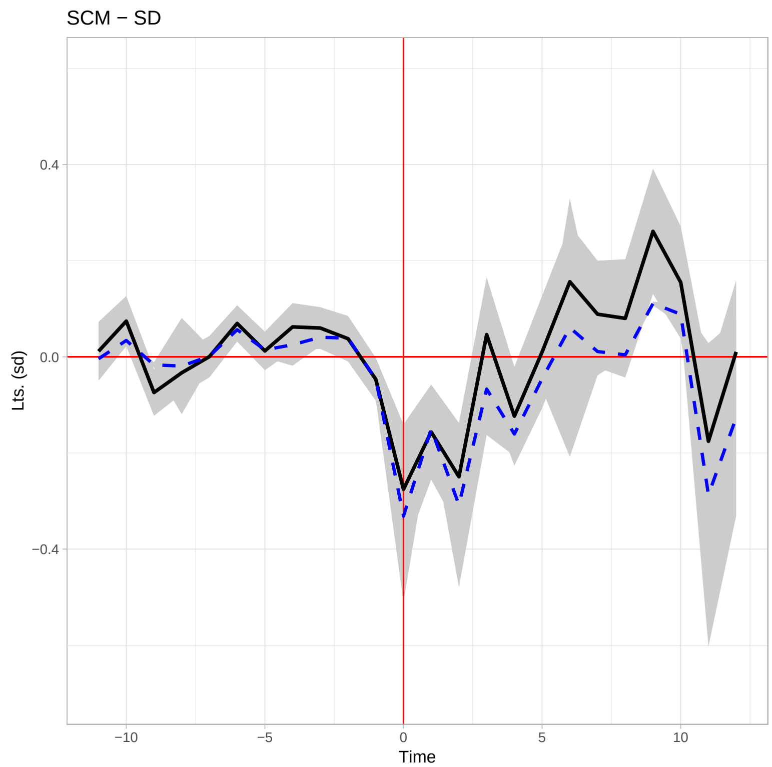
k clusters in such a way as to minimize the average within cluster difference in their consumption of good x (e.g. soda). More formally, given consumption of good x_i for household i, where $x_i = (x_i^{-12}, x_i^{-11}, \ldots, x_i^{11})$ is a vector indicating monthly consumption of the good in 2013 and 2014, we solve th following problem:

$$\text{argmin}_S \sum_{i=1}^{k} \sum_{x \in S_i} ||x_i - \mu_i||^2$$

where μ_i is the median households in cluster S_i. We do this separately for Mexican and CAM households. Finally, so we eliminate households whose mean square error compared to their synthetic control in the pre-treatment period is in the top 10%, this improves the pre-treatment fit. Once the clusters are formed, we take the median household in each one as the representative household of given cluster.

Figure OA-16 presents the estimated treatment effect by month. The y-axis is measured in standard deviations of liters. The solid line reports mean treatment effects and the dashed line median treatment effects, while the gray area corresponds to 99% confidence intervals for the mean effect obtained by bootstrapping. The x-axis is event time, where January 2014 is time zero and December 2014 is time 11. The pre-treatment period shows a reasonably good synthetic control fit in 2013. Immediately after the tax came into effect, we estimate a decline of about 0.2 standard deviations in the consumption of liters of sodas by Mexican households compared to their synthetic controls. This is equivalent to 0.8 liters per household-week (close in magnitude to the RD estimate), but it is short lived, reverting to a an effect of zero 3 months after. The effect becomes less precise with time, but there is no noticeable downward trend. This suggest that there is no long run decline in soda consumption, and given our previous substitution results, it is even less likely that there is a decrease in total caloric consumption. A word of caution is in order, as the SCM imposes more identifying assumptions than the RD method, it is best to take care in interpreting these effects, especially for longer periods of time.

Figure OA-16



Notes: This figure plots causal estimates of the effect of the tax on soda consumption under the assumptions of the Synthetic Controls Method (SCM). Time=0 is January 2014. The Y-axis is measured in standard deviations of liters and kilos respectively. The solid line reports mean treatment effects and the dashed line median treatment effects, while the gray area correspond to 99 percent confidence intervals for the mean effect obtained by boostraping. A treated unit in our SCM is a Mexican household after 2014. Control units are households in 6 Central American countries as described in the text.

G.2 Comparing high vs low consumption households

This subsection uses differences in differences to compare the evolution of consumption of calories before and after the tax for previously low vs high consumption households. We should mention from the start that we view these results as tentative, with weaker identification since in reality both groups we look at were treated.

We are interested in estimating the change in consumption of calories caused by the tax by comparing groups more vs less exposed to it. This requires identifying groups that were hit more heavily by the tax than others. We decided to experiment with "exposure" to taxed goods measured as quantities of those goods bought in 2012-2013 (pre-reform). We use expenses in pesos, but using quantities measured in liters or kilos gave similar results. We define households as "treated" if they were in the top 20 percent of the distribution of expenditure on (future) taxed goods, and as "controls" if they were in the bottom 20 percent[42]. By construction the treatment group will tend to have a higher level caloric consumption from taxed goods. These differences in levels will be absorbed by a household fixed effect. The identification assumption for a differences in differences causal estimate is parallel trends, i.e. that the high expense household would have experienced the same *change* in caloric consumption than the low expense households if there was not tax. This is not a weak

[42]We experimented with other cutoff with similar results. We settled on these ones since they showed slighlty more balanced pre-trends.

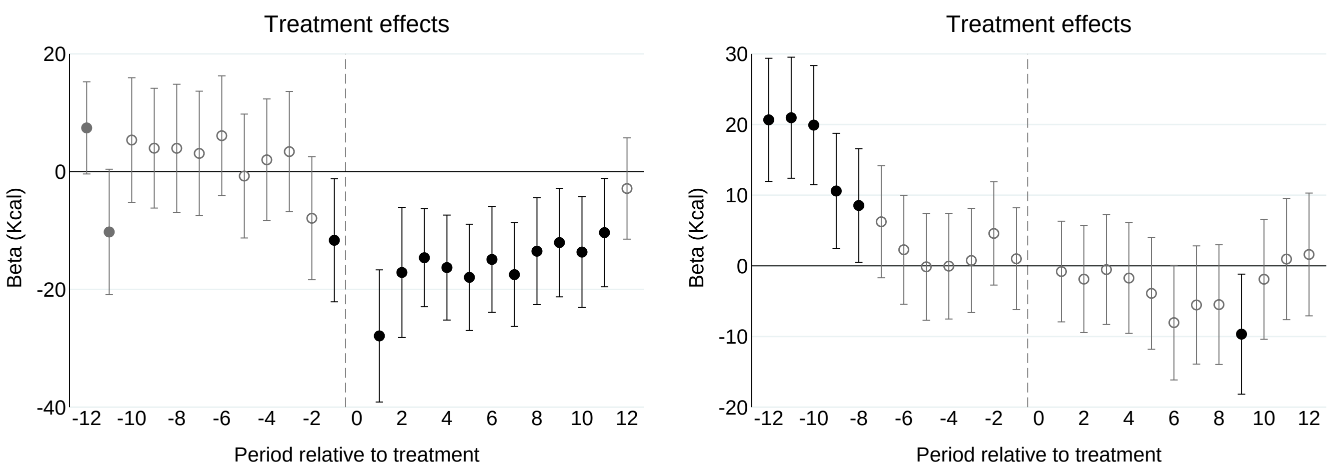
assumption. We will asses if this assumption is reasonable by testing if trends in calorie consumption were indeed parallel before the tax.

Equation 8 presents the specification that we estimate by OLS using monthly data from January 2012 to December 2015. This gives us information 2 years after the tax came into effect.

$$Y_{it} = \alpha_i + \gamma_t + \sum_{k=-24}^{24} \beta_k \, T_i \times I(t = k) + \nu_{it} \tag{8}$$

α_i is a household fixed effect to control for differences in the level of caloric consumption across households, γ_t is a month dummy capturing trends in caloric consumption that apply broadly to treatment and control households. We define $t = 0$ for December 2013, to estimate an event-time DID. The parameters of interest are the β_k's. Parallel pretreatment trends can be tested by an F-test of $\hat{\beta}_k = 0$ for all $k < 0$. The effect of the tax is given $\hat{\beta}_k$'s for all $k > 0$. Errors are clustered at the household level, and the set of barcodes for which calories are measured are kept fixed across time.

Figure OA-17: Differences in Differences: Calories



(a) Taxed Drinks **(b)** Taxed Foods

Notes: Panel (a) displays raw data from January 2012 to December 2015. The solid lines represent average caloric consumption of taxed drinks, and the dashed lines are linear approximations. Panel (b) plots the dif-in-dif $\hat{\beta}_k{}'s$ coefficients from the following regression $Y_{it} = \alpha_i + \gamma_t + \sum_{k=-24}^{24} \beta_k \, T_i \times I(t = k) + \nu_{it}$

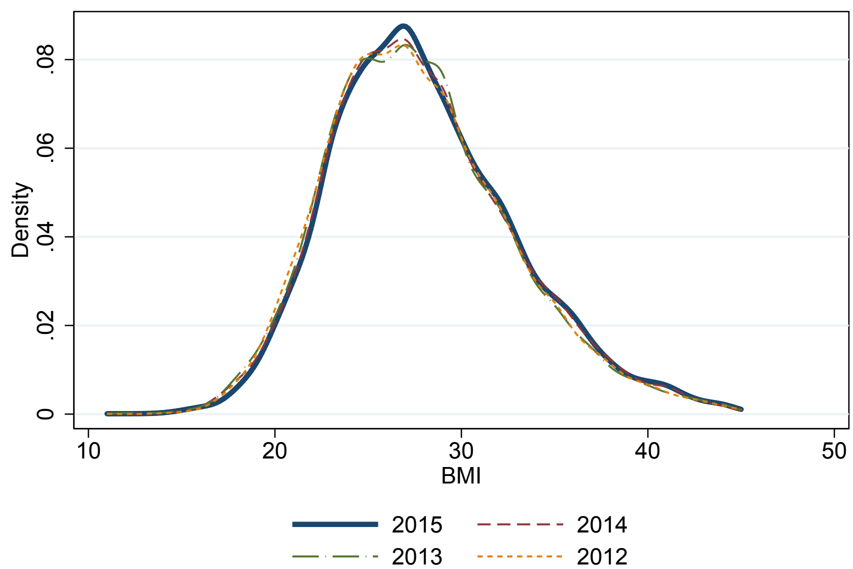
Figure OA-17 plots $\hat{\beta}_k{}'s$ coefficients from equation 8 when the dependent variables is calories from taxed drinks. The first result is that we cannot reject $\hat{\beta}_k = 0$ for all $k < 0$ at standard confidence levels. However balance is not perfect; we observe a decrease in caloric consumption one month before the tax came into effect.[43] After the tax we observe a sharp and precise (although economically small) decreases in calories from taxed drinks purchased, and these differences are eroded in time. One year after the tax we do not find differences between control and treatment groups.

[43] If they were anticipating a price increase we would have expected hoarding, i.e. *increases* in taxed goods purchased, not decreases.

Appendix H. Estimates of effects on BMI

The taxes introduced were aimed at combatting obesity. For this reason, individuals' BMI may be the most relevant outcome to analyze. If the intake of total calories did not change as a result of the taxes, we should not observe significant changes in BMI. Before presenting a differences in differences analysis, Figure OA-18 just plots kernel densities of BMI for several years in Mexico, from two years before and two years after the tax. The resemblance is striking. There was no change in BMI in any part of the distribution.

Figure OA-18: Overweight in Context



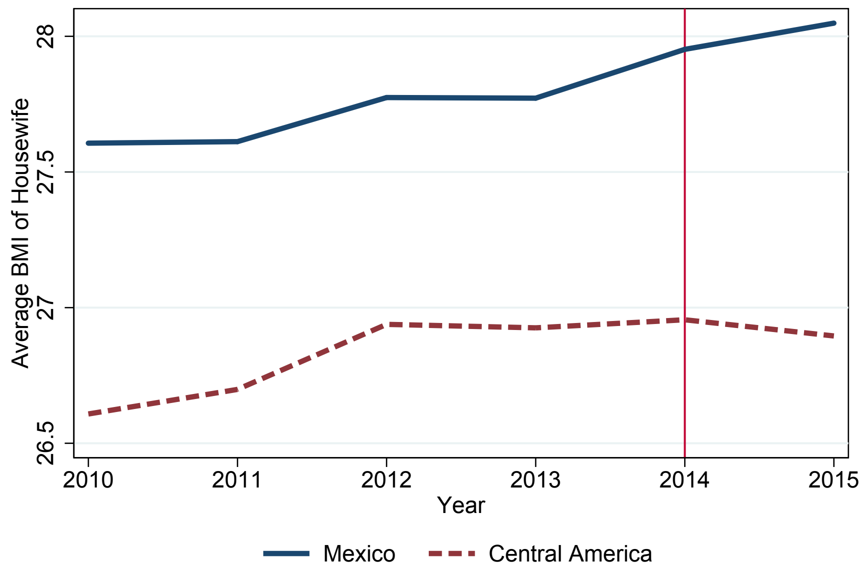
Notes: Source: Kernel density estimates of BMI as reported in KWP.

Figure KWP OA-18 of course does not contain a counterfactual comparison. We would need a control group for which there was no tax in 2014. Our empirical strategy next is to compare Mexico vs its Latin American neighbors. This is reasonable since (a) we find the same pre-trends in BMI, (b) the tend to consume similar baskets of goods, (c) they were not subject to the tax and we were able to get BMI data at the household level from the same source (KWP) using the same methodology.

We use yearly self-reported information on the weight and height of female household heads for participating households in Costa Rica, Guatemala, El Salvador and Panama as a control group[44] for Mexican households. Our identification assumption is that in the absence of the taxes households in Mexico would have experienced a similar change in BMI as households in the these four countries. As shown below this assumption is reasonable; these countries have similar pre-trends in BMI than Mexico.

[44] KWP collects BMI for a subset of 89 percent of male households heads in Mexico, but unfortunately this information is only available for 2 years in Central America. We therefore focus on BMI of the female head. We have 54,143, 4,442, 4,918, 4,026 and 4,315 household-year observations from Mexico, Costa Rica, Guatemala, El Salvador and Panama, respectively on the female heads BMI.

Figure OA-19: BMI Trends in Mexico vs Central American Countries



Notes: The graph simply plots BMI for our sample of female household heads in Mexico, and for the rest of Central American countries, pooling all samples together.

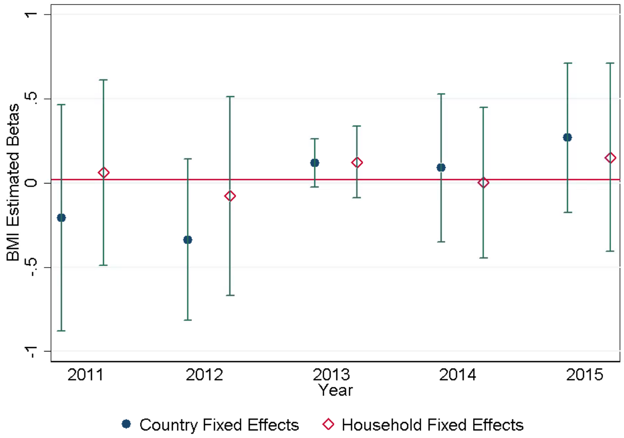
Figure OA-19 shows that —consistent with WHO's data— BMI has increased both in Mexico and the rest of countries in Central America during the period of analysis. This adds confidence that the BMI data is not noise with the same mean each year. Moreover, although BMI is higher in Mexico than in the rest of Central America, the time trends showed by both Mexico and the rest of Central America are relatively similar before the enactment of the tax, supporting the identification assumption of parallel pre-treatment trends.

Graphical evidence suggest that there was not change in the evolution of BMI over time for Mexico after the taxes were introduced. In order to provide statistical evidence we estimate the following difference-in-difference (DD) specification:

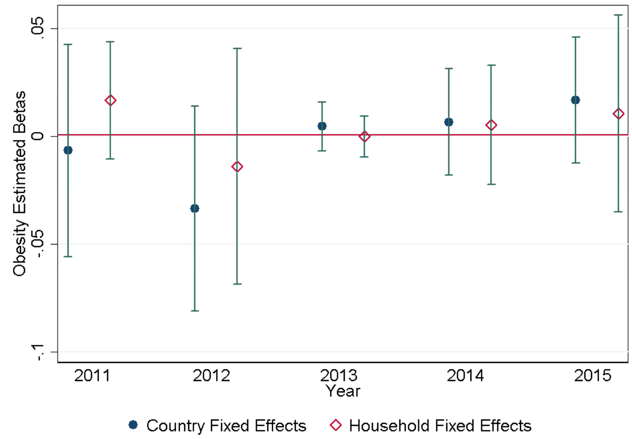
$$BMI_{ijy} = \alpha_j + \theta_y + \sum_{t=2011}^{2015} \beta_t Mexico_j * I(y=t) + \epsilon_{ijy} \tag{9}$$

Where i, j and y denote individual, country and year. The equation includes dummies for 5 years 2011-2015 (θ_y), dummies for each Central American country (α_j) to allow for country-specific BMI levels, and an interaction of the Mexico (*treatment*) dummy with the year dummies. We cluster standard errors at the country level. The β_t's are the coefficients of interest, which measure the differential change in BMI (respect 2010) experienced in Mexico versus other Central American countries each year.

Figure OA-20: BMI and Obesity Differences in Differences Analysis



(a) International Commerce



(b) National Production

Notes: This Figure plots the coefficient estimates from equation 9. Results from years 2011, 2012, and 2013 show that the parallel trends assumption is satisfied. Results from 2014 and 2015 show that there is no effect of the tax.

Because the panels are unbalanced, we present regression results with and without female household head fixed effects. Figure OA-20 plots the estimated β_t's along with their 95 percent confidence intervals. The joint F-test for $\beta_j = 0 \quad \forall\, j \in \{2011, 2012, 2013\}$ is not rejected (p-value=0.17), suggesting that the parallel trends assumption holds. The coefficients for 2014 and 2015 show no effect of the tax on BMI for Mexico. The effect of the tax on weight may take time, but the fact that β_{2015} is larger than β_{2014} is discouraging. Panel B of figure OA-20 uses the fraction of obese population as a dependent variable and reaches similar conclusions. Given the strong relationships between household members BMIs found in the literature, we believe our results may apply more broadly to other household members.[45]

[45] We actually estimate a coefficient of 0.46 (t-stat=95) in a regression of male and female household heads BMI's. In power simulations that use our exact empirical specification we obtain that we are able to detect effect sizes of about 0.75 BMI points and 1.3 kilos with 90 percent power and 95 percent confidence.