Product reformulation with endogenous unobservables: Evidence from the soft drinks industry levy in the UK

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Abstract

Tax policies can correct distortions due to externalities and behavioral biases, but their design is crucial for aligning economic efficiency and equity. This paper examines how the multi-tier structure of the 2018 UK Soft Drinks Industry Levy led firms to reduce sugar content in their products, achieving a substantial reduction in sugar consumption while also lowering the tax burden on consumers. I model the endogenous relationship between sugar content and products' unobserved characteristics, like taste and quality, using a factor structure to estimate that reformulation achieved a further 38% reduction in sugar intake while preventing an additional 15% increase in prices. Moreover, I find that smaller firms were most affected, while larger firms adopted new technologies to meet their reformulation needs. These results highlight the potential of well-crafted taxes to internalize social costs and promote innovation to reduce harm at its source.

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1 Introduction

Excessive sugar consumption is a primary contributor to the global obesity crisis, with soft drinks standing out as one of the leading sources of sugar intake —particularly among younger and economically disadvantaged populations. In response, governments have increasingly turned to taxes on sugary drinks to curb overconsumption, sparking concerns about the distributional impact of these policies. The design of these taxes plays then a critical role in aligning their efficiency and equity. By shaping firm incentives, well-crafted tax structures can encourage non-price responses, such as product reformulation, that lower sugar content per product while simultaneously reducing the tax burden on consumers.

This paper studies the supply-side responses to one such policy: the UK Soft Drinks Industry Levy implemented in 2018. First, I document how firms reacted by reformulating their products, lowering their sugar content to just below the levy thresholds to minimize or avoid the tax. This reformulation not only contributed to a reduction in sugar intake but also diminished unobserved product utility, leading to less differentiation and greater price competition. I then develop an equilibrium model of product reformulation that combines Interactive-Fixed-Effects (IFE) with micro-founded moments to break down and quantify the welfare effects of these changes. This approach captures the potential relationship between a product's sugar content and its unobserved traits, like quality or taste. By doing so, the model addresses a common endogeneity problem between observed and unobserved product characteristics. It also accounts for how changes in observed characteristics can trigger simultaneous adjustments in unobserved ones. This allows for partially observed reformulation and extends the use of Interactive Fixed Effects to counterfactual analysis and policy evaluation.

My findings show that reformulation enhanced the policy's impact, leading to a further 38% reduction in sugar intake while preventing an additional 15% price increase. This significantly lowered the tax burden on consumers but also reduced fiscal revenues. I also find that smaller firms were more affected and had lower reformulation rates, suggesting they face higher barriers to adapting their products. Meanwhile, larger firms adopted new technologies to meet their reformulation needs and prevent further revenue losses. These

results demonstrate how well-designed taxes can correct consumer biases, drive industry innovation, and prevent harm at its source. They also suggest the need for complementary policies, such as reformulation subsidies or technical support, to help independent firms remain competitive.

Discussions on corrective food policies have traditionally focused on consumer-side responses and their effectiveness. However, recent research underscores the critical role of firm responses to these policies, such as product reformulation (Barahona, Otero, and Otero, 2023; Griffith, O'Connell, and Smith, 2017) and adjustments to advertising schedules (Dubois, Griffith, and O'Connell, 2018). Shifting attention to supply-side dynamics also raises important questions about the role of market power in shaping the efficacy of these interventions (O'Connell and Smith, 2020). It is now understood that supply-side responses can significantly strengthen —or undermine —the effectiveness of corrective policies and must therefore be carefully considered in their design. However, accounting for firm responses requires a comprehensive understanding of both consumer demand and firms' decision-making processes. Each of these tasks presents its unique set of challenges.

On the demand side, traditional approaches that rely solely on prices and a narrow set of product characteristics have shown limited effectiveness in explaining differences in consumption patterns on food and drink across countries (Dubois, Griffith, and Nevo, 2014). This shortcoming can be partly attributed to the nuanced nature of these products, as foods and beverages with identical ingredients may be perceived differently based on their preparation methods, making difficult an objective and comprehensive characterization of these products. Additionally, consumers often exhibit heterogeneous preferences over the same set of products, further complicating the analysis of demand in these markets. On the supply side, firms face the complex challenge of defining their product offerings in a dynamic and competitive environment. While this provides multiple opportunities to study firms product decisions, it also expands their decision space, significantly increasing the computational demands required to analyze these choices

This paper addresses these challenges through several innovations. First, it explicitly allows unobserved product characteristics to influence consumer demand in an additive way, acknowledging the limitations analysts face in observing all relevant product dimen-

sions. Second, it combines Interactive Fixed Effects with moments derived from firms' decision-making processes to allow unobserved product dimensions, such as quality or taste, to be arbitrarily correlated with observable characteristics like sugar content. Third, it accommodates heterogeneous consumer preferences for both observed and unobserved characteristics. Fourth, defines the firm problem as a two-stage game where firms first define the characteristics of all their products simultaneously and then engage in Bertrand price competition. Fifth, it rationalizes the observed stickiness in product offering by introducing a fixed per-product reformulation cost. This helps the model capture the slow moving dynamics in product offering.

I combine these elements in an equilibrium model of product reformulation that allows firms to respond to a change in their expected profits, such as the introduction of a corrective tax. The observed characteristics will be the nutritional information included in the drink's packaging while the unobserved dimensions will be the products' perceived quality, which I associate with its taste and experience.

Model estimates show that product reformulation accounts for 28% of the observed reduction in sugar intake and prevents an additional 15% increase in prices. The reduction in products sugar content helps firms minimize or avoid the tax, this decreases fiscal revenues and lowers the burden on consumers - mitigating potential distributional concerns. Moreover, reformulated products contain less sugar but also exhibit lower unobserved quality compared to their pre-reformulation counterparts. This reduction in quality diminishes product differentiation and intensifies price competition. Additionally, small firms were the most affected, and the ones with the least number of reformulated products. This suggests they face greater barriers to adjust their products in response to the policy. Also firms appear to price their goods in a way that it is close to a perfect pass-through of the tax.

A regression analysis of estimated marginal costs reveals structural differences for reformulated products, indicating that firms employ a distinct underlying technology for their production. This finding suggests that the tax incentivized firms to adopt or develop new production technologies to meet their reformulation needs, and thus, driving innovation within the industry.

This paper contributes then to four branches of the empirical literature:

First, it contributes to public economics and the study of corrective taxes by highlighting the critical role of tax design in shaping non-price responses from firms. Specifically, it demonstrates how product design choices can simultaneously prevent price increases, reduce the tax burden on consumers, and address externalities and internalities at their source. This minimizes potential distributional concerns stemming from variations in the marginal utility of money across consumers and introduces a new mechanism through which corrective taxes influence welfare —one not considered in the standard optimal corrective taxation framework (Allcott, Lockwood, and Taubinsky, 2019). This underscores the importance of the targeting principle while revealing the limitations of indirect taxation through downstream goods.

Second, it adds to the health economics literature on the equilibrium effects of corrective food policies in two ways: (1) it shows the potential of these policies to induce innovation and drive technological change, enabling the development of healthier products; and (2) to the best of my knowledge, this is the first paper to examine the welfare effects of product reformulation driven by such policies while accounting for unobserved changes in taste and perceived quality that accompany reductions in sugar content. This approach not only acknowledges the nuanced nature of these products, but also the heterogeneity in consumer preferences, providing a more comprehensive understanding of the welfare implications of these interventions.

Third, this paper makes two contributions to the empirical Industrial Organization literature: (1) it advances the analysis of demand estimation with endogenous unobservables by proposing the use of factor models to address the endogeneity issues arising from the potential correlation between observed and unobserved product characteristics; and (2) it introduces a framework for studying partially observed product reformulation, capturing changes in a product's unobserved characteristics when these changes can be inferred from changes to the observed ones. This dual contribution provides a novel methodological approach to analyzing product-level responses in markets with subtly differentiated goods like food and beverages.

Fourth, this paper contributes to the applied econometrics literature on factor models

in large panels. It provides a clear example where classical regularization conditions traditionally used to separately identify factors and loadings may be inconsistent with the economic interpretation of these parameters. Instead, the paper proposes leveraging moments derived from the underlying economic model, offering a more theoretically grounded approach to identification and estimation. This intuitive interpretation enables a more meaningful understanding of the parameters, allowing them to be used for counterfactual simulations and policy evaluation.

The structure of the rest of the article is as follows. The next section provides an overview of the UK's soft drinks industry levy, including the challenges encountered during its announcement and implementation. Section 3 outlines the data utilized and documents five facts of the UK's soft drinks market response to the industry levy. Section 4 introduces my model of product reformulation and explains how it accounts for endogenous unobservables with partially observed product changes. Section 5 discusses the model identification and Section 6 explains my empirical approach for estimation. Section 7 presents and discusses the results of the estimation. Section 8 presents the policy counterfactual to measure the welfare effects of the Soft Drinks Industry Levy. Finally, Section 9 concludes by summarizing the findings from the model and discussing their implications for the effectiveness of corrective taxes and food policies in general.

2 Soft drinks industry levy

The UK Soft Drinks Industry Levy[1] was formally announced on the 2016's March budget and implemented in April 2018. The levy applies to non-alcoholic beverages containing added sugar or sugar-containing substances, excluding fruit juice, vegetable juice, and milk. Additionally, beverages classified as "flavour concentrate" are also subject to the levy. For classification purposes, sugar includes sucrose, glucose, fructose, lactose, and galactose, but excludes sugar replacements like stevia, aspartame, and sucralose.

Certain drinks are exempt from the levy. These include beverages that are at least 75% milk or milk substitutes, alcohol replacements, and drinks made solely with fruit or vegetable juice without added sugar. Additionally, liquid drink flavourings, powdered drinks, and beverages prepared by mixing liquids and served in an open container are not subject to the levy. Other exempt categories encompass infant formula, follow-on formula, or baby foods, as well as formulated foods intended for total diet replacement or special medical purposes.

The levy amount varies based on the sugar concentration of the liable drink. Drinks with a total sugar concentration of less than 5 grams per 100ml have their levy set to 0, effectively exempting these products from the tax. For drinks with a sugar concentration between 5 grams and 8 grams per 100ml, the levy is 18 pence per litre. Meanwhile, drinks with a sugar concentration of 8 grams or more per 100ml incur a levy of 24 pence per litre. This is summarized in Table 1.

Sugar per 100ml	Tax (per liter)
Less than 5 grs	£0.00
Between 5 and 8 grs	£0.18
More than 8 gr	£0.24

Table 1: Levy rates based on sugar concentration

Every year, the levy generates about £340 million, with 96.6% of these revenues coming from products in the highest levy tier[2]. However, this total is noticeably lower than the £520 million originally projected when the policy was announced[3]. One reason for the

[1] https://www.gov.uk/money/soft-drinks-industry-levy
[2] HM Revenue & Customs - Soft Drinks Industry Levy statistics commentary 2024
[3] HM Treasury, Budget 2016 Policy Costings, March 2016 p12

shortfall is that firms' response was stronger than expected, as they reformulated their products to reduce sugar content. This outcome was, in fact, a key goal of the policy.

Finally, although levy funds were initially intended for childhood obesity programs, they have gradually been absorbed into the general tax pot since the policy's first year. The government has announced that, starting from 2025, the soft drinks industry levy will be gradually increased over the next five years to reflect accumulated inflation, ensuring its real terms value is maintained.

3 Data

I use data from various sources to study how the market responded to the Soft Drinks Industry Levy. I focus on the aspects that shape competition in this market, namely data on purchases, prices, and product composition coming from a household consumption panel. Additionally, I look at changes on the ownership structure of firms from a tracker of capital market transactions and gather data on key input prices from the UK's Office of National Statistics. I then combine information from these sources to presents a novel set of facts illustrating what happened in the industry after the policy took effect. In summary, the levy led to a drop in sugar content, which intensified price competition and reduced market concentration. As a result, product differentiation seems to have diminished in the market, which may help explain the increase in mergers and acquisitions in recent years.

3.1 Data sources

My three sources of data are: the Kantar Worldpanel survey, a nationwide consumption panel from a commercial provider; official price data from the UK's National Office of Statistics (ONS); and information on financing deals, including mergers and acquisitions, from Pitchbook, a large data provider of market and finance operations. I describe each of these sources below:

3.1.1 Household consumption survey

The Kantar Worldpanel survey provides comprehensive data on fast-moving consumer goods purchased by approximately 35,000 households across the UK over a period of 15 years. Participating households utilize handheld scanners to record their purchases and receive non-monetary incentives for their engagement. This survey also offers data on household demographics and product nutritional information, which I leverage to monitor changes in product compositions over time.

3.1.2 Input prices

In my analysis, I construct demand instruments using data on the prices of goods crucial for the soft drinks industry or relevant due to their impact on logistics. These prices serve as regional cost shifters for the estimation process. I source this data from the National Office of Statistics (ONS), which provides the price quotes used to calculate the Consumer Price Index (CPI) and data on industrial output prices from the Producer Price Inflation (PPI) time series.

3.1.3 Corporate deals

I track changes in firm ownership and market concentration using data from Pitchbook, a widely recognized source for tracking financing deals and capital market transactions. This dataset provides detailed insights into mergers, acquisitions, and investment activity, allowing for a comprehensive view of how ownership structures evolve in response to market dynamics.

Between 2001 and 2024, Pitchbook records a total of 1,012 corporate deals involving 525 companies, with investments totaling £5.6 billion (USD$6.92 billion). In terms of capital allocation, 64% of these transactions correspond to Mergers and Acquisitions, while 15% represent investments by Angel and Venture Funds, and 13% are Initial Public Offerings (IPOs). This distribution highlights the predominant role of corporate consolidation in shaping the market, alongside significant contributions from early-stage investments.

Deal Type	Count	Capital Invested	% of Total
Mergers/Acquisitions	222	£3,717	64%
Angel & Venture Capitals	703	£850	15%
IPOs	9	£743	13%
Other	123	£540	9%
Total	1,057	£5,850	100%

Table 2: Corporate deals by type

3.2 Key facts from the post levy market

The Soft Industry Industry Levy had a significant impact in consumers' sugar intake. As shown in Figure 1, there was already a slight trend toward lower-sugar products before the policy was introduced. However, once the levy took effect, the average sugar content per item sold dropped sharply by around 40%, marking a significant shift in the market.



Figure 1: Sugar consumption fell by 40% since the industry levy

This change in sugar intake can't be explained by price alone. Figure 2 reveals the price of both, sugary and non-sugary products increased with the introduction of the levy and that this increase in prices continued afterwards. This suggests firms priced their products strategically to keep relative pricing after the tax was introduced.

A more compelling explanation for this drop in sugar intake is found in products' composition. More specifically, changes to it. As seen below in Figure 3, before the tax,

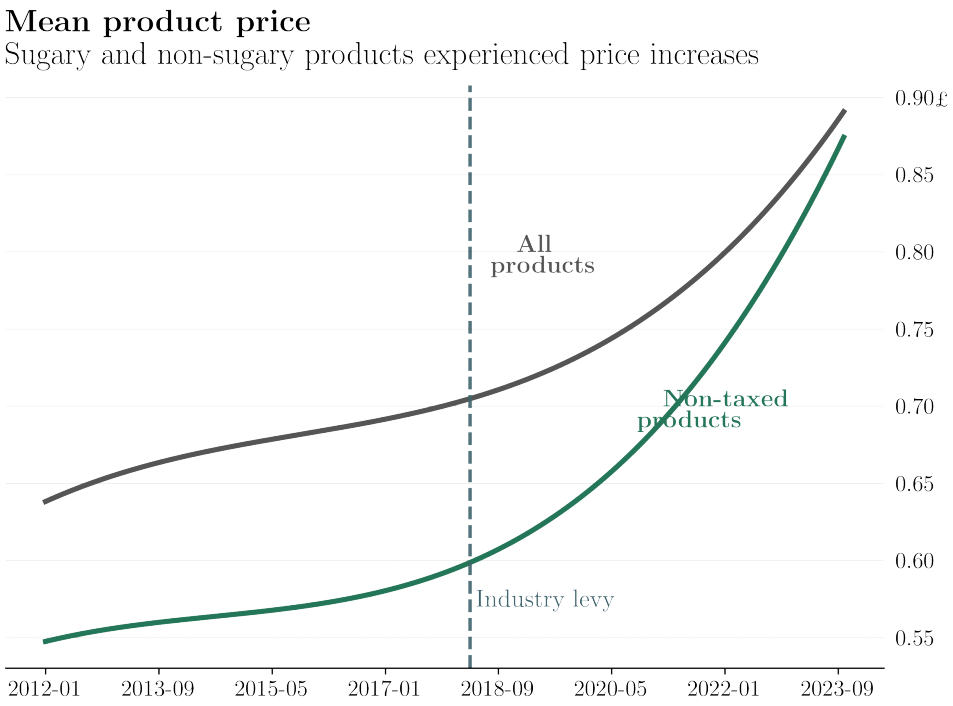


Figure 2: Prices of taxed and non-taxed products increased

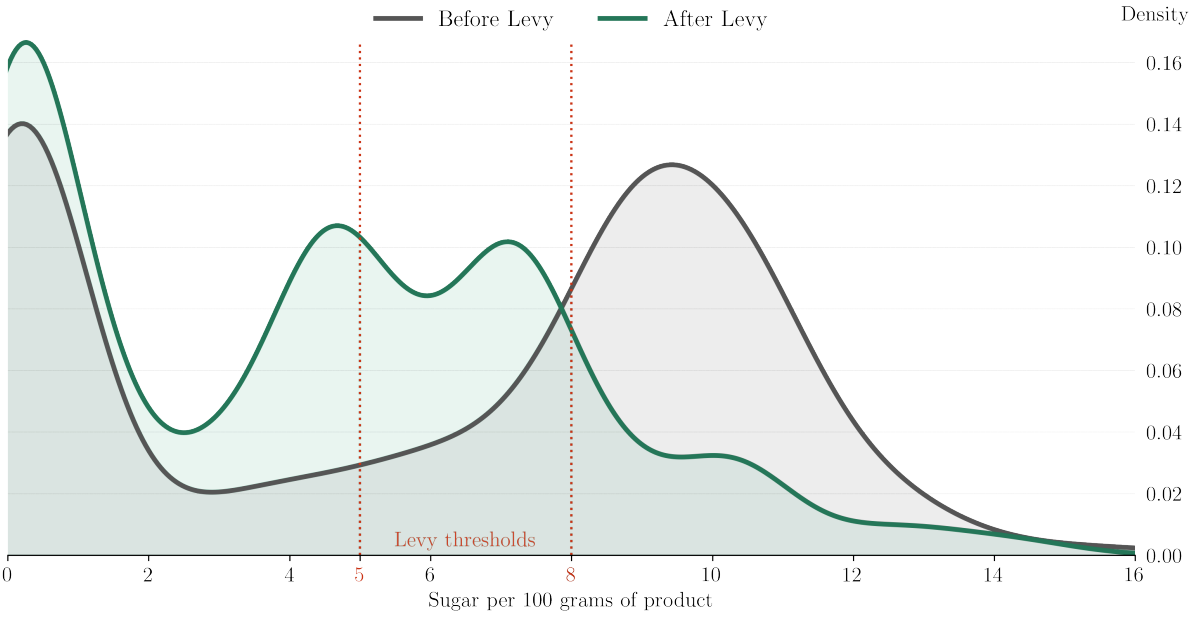


Figure 3: After the levy, products have less sugar and cluster at the levy thresholds

most sugary products tended to be in high end of the sugar content distribution. After the tax was introduced, products' sugar content tended to cluster just below the levy threshold. This means that between 2016 and 2018, firms reformulated their products by cutting down the amount of sugar in them. It also implies that firms firms took into account the design of the policy and responded adjusting their products to fully or partially avoid the levy.



Figure 4: Firms waited until the introduction of the levy to reformulate their products

The timing of this reformulation is not casual. Although the industry had previously experimented by reducing the sugar content of less popular products, it was not until the policy was announced that that they started reformulating their more popular ones. As pictured in Figure 4, the industry's efforts to cut down the sugar-content of their products intensified with the policy announcement in 2016 but spiked in 2018 when the levy came into effect.

Interestingly, reformulation appears to have influenced not only product composition, but also the broader competitive dynamics of the market. This effect is particularly evident in the reduced price dispersion across taxed products (Figure 5), which suggests heightened competitive pressure on prices. Notably, the most pronounced reduction in price variability occurred within the mid or standard rate tax tier, underscoring the tax's role in shaping market behavior in this segment. By contrast, non-taxed products showed an opposite trend, with price dispersion widening as these items claimed a larger share

of the market. These contrasting trends across product categories lead to the belief that the tax affected firms in diverse ways depending on their positioning within the market's product space.

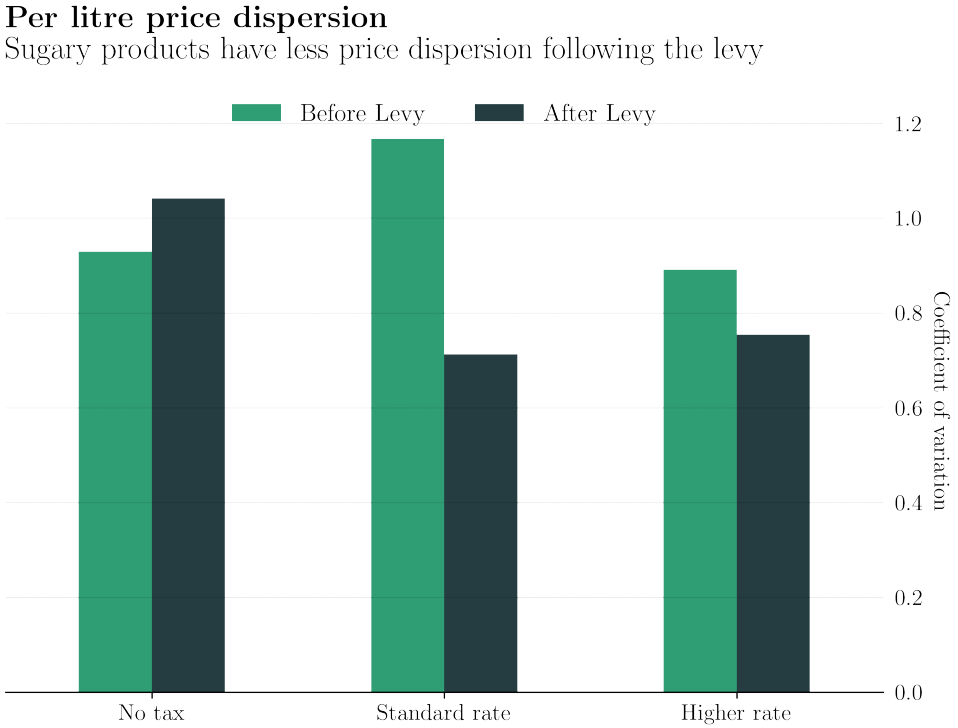


Figure 5: Reduced price dispersion signals a more intense price competition

The change in the market's competitive dynamics is further underscored by the noticeable decrease in market concentration following the tax implementation. As revealed in Figure 6, the product-level Herfindahl-Hirschman Index (HHI) experienced a downward trend across markets, signaling a more evenly distributed competitive landscape. Moreover, not only did the average HHI decline, but its variability also diminished, suggesting a stabilization in market concentration levels.

Finally, these changes may provide insights into the gradual and sustained rise in the number of mergers and acquisitions (M&A) within the market for beverages, as depicted in Figure 7. While the frequency of M&A operations increased over time, the total capital involved remained relatively stable. This trend suggests that these transactions were predominantly focused on smaller firms, potentially as a response to the shifting competitive landscape and market dynamics.

Finally, the changes described above may help explain the gradual rise in mergers and acquisitions (M&A) seen in Figure 7. Notably, while the number of M&A deals increased

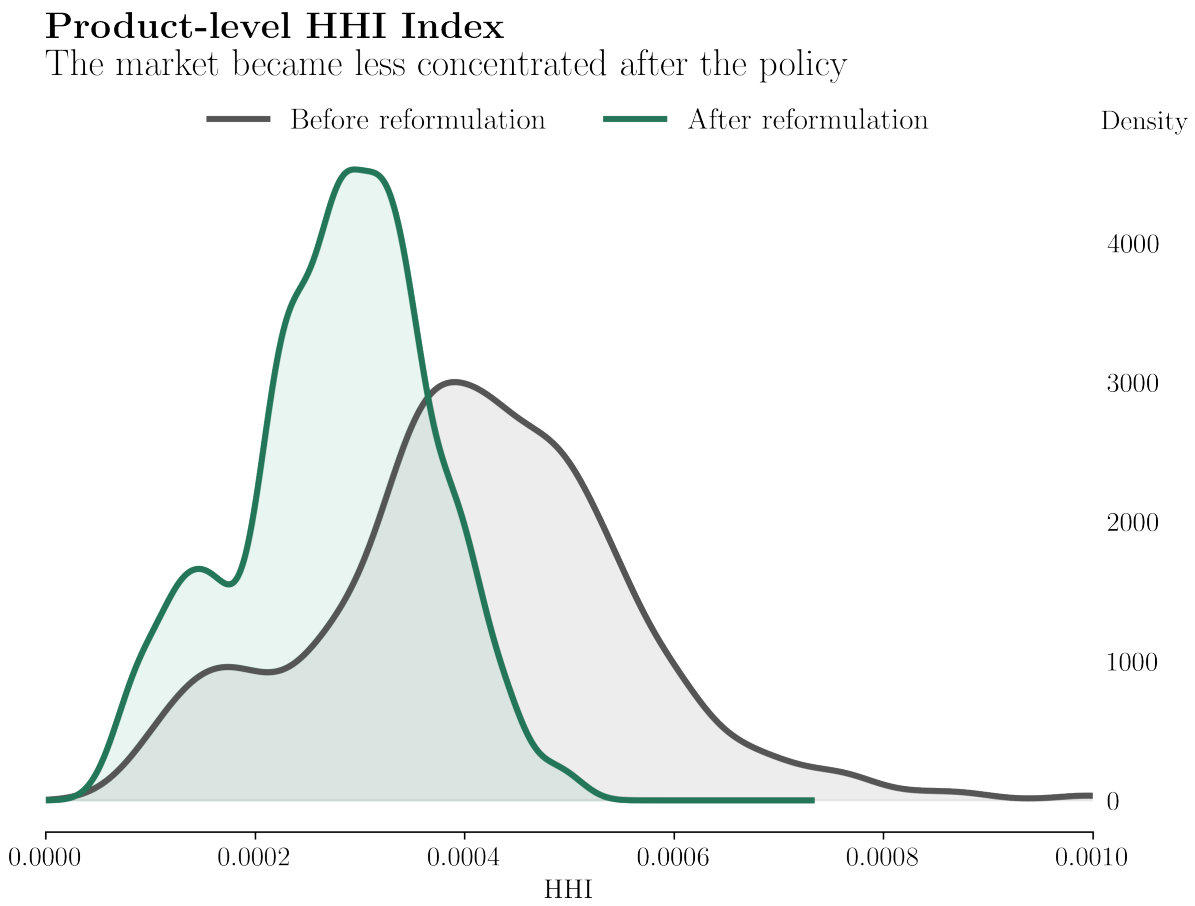


Figure 6: Markets became less concentrate after the tax.

over time, the total capital involved remained relatively stable. This points towards smaller firms being the primary targets of these transactions and that consolidation may have been a strategic response to shifting competitive pressures and evolving market dynamics.

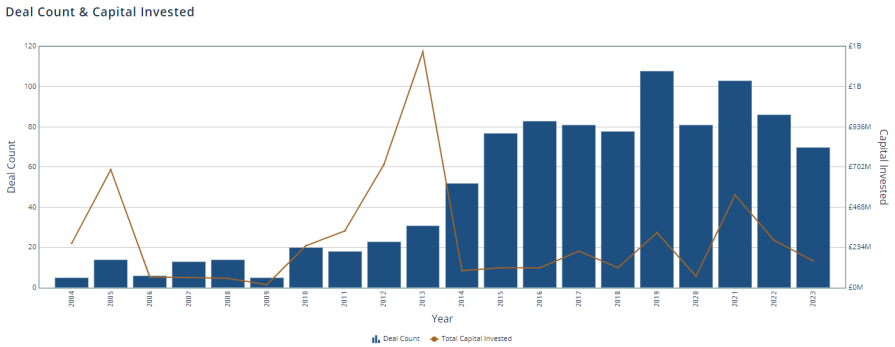


Figure 7: Merge and Acquisition operations increased with the tax implementation.
Source: Pitchbook

3.3 Changes to the soft drinks market after the industry levy

The Soft Drinks Industry Levy had a notable impact on the market, primarily by reducing consumers' sugar intake, which is a key indicator of the policy's effectiveness in addressing excessive sugar consumption. This reduction resulted largely from two mechanisms: higher prices and changes to products' composition aimed at lowering their sugar content. Reformulation, in particular, allowed many firms to partially or fully avoid the tax and potentially limiting further price increases. However, despite these gains, the overall rise in prices for both sugary and non-sugary drinks suggests that firms maintained relative pricing across products. This strategic response undermines the policy's intended effect, highlighting a tension between its success in altering product composition and its unintended consequences on pricing dynamics.

4 Model

To understand these changes and balance their effects in the soft drinks market, I propose a model that focuses on the key factors shaping the policy outcomes. It tracks how prices and product characteristics evolve after the tax was implemented, emphasizing the main features of the drinks while recognizing that some of these traits, such as their taste and quality, may not be directly observable by an analyst. It captures consumers diversity by allowing for variations in how individuals value prices and product attributes —including the unobserved ones. What sets this model apart is its consideration of how changes in the makeup of products, such as reductions in sugar content, may impact their taste and overall quality experienced by consumers. The model then allows for the possibility that observed and unobserved characteristics are correlated, reflecting the idea that firms design their products holistically, rather than choosing sugar content and other attributes in isolation. By combining these elements, the model provides a comprehensive way to unwrap the observed market changes, and assess the extent to which they can be attributed to price adjustments versus the effects of product reformulation in consumer choices. This highlights the policy's two primary mechanisms for reducing sugar-intake: prices and reductions in products' sugar content.

To have unobserved product characteristics play an explicit role in model, I include them as interactive fixed effects (Bai, 2009; Moon and Weidner, 2015). These are also known as factor models in the large-panel econometrics literature. The idea behind them, is to model product and market heterogeneity as the multiplication of dimension-specific fixed-effects that need to be estimated. This approach allows the unobserved drink characteristics, treated as a vector of product fixed-effects, to be arbitrarily correlated with the observed ones. Similarly, it allows heterogeneity in consumer preferences across markets by estimating market-specific preferences over these characteristics. This flexibility is necessary if, for example, one believed that consumers care differently about a drink's *taste*, and that it can be influenced by the amount of sugar on a product. Formally, this approach relaxes the mean-independent fixed effect assumption, which is commonly used to account for the utility effect of unobserved characteristics in models of differentiated products (Berry, 1994).

Preference heterogeneity across prices and drinks' characteristics is captured in a discrete choice framework with random coefficients. I then aggregate individual choice probabilities to match the observed market shares, as in Berry, Levinsohn, and Pakes, 1995. This choice allows me to include information on prices and track product composition, including drinks nutritional information and any changes to it. I also use this information to identify when a product get reformulated.

Finally, to understand the supply-side responses to the tax, I model firms as engaging in a two-stage game in every period: first, they simultaneously decide what products to offer the market, and then, after observing their rivals' offerings, they compete on prices in a Bertrand manner. To account for the relatively high inertia in product offerings observed in the data, I include a reformulation cost that firms must pay to alter the characteristics of one of their products.

This sections continues by specifying my demand model with endogenous unobserved characteristics. It then shifts attention to the supply side, examining how firms define their products and set prices while considering the reformulation costs. Finally, it discusses the application of the model to analyzing the effects on the soft drinks market following the introduction of the 2018 Soft Drinks Industry Levy.

4.1 Demand with endogenous unobserved characteristics

My demand model draws from the literature on discrete choice across differentiated products. As in Berry, Levinsohn, and Pakes (1995), market shares are obtained by aggregating individual choice probabilities. These probabilities depend on two main factors: the market-specific mean utilities (δ_{jt}) of all products in the market, and idiosyncratic preference shocks captured by consumer-specific random coefficients (μ_{ijt}), which can depend on both prices and observed product characteristics. Σ is the random coefficients variance-covariance matrix.

$$s_{jt}(\delta \mid \Sigma) = \int_{-\infty}^{\infty} \frac{e^{\delta_{jt}+\mu_{ijt}(p_{jt},x_{jt})}}{1+\sum_{k\in\mathcal{J}_t} e^{\delta_{kt}+\mu_{ikt}}} dF(\mu \mid \Sigma)$$

Products' mean utilities depend on product prices, a set of M observable characteristics (x_j), and the utility effect of unobserved characteristics (ξ_{jt}). Among these observable

characteristics are nutritional values, as well as details about each product's size and format, among others.

$$\delta_{jt}(x_j, f_j) = \alpha_t \cdot p_{jt} + \beta_t \cdot x_j + \xi_{jt}$$

Similar to observed characteristics, I assume consumers also have preferences for unobserved characteristics. Therefore, the utility effect ξ_{jt} can be decomposed into the product or interaction[4] of two components: *factors* representing a beverage's unobserved attributes (a vector of fixed effects, f_j) and *loadings* (λ_t) that capture market-specific preferences for those attributes. An additional error term, e_{jt}, accounts for any other exogenous demand shock affecting a product's demand in a particular market and time.

$$\xi_{jt} = \lambda_t \cdot f_j + e_{jt} \tag{1}$$

These factors and loadings are treated as parameters to be estimated from data coming from a large panel. This setup allows f_j to be identified as an $R \times 1$ vector of characteristics that the analyst cannot fully observe —either due to a lack of data on certain dimensions (e.g., advertisement) or because the dimension is inherently difficult to quantify (e.g., taste). Such unobserved characteristics might also include information on undisclosed ingredients or proprietary manufacturing methods that give a product its unique flavor or experience.e.

The most noteworthy aspect of these fixed-effects vectors is that they can be arbitrary correlated with the observed characteristics x_{jt}. As a result, unlike many discrete-choice models for differentiated products, I have no need to assume independence between the observed characteristics and the utility effect of the unobserved ones. In consequence, through the factors and loadings, the model addresses the endogeneity problem that arises from firms setting all their product attributes simultaneously in a holistic way - rather than having them choosing them in isolation.

$$\mathbb{E}[\xi_{jt} \mid x_{jt}, p_{jt}] \neq 0$$

[4]Thereby the name *Interactive Fixed Effects* used in Bai (2009)

4.2 Supply side

Firms engage in a two-stage competitive process. First, they all establish their product offerings simultaneously. Then, after reviewing the availability of products in the market, they engage in price competition following a Nash-Bertrand game. Thus, a firm's profits f depend on products prices, marginal costs, and the full set of available products (J_t), as shown below.

$$\Pi_{ft}(J_t, \{p_{jt}\}_{j \in J_t}) = \sum_{j \in J_{ft}} (p_{jt} - c_{jt} - \tau_{jt}) \times s_{jt}(\cdot) \tag{2}$$

Where the product's marginal cost c_{jt} depends on its observed and unobserved characteristics. A product's industry tax τ_{jt} is calculated based on sugar concentration[5] and size. Since both sugar concentration and size are readily observable on the product's nutritional label, they form part of x_j. Then, by denoting sugar concentration as (g), the total tax on a product can be expressed as:

$$\tau_{jt}(g_j \in x_j) = \begin{cases} 0 & \text{if } g_j < 5 \\ 18 * size & \text{if } 5 \leq g_j < 8 \\ 24 * size & \text{if } g_j \geq 8 \end{cases} \tag{3}$$

Firms set their product offering common to all markets within a given period. This involves defining the complete set of characteristics of each product. Thus, the firm aims to set its product offering to maximize the expected market profits conditional on its information set, denoted as I_f. In doing so, the firm faces a reformulation cost (κ) to alter the characteristics of one item on its menu. This reflects the fixed costs of adjusting production lines and the logistical challenges necessary to deploy the changed product in the market. As a result, the firms' problem can be written as:

$$\Pi_f = \max_{J_f = \{x_j, f_j\}} \max_{\{p_{jt}\}_{j \in J_{ft}}} \mathbb{E}\left[\Pi_{ft} \mid I_f\right] - \kappa(J_{ft-1}, J_{ft}) \tag{4}$$

Following Petrin, Ponder, and Seo (2022), the information set varies across firms and may or may not include details on cost shifters, information about its own and others' product offerings, and signals related to these variables. Because of the uncertainty on

[5]Measured in grams per 100ml.

the market conditions, firms may sometimes make mistakes on their product offering. However, under rational expectations, firms anticipate future events accurately, resulting in errors that, on average, cancel each other out (Hansen and Singleton, 1982). As a consequence, the first-order conditions of profit maximization can be expected to hold on average.

$$\mathbb{E}\left[\frac{\partial \Pi_f}{\partial x_j} \mid I_f\right] = 0, \quad \mathbb{E}\left[\frac{\partial \Pi_f}{\partial f_j} \mid I_f\right] = 0 \tag{5}$$

These conditions can then be used to break down ξ_{jt} and identify the unobserved product characteristics (f_j) and consumers preferences over those characteristics (λ_t).

4.2.1 Cost parameters

I assume costs are based on the industry's manufacturing process. Typically, soft drinks companies create a concentrated syrup that defines the drink's taste, flavor, and nutritional content. This syrup is sent to processing facilities, that add water and CO_2 as specified by the syrup makers and package the final product into cans, bottles, etc. The packaged drinks are then distributed to wholesalers or retailers for sale. Therefore, each beverage can be seen as the combination of multiple inputs (W_z) that collectively determine its observed and unobserved characteristics as outputs.

I assume that for any given set of output characteristics, firms select the combination of inputs that minimizes the products marginal costs, given the prevailing input prices (p_w). Consequently, the marginal cost function takes the form:

$$c_{jt} = \min_{\{W_z\}} f_c\big(x_j, f_j, p_w \mid \rho\big) \tag{6}$$

Where ρ is the vector of parameters of the marginal cost function.

5 Identification strategy

My identification strategy follows a sequential approach, where each stage builds on the parameters found in the previous ones until all model parameters are identified. The process begins with the estimation of demand parameters, including the utility effect of unobserved product characteristics (ξ_{jt}). Using these demand estimates, I recover products' marginal costs based on the first-order conditions of the pricing game. With these recovered costs, I then estimate the marginal cost function and identify the cost parameters ρ. Next, incorporating insights from Hansen and Singleton (1982), I use moments derived from the firm's first-stage problem to identify the remaining factors and loadings. Finally, I establish bounds on reformulation costs by examining firms' reformulation decisions and comparing the realized profits of reformulated products with their counterfactual profits had reformulation not occurred. Table **??** provides a overview of the identification process.

Type	Parameter(s)	Method	Reference
Mean utilities	$\delta^{(\Sigma)}$	Demand inversion	Berry (1994)
Demand parameters	$\Sigma, \alpha, \beta, \xi_{jt}$	LSMD	MSW (2018)
Marginal Costs	c_{jt}	Pricing FOC	BLP (1995)
Cost parameters	ρ	Translog function	CJL (1973)
Factors & Loadings	λ_t, f_j	Supply moments	HS (1982)
Reformulation costs	κ	Partial identification	-

Table 3: Overview of the identification process

5.1 Demand side parameters

The identification of the demand side parameters follows the main argument in Moon, Shum, and Weidner (2018) for their LSMD estimator. That is, conditional on the variance of the random coefficients (Σ), we can find a unique one-to-one mapping between market shares and the market mean utility of a product δ_{jt} by solving the system of non-linear equations given by 7 (Berry, 1994; Berry, Gandhi, & Haile, 2013):

$$\delta_t^{(\Sigma)} = \{\delta_{jt} \in \mathbf{R} / \mathfrak{s}(\delta_{jt}, \delta_{-jt} \mid \Sigma) = s_{jt} \, \forall j \in J_t\} \tag{7}$$

Now, conditional on $\delta_{jt}^{(\Sigma)}$, we can determine the remaining demand parameters[6] using the Interactive Fixed Effects estimator proposed by Bai (2009). However, the crucial remaining problem is identifying the true value of the random coefficients Σ_0. Moon and co-authors resolve this by including a set of instruments (z_{jt}) as auxiliary regressor in the Interactive Fixed Effects regression, as shown in Equation 8.

$$\delta_{jt}^{(\Sigma)} = \alpha_t \cdot p_{jt} + \beta_t \cdot x_j + \lambda_t \cdot f_j + \gamma \cdot z_{jt} + e_{jt} \tag{8}$$

Because of the exclusion restriction on the instruments, these auxiliary regressor are expected to have coefficients γ equal to 0. They then show this condition holds if and only if $\Sigma = \Sigma_0$. As a result, it is possible to identify Σ_0 by determining the value of Σ that makes the norm of the coefficients of the auxiliary regressors equal to 0.

$$\Sigma = \Sigma_o \iff \gamma(\Sigma) = 0 \tag{9}$$

Where γ is the solution to the Interactive Fixed Effects regression from minimizing the expected square errors.

$$\gamma(\Sigma) = \arg\min_{\gamma} \min_{\alpha_t, \beta_t, \gamma} \mathbb{E}\left[\left(\delta_t^{(\Sigma)} - (\alpha_t \cdot p_{jt} + \beta_t \cdot x_j + \lambda_t \cdot f_j + \gamma \cdot z_{jt}) \right)^2 \right] \tag{10}$$

5.2 Marginal costs and cost parameters

The competitive process in which firms set up their prices provides an equation for a product's markup as a function of the demand paramters found in the previous step. As in Berry, Levinsohn, and Pakes (1995), I use these set of equations to determine products' marginal costs (c_{jt}).

$$\frac{\partial \Pi_{ft}}{\partial p_j} = 0 \rightarrow c_{jt} = p_{jt} + \frac{S_{ft}}{\partial s_{jt} / \partial p_{jt}} \tag{11}$$

I assume the solution to the cost minimization problem in Equation 6 follows a translog functional form. This function then treats drinks' characteristics as the output the firm aims to produce using a set of inputs with prices given by p_w. As a result, these parameters

[6] At this stage, we can only jointly identify $\lambda_t \cdot f_j$.

can be identified by minimizing the square errors of the marginal cost regression on Equation 12.

$$
\begin{aligned}
c_{jt} = & \sum \rho_x x_j + \sum \rho_f f_j + \sum \rho_p p_w + \sum \rho_{x2} + \dots \\
& + \sum \rho_{xp} x_j p_w + \sum \rho_{fp} f_j p_w + \sum \rho_{xf} x_j f_j \\
& + \sum \rho_x f p x_j f_j p_w + \eta_{jt}
\end{aligned}
\tag{12}
$$

5.3 Factors and loadings

It is common for panel data models to incorporate individual and market/time effects to control for heterogeneity in cross section and over time. These individual and time effects usually enter the model additively, but they can also be interacted multiplicatively, thus giving rise to so-called Interactive Effects (Bai, 2009; Moon & Weidner, 2015), also referred to in the literature as a factor models (Ahn, Hoon Lee, & Schmidt, 2001; Holtz-Eakin, Newey, & Rosen, 1988; Pesaran, 2006). The multiplicative form captures the heterogeneity in the data more flexibly, since it allows for common time-varying shocks to affect the cross-sectional units with individual specific sensitivities and permitting arbitrary correlations between the regressors and the interactive effect parameters. In my product reformulation model, factors (f_j) represent instead a product's unobserved characteristics while factor loadings (λ_t) capture consumers' preferences over these characteristics in a given market. Thus, simultaneously capturing the cross sectional heterogeneity on both dimensions.

The literature on Interactive Fixed Effects primarily focuses on addressing endogeneity issues in the regressions, relegating the identification of the factors and loadings to a secondary concern and even treating them as nuisance parameters to be only jointly identified as $\lambda_t \cdot f_j$ (Moon, Shum, & Weidner, 2018; Moon & Weidner, 2015). In the few cases researchers are interested in individually identifying the Interactive Effects, researchers have used convenient regularization conditions to do it. One of the most common combination of these conditions is imposing a scale normalization over the factors and assuming that the various factors and loadings are uncorrelated with each other. These conditions are summarize below in Eq. 13.

$$F^t F = \mathbb{I}, \quad \Lambda^t \Lambda = \sigma_\lambda \mathbb{I} \tag{13}$$

These conditions can be harmless when the factors are treated as common exogenous shocks and loadings represent the specific sensitivities to these shocks. However, they can contradict the underlying economic theory when factors and loadings are associated to the model fundamentals. In my model, these conditions would imply that the unobserved product characteristics are allowed to be correlated with the observed ones, but they cannot be correlated with each other. Similarly, consumers' preferences over the different unobserved characteristics couldn't be correlated with each other either. These restrictions are highly unrealistic, as the endogeneity problem arising from the simultaneity of firms' decisions regarding observed and unobserved characteristics extends to interactions within the unobserved characteristics as well.

To avoid these inconsistencies, I take a two-step approach to identifying factors and loadings. I first focus on resolving the endogeneity issue in the demand equation and jointly identify $\lambda_t \cdot f_j$ (or ξ_{jt}) alongside an initial set of parameters that allow me to then identify products' marginal costs and the cost parameters. Once these have been found, I move to the second step, where I separately identify the factors and loadings by combining the previously found parameters with moments derived from the first-order conditions of the product portfolio problem from Equation 4.

Intuitively, my approach first identifies a set of feasible solutions for the factors and loadings by leveraging only demand-side information. Then, it refines this identification by incorporating micro-founded moments from the supply side to isolate the unique solution that aligns with firms' behavior[7]. As shown by Bai (2009), this second step is crucial, as expressing the factor structure from Equation 1 in matrix form reveals that the equation holds under any invertible transformation represented by a matrix H. In other words, any transformation of the factors, when multiplied by the inverse transformation of the loadings, would still satisfy the factor structure on the utility effects of the unobserved characteristics. As a result, more information in needed to identify the true factors and loadings and isolating the effects of product unobserved characteristics and consumer

[7]Subject to scaling transformations.

preferences for those characteristics.

$$\mathbf{E}[\Xi] = \Lambda F^t = (\Lambda H^{-1})(HF^t) = \Lambda' F'^t$$

The moments I use incorporate information from the supply-side of the market to identify the factors and loadings. They are the same as the ones used by Petrin, Ponder, and Seo (2022) and are presented in Equation 14. Their approach proposes using moments inspired on Hansen and Singleton (1982) to account for the endogeneity across observed and unobserved characteristics. These moments build on the assumption that *"firms choose product characteristics to maximize expected profits given their beliefs at that time about market conditions and that the "mistake" in the amount of the characteristic that is revealed once all products are on the market is conditionally mean independent of the firm's information set."* This allows them to recover unbiased coefficients, leading to an upward reassessment of the original BLP markups and elasticities. However, their framework does not allow for counterfactual analysis involving the unobserved product characteristics, a key feature in my approach to study product reformulation.

$$\mathbb{E}\left[\frac{\partial \Pi_f}{\partial f_j} \cdot z_j\right] = 0 \tag{14}$$

Theorem 1. *The set $\{f_j, \lambda_t\}$ satisfies Equations 14 and 1 if and only if it is a affine transformation of the true model parameters $\{f_0, \lambda_0\}$.*

Proof. **Not in this draft.**

□

5.3.1 Number of factors

A common concern with identification in factors models relates to the number of factors to include. The greater flexibility offered by the multiplicative form of the interactive fixed effects places the responsibility on the econometrician to determine the appropriate number of fixed effects to include in the model. Theoretically, this number can be consistently estimated from the data (Bai, 2009; Supplemental material). However, practical challenges arise when doing this in empirical work (Ahn, Lee, & Schmidt, 2013; Onatski,

2010), and my product reformulation model is no exception to this. Nonetheless, Moon and Weidner (2015) show that, under general assumptions, the limiting distribution of the interactive fixed effect estimator is independent of the number of factors used in the estimation, provided that this number is not underestimated. This implies that while the exact count of factors may not be critical, ensuring that it is not underestimated is essential for obtaining reliable estimates.

I then choose to rely on economic theory rather than purely econometric criteria to determine the number of factors. The key objective is to include enough factors to properly address the endogeneity between observed and unobserved characteristics —the very reason for incorporating Interactive Fixed Effects in the model. To ensure stability, I set the number of factors R such that adding an additional factor no longer affects the estimated coefficients. This approach provides a principled way to select R, balancing theoretical motivation with empirical robustness, as expressed in Eq. 15.

$$\begin{aligned} \hat{\alpha}^{(R+1)} &= \hat{\alpha}^{(R)} \\ \hat{\beta}^{(R+1)} &= \hat{\beta}^{(R)} \end{aligned} \tag{15}$$

5.4 Reformulation costs

Firms' reformulation decisions provide valuable insights into the reformulation costs they face and can be used to set bounds on these costs. In particular, by comparing the counterfactual profits under the tax of a firm with and without the reformulated product j', one can infer the implicit cost threshold at which reformulation becomes a viable strategy. If a firm chooses to reformulate, it suggests that the expected increase in profitability—whether through lower tax liability, increased demand, or competitive positioning—outweighs the associated costs. Conversely, if a firm opts not to reformulate, it implies that the costs exceed the expected benefits. By systematically analyzing these decisions across firms and products, I can establish a range within which reformulation costs are likely to fall, providing a structural basis for understanding firms' strategic responses to the tax.

$$\max_{j:Not\ Reformulated} \Pi_f(j') - \Pi_f(j) \leq \kappa \leq \min_{j:Reformulated} \Pi_f(j') - \Pi_f(j) \tag{16}$$

6 Empirical approach

My approach to estimating the model largely mirrors the identification strategy through its sample analogues. However, in the empirical work, new practical challenges arise that must be addressed. In this section, I focus on three of these challenges: efficiently estimating the non-linear demand with interactive fixed effects with an unbalanced panel, separately estimating the true factors and loadings,and capturing changes in unobserved characteristics that may occur when products are reformulated.

6.1 Efficient estimation of factor models with unbalanced panels

I estimate the demand parameters using an adaptation of the Least Squares - Minimum Distance (LSMD) estimator from Moon, Shum, and Weidner (2018) to accommodate unbalanced panels, which are common in empirical work. In essence, the LSMD estimator jointly determines the variance-covariance matrix of the random coefficients and the demand parameters by identifying the value of Σ that minimizes the norm of the estimated gammas from the auxiliary regression in Equation 8. To estimate the coefficients of the auxiliary regression, it relies in the original BLP demand inversion to linearize the problem and then applies the Interactive Fixed Effects estimator from Bai (2009) to recover the coefficients. This procedure is repeated iteratively until convergence.

Although Bai's approach to estimating Interactive Fixed Effects is highly efficient for balanced panels, its application becomes unclear when the sample contains missing observations or experiences attrition. While Bai, Liao, and Yang (2015) propose methods to handle unbalanced panels, these approaches are computationally intensive and unsuitable for large panels like the one used in this study. Moreover, its computational complexity grows exponentially with the number of factors included in the model, posing further challenges to its application.

I then deviate from Moon and co-authors' implementation and instead adopt the approach proposed by Norkutė, Sarafidis, Yamagata, and Cui (2021) and Cui, Norkutė, Sarafidis, and Yamagata (2022) to estimate the Interactive Fixed-Effects regression resulting after the BLP demand inversion. Their two-step method involves first de-factorizing the regressors and running a traditional OLS regression to find a first estimate of the

coefficients. Then it uses these estimates to de-factorize the dependent variable and run a second OLS regression with all the de-factorized variables. They show this approach recovers the true parameters and that their estimator in unbiased, in contrast to Bai's. Therefore, there is not need for an additional bias corrrection stage in the estimation of demand.

6.2 Identifying the factor and loadings separately

As previously discussed, it is possible to estimate the model demand and cost parameters without separately identifying the factors and loadings using the LSMD estimator. However, this approach does not allow to distinguish between shifts in consumer preferences and changes in product characteristics. This limitation poses a challenge in accurately interpreting the outcomes of the policy and makes it impossible to run counterfactual analysis to measure its effects properly. To overcome this issue, I use the product between the instruments and the First-Order-Conditions (FOCs) of the firm's menu choice problem as moments (Equation 14) to provide additional structure to the model and separate changes in demand drivers, ensuring that preference shifts and product alterations are not confounded. For a single-product firm, the FOC is given by:

$$\frac{d\Pi_f}{dx_j} = \overbrace{(p_j(\cdot) - c(\cdot))\,\frac{\partial s_j}{\partial x_j^m}}^{\text{Direct effect on market shares}} + \overbrace{\left(\frac{\partial p_{jt}(\cdot)}{\partial x_{jt}^m} - \frac{\partial c(\cdot)}{\partial x_j^m}\right) s_{jt}}^{\text{Direct effect on margins}} + \overbrace{(p_{jt}(\cdot) - c(\cdot)) \sum_{l \in \mathcal{G}_f} \frac{\partial s_j}{\partial p_l} \frac{\partial p_{lt}}{\partial x_{jt}^m}}^{\text{Indirect effect on shares through prices}} \tag{17}$$

As seen above, computing these moments requires knowing the partial derivatives of the equilibrium prices with respect to product characteristics, which are unknown during estimation and essential to solving the firm's problem. However, one can find these derivatives following a similar approach to the one used in Villas-Boas (2007) to find the partial derivatives of retailer prices with respect to the wholesale ones. This involves implicitly differentiating the first-order conditions of the pricing game from Equation 11 to get system of linear equations one can solve for the partial derivatives needed.

Equation missing. (18)

I then use GMM and iteratively compute the sample analogues of moments described in Equation 14 by repeatedly solving the system of equations in 18 and then using these solutions to compute the moments. Therefore, the true factors and loadings are the solution to the following problem:

$$\hat{F}, \hat{\Lambda} = \arg \min_{\{f_j, \lambda_t\}} m(f, \lambda)^t \cdot m(f, \lambda) \tag{19}$$

with

$$m(f, \lambda) = \frac{1}{T} \sum_{t \in \mathcal{T}} \left[\frac{\partial \Pi_f}{\partial f_j} \cdot z_j \right]$$

6.3 Capturing unobserved reformulation

In the initial review of the data, I showed that firms reformulated their products to reduce their sugar content in order to mitigate or lessen their tax burden. Sugar a key ingredient in this category, as it affects the taste and feeling of the product. These are dimensions that consumer value dearly but are hard to track by an external analysts. Therefore, the change in sugar content can be anticipated to affect products' unobserved characteristics (f_j).

To enable the model to incorporate these unobserved changes to f_j, I denote the characteristics of the product after reformulation as $(x_{j'}, f_{j'})$ and define the unobserved mean market utility (ξ_{jt}) as:

$$\xi_{jt} = \begin{cases} \lambda_t \cdot f_j + e_{jt} & \textit{before reformulation} \\ \lambda_t \cdot f_{j'} + e_{jt} & \textit{after reformulation} \end{cases} \tag{20}$$

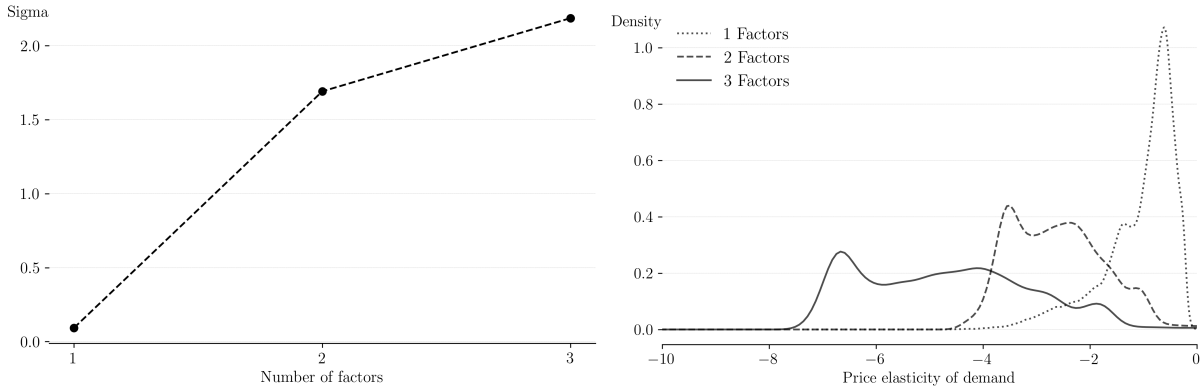
Therefore, by treating the reformulated product as a new product with its own estimated vector of f_j, the model can effectively capture the utility effect of unobserved changes to f_j that result from reformulation.

7 Results

These results are preliminary, please do not circulate without consent.

I estimate the model using different numbers of factors to see how the additional flexibility of adding more parameters affects the results. As expected, adding more factors allows the model to capture greater heterogeneity, leading to some variation in the estimates. However, after a certain point, these differences become smaller, suggesting that the estimates are stabilizing - validating the idea that an econometric criteria like the one previously described can help determine the right number of factors.

Instead of directly comparing coefficients across specifications, I focus on two model outcomes with clearer economic significance: the variance of the random coefficients and the estimated price elasticities, both shown in Figure 8. The variance of the random coefficients reflects the role of consumer heterogeneity in shaping market outcomes, while the distribution of price elasticities serves as a measure of the product differentiation captured by the model. These two metrics offer a more intuitive way to evaluate how adding more factors enhances the model's ability to explain economic outcomes.



(a) Variance of the random coefficient (b) Distribution of demand price elasticities

Figure 8: Comparison of estimates across numbers of factors

The figures above illustrate that as the number of factors increases, consumer heterogeneity plays a larger role in shaping market outcomes, and the model becomes more effective at capturing variation across products. This suggests that incorporating additional factors allows for a richer representation of differences in consumer preferences and product characteristics, ultimately improving the model's ability to reflect real-world purchasing behavior.

I now use the estimates from the model with the largest numbers of factors ($R = 3$) to study the evolutions of the soft drinks market after the introduction of industry levy.

7.1 Unobserved utilities and product differentiation

The model enables comparing the utility effects of unobserved product characteristics before and after reformulation, as shown in Figure 9. Overall, reformulation led to a decline in the unobserved utility of products and a reduction in its dispersion. This suggests that reformulated products became more similar to one another, leaving less room for differentiation. As a result, competition may have intensified, with firms relying more on pricing strategies rather than distinct product attributes to attract consumers.

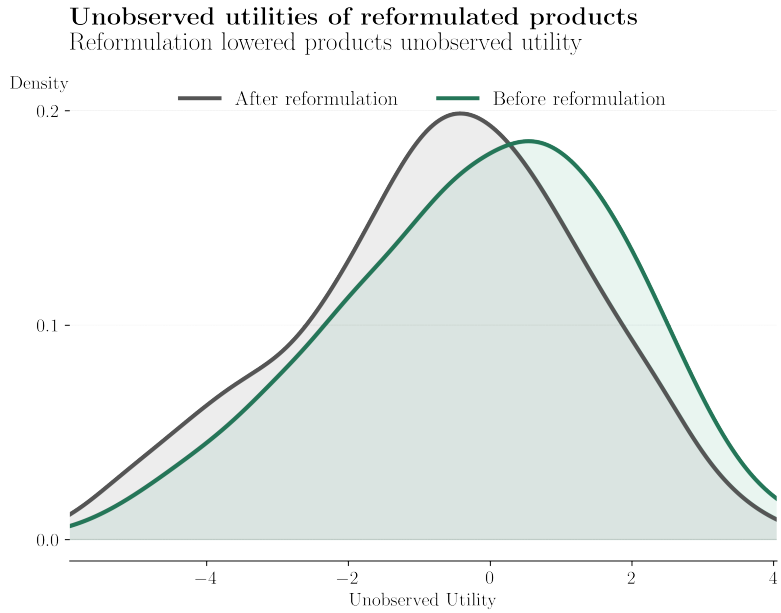


Figure 9

The change in unobserved utilities could also stem from a shift in consumer preferences for the unobserved product characteristics. Fortunately, the model allows for a decomposition of this change, confirming that the variance of the factors has indeed decreased. As shown in Figure 10, the shrinking of the product space is particularly strong in the first latent characteristic. This reveals that reformulation not only reduced sugar content but also altered drinks unobserved characteristics.

I confirm the relationship between sugar, other observed characteristics, and the unobserved product dimensions by running a simple OLS regression of the estimated factors

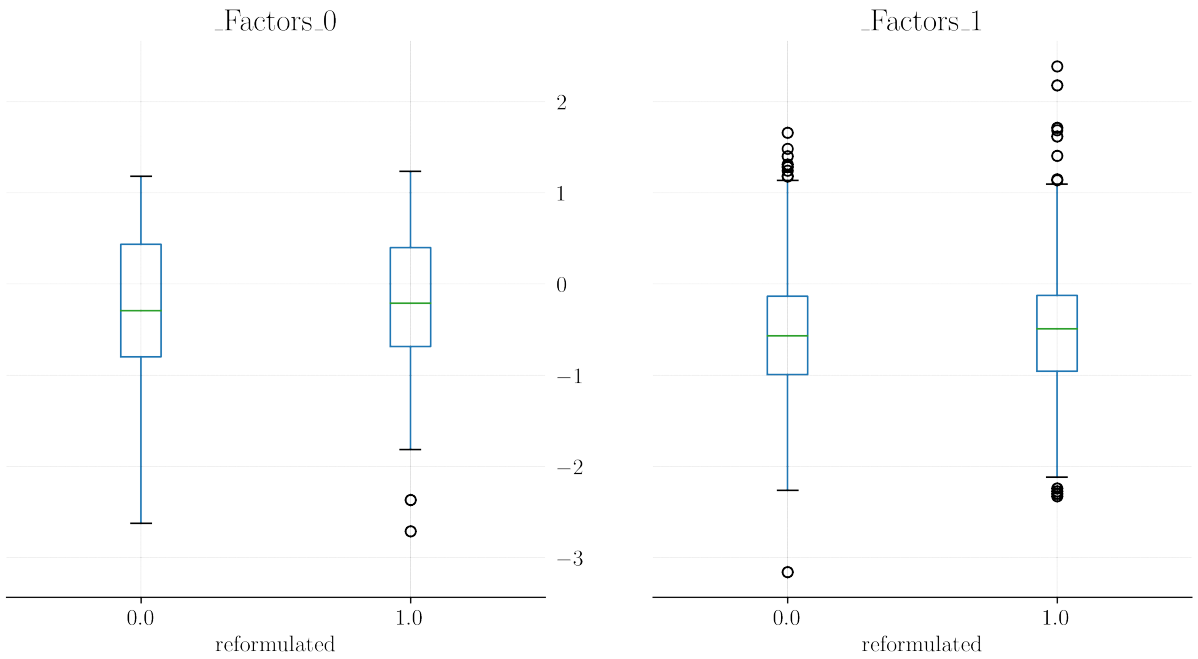


Figure 10: Factors before and after reformulation

on the observed characteristics, including prices. The results of this analysis, presented in Table 4, provide further evidence of the connection between a product's sugar content and its broader set of attributes, both observed and unobserved.

	cpi_prices	private_label	flavour.Lemonade	flavour.Other	sugars	protein	sodi
Factors_0	0.82***	0.0	0.04***	-0.02***	-0.02***	-0.36***	-0.0
	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Factors_1	-0.37***	-0.01***	-0.12***	-0.03***	-0.03***	0.97***	-0.0
	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 4: Results of regressing the factors on the observables

7.2 Costs and the adoption of technology

I now study whether reformulated products exhibit structural differences in their cost structure compared to their pre-reformulation versions. Understanding these differences is important, as changes in the products cost structure can signal shifts in production processes or input substitution requirements.

To assess this, I estimate a translog cost function using the recovered marginal costs and compare the results across reformulated and non-reformulated products. As shown in Figure 11, the regression reveals notable structural differences in the estimated marginal

cost function, suggesting that reformulated products follow a distinct cost structure from their earlier versions. This finding implies that firms likely adopted or developed new production technologies to accommodate reformulation, rather than making minor adjustments to existing processes.

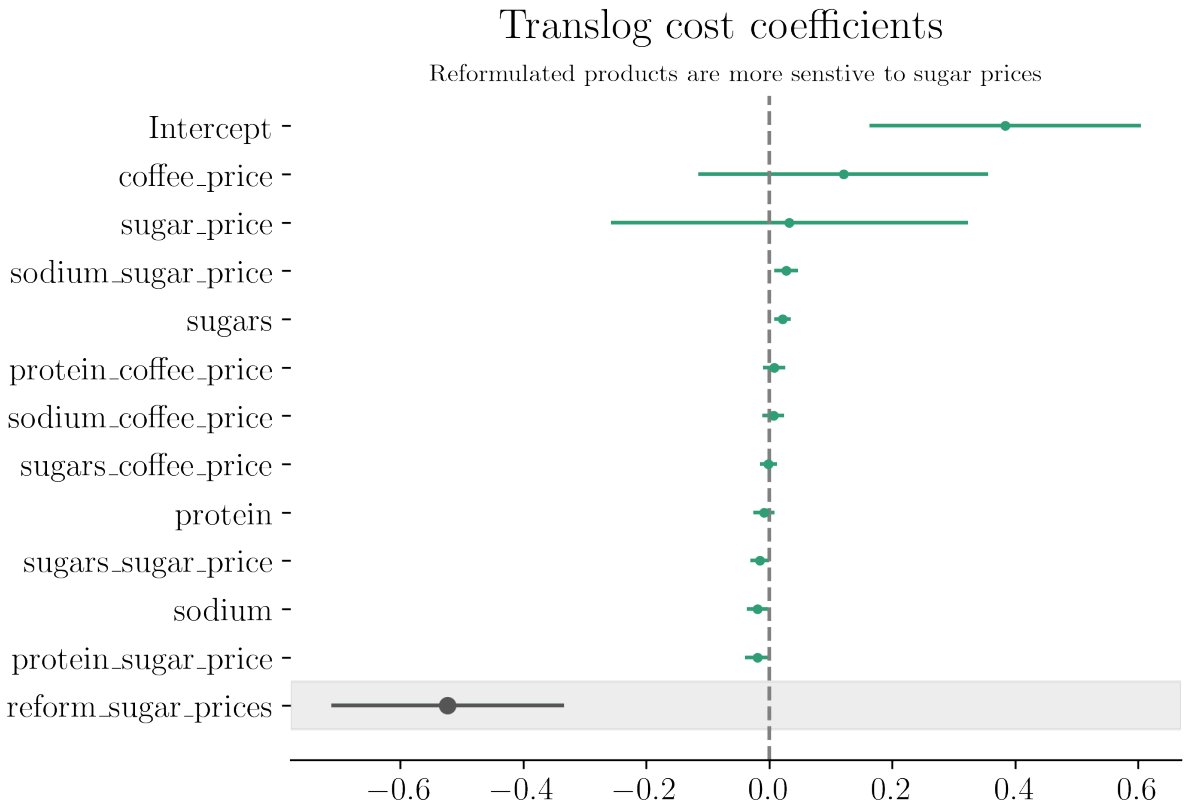


Figure 11: Reformulated products have structural difference in their cost structure

These results underscore the potential of corrective policies not only to change firm behavior but also to drive innovation within the market. By incentivizing reformulation, the levy pushed firms to go beyond simple cost-saving strategies and instead explore new production methods and ingredient substitutions to avoid the tax while maintaining products appeal to consumers and keeping costs under control. This suggests that well-designed fiscal policies can act as catalysts for industry-wide shifts, encouraging firms to invest in research and development to meet regulatory requirements without sacrificing competitiveness.

8 Counterfactuals

The model provides a framework for examining various empirical questions related to the soft drinks market and the design of the Soft Drinks Industry Levy. In this analysis, I focus on two aspects key to the policy effectiveness: First, measuring how much of the observed outcomes can be attributed to product reformulation and assessing its welfare implications. Second, given the recent industry consolidation through mergers and acquisition, I study the effects of increased concentration on the policy's overall impact.

8.1 The effect of product reformulation on policy outcomes and welfare

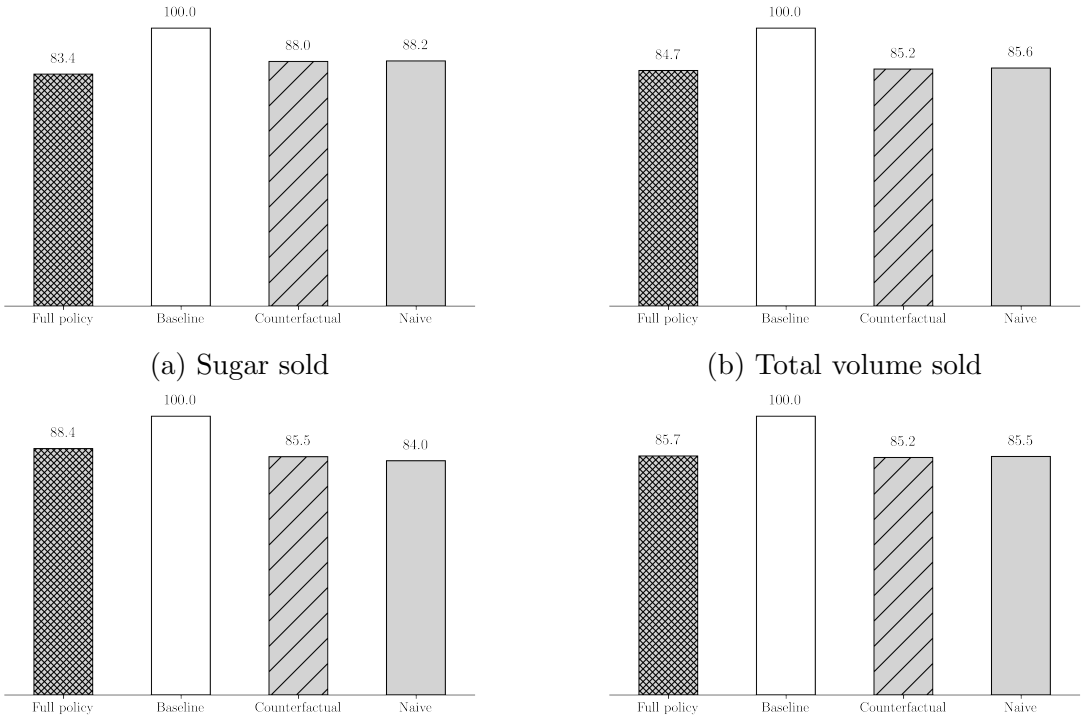
The analysis of corrective taxes has traditionally focused on their price effects and consumer responses to price increases. However, as I have shown here, these policies also have the potential to induce additional supply-side responses, such as product reformulation, that can boost the policy outcomes and prevent price changes. To disentangle and quantify the effects of reformulation and price adjustments due to the Soft Drinks Industry Levy, I define and compare four alternative scenarios:

1. **Baseline** - This scenario represents a world without the corrective policy, where no tax is introduced and no reformulation occurs. The product menu remains unchanged from March 2016, when the Soft Drinks Industry Levy was announced.

2. **Näive** - This scenario reflects the idealized view of how policymakers often expect a corrective tax to function. It assumes full pass-through of the tax to prices, with firms making no strategic price or product adjustments beyond the tax itself.

3. **Counterfactual** - This scenario serves as a benchmark for isolating the effects of product reformulation. The tax is implemented, but firms are restricted from modifying their product offerings. Instead, they can only adjust prices, doing so optimally across their entire portfolio. This setup allows for cross-product subsidies and the preservation of relative price structures.

4. **Full policy** - This scenario represents the real-world implementation of the policy. Firms not only reformulate their products as observed in the data but also set prices optimally across their portfolio, incorporating both strategic pricing and reformulation responses.



(a) Sugar sold

(b) Total volume sold

(c) Firm profits

(d) Consumer surplus

Figure 12: Percentage relative to the baseline scenario

In Figure 12 I compare market outcomes under different scenarios against the Baseline. As expected, the Full Policy scenario is the most effective in reducing total sugar sold, leading to a 16.6% decline in sugar consumption, compared to a 12% reduction in the Counterfactual scenario, where reformulation is not allowed. This suggests that product reformulation enhances the policy effects by 38% while allowing firms to achieve 3% higher profits compared to the scenario without reformulation. Consumer surplus, on the other hand, remains nearly unchanged across the different policy scenarios. Interestingly, the Naïve scenario produces a similar outcome to the Counterfactual scenario, where firms can adjust prices across their entire product portfolio. This indicates that firms' strategic pricing does not play a significant role in shaping the policy outcomes.

Figure 13 shows that the impact of the policy varies across firms, with smaller firms being the most affected under all scenarios. This is primarily because they are more

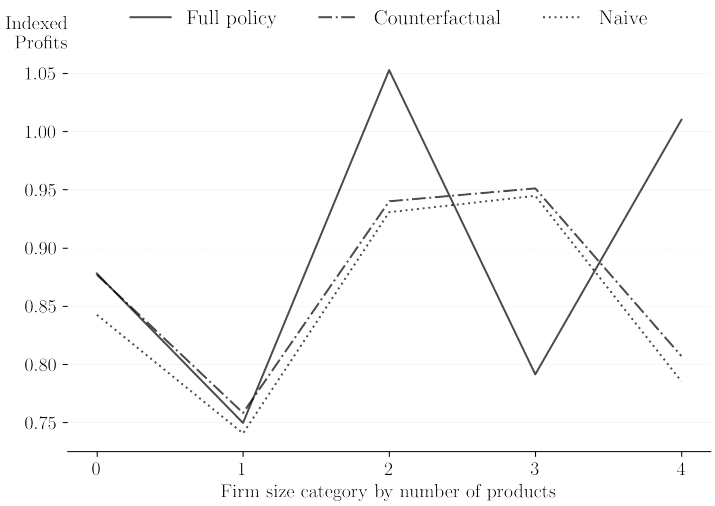


Figure 13: Profits relative to the Baseline

exposed to the tax, having fewer products in their portfolio to offset its effects. In contrast, larger firms can mitigate the impact by keeping a significant share of their offerings outside the tax's reach. Interestingly, reformulation appears to have been particularly beneficial for medium and large firms, helping them preserve revenues—and in some cases, even increase profits.

Furthermore, Figure 14 shows that the differences in policy impact across firms are closely linked to their reformulation efforts. Firms that reformulated a larger share of their products generally achieved better market outcomes, reinforcing the idea that product adaptation played a key role in mitigating the tax's effects. However, this also highlights the unequal capacity of firms to adjust, as smaller firms may face higher barriers to reformulation due to resource constraints or limited access to reformulation technologies.

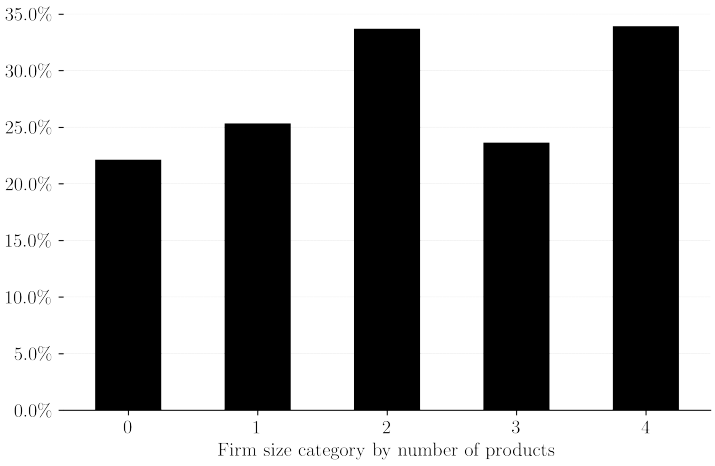


Figure 14: Share of reformulated products by firm size category

This disparity suggests that additional policy interventions, such as reformulation subsidies or technical support, could help smaller firms adapt while maintaining the policy's goal of reducing sugar consumption. Supporting firms during this transition could minimize revenue losses and enhance market competition by preventing the consolidation of the industry in fewer players.

9 Conclusions

This paper expands the analysis of corrective taxes by incorporating supply-side non-price responses, particularly product reformulation, as a central mechanism through which markets react to taxation. Rather than viewing these policies as simple price-based interventions, my findings show that taxes can reshape firms' product offerings, drive innovation, and influence long-term industry dynamics, including ownership structures and product differentiation.

My results reveal that product reformulation accounts for 38% of the total decline in sugar consumption achieved by the UK's Soft Drinks Industry Levy. This not only amplified the policy's impact but also allowed larger and medium firms to mitigate revenue losses, demonstrating that well-designed corrective taxes can prevent externalities at the source rather than merely shifting consumer choices toward less harmful alternatives. It also reveals that smaller firms have higher difficulties adjusting their product portfolios, implying that additional policy interventions like reformulation subsidies or technical support could lessen the burden on these firms and help them stay independent. Thereby preventing the loss of competition due to industry consolidation. This approach has direct implications for how policymakers design such interventions and highlights the importance of the targeting principle in corrective taxation.

Additionally, my findings suggest that firms do not simply comply with taxes but actively innovate and adapt their production processes in response. Structural shifts in firms' cost functions indicate that reformulation goes beyond surface-level adjustments, reflecting deeper transformations in their production technologies. This expands our understanding of corrective taxation by showing how it can stimulate technological advancements and encourage firms to develop healthier products, aligning business incentives with public health objectives.

On the methodological side, this paper introduces a novel product reformulation model that explicitly accounts for unobserved product characteristics and their endogenous relationship with other observable attributes. By leveraging Interactive Fixed Effects (or factor models), the approach captures unobserved product heterogeneity while allowing changes in observed characteristics to influence unobserved ones. This provides a richer

framework for analyzing firm behavior and consumer demand, particularly in markets where differentiation is subtle and difficult to quantify, such as food and beverages. Additionally, the paper extends the use of factor models beyond demand estimation, demonstrating their value for counterfactual simulations and policy evaluation, enhancing the tools available for studying market interventions in complex product spaces.

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