

# Shrinkflation and Consumer Demand\*

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## Abstract

This paper investigates shrinkflation—the phenomenon of reducing product size while maintaining or slightly increasing prices—in the U.S. retail grocery market. We analyze a decade of retail scanner data to assess the prevalence and patterns of product size changes across various product categories. Our findings demonstrate that product downsizing is notably more prevalent than product size increases and typically occurs without a corresponding decrease in price. Consequently, consumers end up paying more per unit volume. The study also reveals that shrinkflation is a common strategy not just among manufacturers, but also at the retail level. We further find that consumers are more responsive to price adjustments than to changes in product size. This finding suggests that reducing product sizes is a more effective strategy for retailers and manufacturers to increase margins or respond to cost pressures, offering valuable implications for retail and consumer economics.

Keywords: Shrinkflation, Product Size, Package-downsizing, Inattention

JEL Codes: D12, L10, M31

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\*Researcher's own analyses are calculated (or derived) based in part on data from NielsenIQ Consumer LLC and marketing databases provided through the NielsenIQ Datasets at the Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researcher and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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# 1 Introduction

Retail grocery pricing is traditionally characterized by frequent changes, where price adjustments are the principal strategy for retailers and manufacturers to increase their margins. However, current discussions have shifted to explore another aspect: product size changes. This trend, widely referred to as 'shrinkflation', has been increasingly highlighted in global news, suggesting a tendency among firms to subtly raise effective prices by reducing product sizes (Lempert, 2023; Barrett and Rachwani, 2023; BBC News, 2023). This phenomenon has caught the attention of consumer protection agencies and political circles (Toeniskoetter, 2022; European Parliament, 2022), prompting some supermarkets to introduce warning labels to underscore producers' shrinkflation tactics (Vidalon, 2023). Yet, the extent and consumer response to shrinkflation remain underexplored.

From a behavioral economics viewpoint, product downsizing emerges as a potential strategy for retailers and manufacturers to inflate profit margins, potentially exploiting consumer inattention or difficulties in comparing product sizes. If widely adopted, this strategy could significantly contribute to the broader trend of rising retail margins and profits (Döpfer et al., 2022). Moreover, shrinkflation could disproportionately affect low-income households and their ability to afford groceries (Davidson, 2023; Danley, 2022).

This paper investigates the U.S. retail market over the past decade to assess whether reductions in product size are a recent development. We aim to discern the prevalence of product size decreases compared to increases and whether product downsizing is particularly pronounced within certain product groups. Additionally, the study examines whether these size adjustments are implemented uniformly by manufacturers at a national level or are more localized decisions made by retailers. We further explore consumer sensitivity to size changes relative to price adjustments and how these two factors interact.

In the first part of this article, we use the full sample of product offerings in the U.S. retail grocery market, with a focus on identifying trends of product size decreases and increases at the store level. Our results indicate that product downsizing is not confined to recent years but a consistent trend across all observed years. We find that reductions

in product size occur about three times more often than increases. Our findings show that size decreases are widespread across various product categories. They are notably prominent in categories such as candy and snacks but also extend commonly to categories like detergents and hair care products.

Next, we investigate the characteristics of product size decreases. Our research shows that size decreases usually occur with little or no accompanying price changes. This price stickiness is not apparent for product size increases, which are typically associated with price hikes. A closer analysis of the absolute changes in price per unit volume highlights that product size decreases generally result in a less favorable outcome for consumers, as they end up paying more for the same volume. Conversely, product size increases enhance value for consumers. We also find that consumers, on average, slightly reduce their absolute total purchase volume in response to size decreases, whereas they tend to increase their total volume following size increases. In both scenarios, the resulting changes in revenue for sellers are net positive.

We further examine the nature of product size changes, uncovering that these changes are typically not national occurrences affecting all markets simultaneously. Rather, they represent ongoing developments that vary across individual stores and retail chains. Our analysis reveals a compelling pattern: while manufacturers occasionally instigate size reductions by entirely replacing products with smaller versions, this is not the predominant trend. Size reductions more commonly occur at the retail level, with stores choosing to substitute a manufacturer's product with a smaller version while the larger product continues to be available in other stores. Thus, we conclude that both retailers and manufacturers—rather than manufacturers alone—are key contributors to the widespread phenomenon of shrinkflation within the U.S. retail grocery market. This nuanced understanding underscores the complexity of shrinkflation and its varied manifestations across the retail landscape.

We finalize our analysis with an empirical examination of consumer responses to product price and size variations. By leveraging data on weekly sales at the store-product level, alongside corresponding product size offerings and prices, we estimate the elasticities associated with both price and size. Our findings indicate a significantly higher sensitivity

of the average consumer to price fluctuations as opposed to changes in product size. Our model predicts that a 1 percent hike in price leads to a 1.32 percent decline in sales on average, whereas a similar rise in product size tends to increase sales by approximately 0.004 percent. We then use an instrumental variable approach to tackle potential endogeneity concerns of prices and package size. Similar to [DellaVigna and Gentzkow \(2019\)](#), we instrument both product price and size with the corresponding average values observed in different stores of the same chain but located outside the focal market area. The price elasticity is -1.95, while the estimate of the package size elasticity is 0.76. The observed disparity in price and size elasticities offers a compelling insight for retailers and manufacturers: In scenarios where increasing margins or responding to cost pressures is necessary, reducing package sizes may be a more effective strategy than raising prices.

Finally, we evaluate if price and package size elasticities differ for products that are decreasing in size compared to those that increase in size. We find that price elasticities between products do not differ. However, when considering a packed size decrease, we observe substantially fewer package size-sensitive consumers. Accordingly, we see that consumers react less strongly to package size decreases compared to increases, while price elasticities are similar. One interpretation of the result is that retailers or manufacturers make size increases more salient, leading to more pronounced consumer reactions while size decreases are hidden.

We contribute to multiple streams of literature in marketing, industrial organization, and behavioral economics. Our approach is closely related to a research note by the U.S. Bureau of Labor Statistics. ([McNair, 2023](#)) examines occurrences of product upsizing and downsizing in the CPI sample, conditional on product type, and explores their impact on CPI measurements.<sup>1</sup> Their findings indicate significant downsizing in categories such as ‘Baby food’, ‘Snacks’, ‘Fresh biscuits’, ‘rolls’, ‘muffins’, and ‘Household paper products’. The article concludes that, although a small number of prices in the CPI experience downsizing annually, it notably affects the indexes for specific item categories where size reductions are common. We confirm these results in a richer data set, showing a notable

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<sup>1</sup>Related work by [Ochirova \(2017\)](#) demonstrates the impact of product downsizing on inflation in the United Kingdom.



number of product decreases in these categories, and extend the analysis by presenting detailed characteristics of product shrinkage and evaluating consumer responses.

Moreover, several smaller-scale studies investigate consumer packaging and responses to changes in packaging size. For instance, [Kim \(2024\)](#) examines the South Korean milk market and finds a consumer preference for package downsizing. Studies by [Cakir et al. \(2013\)](#) and [Çakır \(2022\)](#) provide evidence of package shrinking and higher consumer prices for shelf-stable tuna, peanut butter, and ice cream. [Meeker \(2021\)](#) develop a structural model illustrating consumer inattention to product size decreases. [Yonezawa and Richards \(2016\)](#) study the effects of product downsizing on price competition in the cereal industry. Our study contributes to the literature as the first comprehensive analysis of the prevalence of size changes, the differences between size increases and decreases, and consumer reactions across various product groups.

More broadly, we document an empirical pattern within the U.S. retail grocery market. This research adds to influential papers that demonstrate uniform pricing behavior of various goods by retail chains across different geographies ([DellaVigna and Gentzkow, 2019](#)), highlight the heterogeneous impact of advertisement on consumer demand across products ([Shapiro et al., 2021](#)), document price promotions across products in stores ([Hitsch et al., 2021](#)), and reveal the significance of pink-taxes across products ([Moshary et al., 2023](#)). Similarly, we analyze various products in different stores within the grocery market and underscore the importance of size shrinking as a noteworthy phenomenon.

Finally, there is also a consumer behavior literature that examines consumers' ability to perceive changes in product sizes. [Ordabayeva and Chandon \(2013\)](#) present a series of experiments indicating that consumers tend to underestimate increases in product sizes, whereas [Chandon and Ordabayeva \(2017\)](#) contend that consumers are acutely aware of product downsizing, successfully recognizing product shrinkage in experimental settings. Further, [Yao et al. \(2020\)](#) conduct both field and laboratory experiments, uncovering that consumer responses to decreases and increases in product sizes are analogous when price information is accessible. Our research augments the existing body of work in consumer behavior by employing retail scanner data. Distinctively, our findings reveal significant disparities in consumer reactions to product size expansions and reductions. We observe

that size expansions frequently coincide with price hikes, while reductions in size typically occur without any change in price. Moreover, our analysis suggests that consumers exhibit a markedly higher sensitivity to variations in price than to alterations in size, highlighting a critical dimension of consumer decision-making in the retail context.

## 2 Data

The backbone of our analysis is the Nielsen Retail Scanner data provided by the Kilts Center at the University of Chicago, covering the years 2010 to 2020. We exclude observations prior to 2010 as product size changes are not recorded. The Nielsen Retail scanner documents weekly quantities and prices of approximately 4 million products sold across a spectrum of up to 50,000 retail establishments, including grocery stores, drugstores, mass merchandisers, and other types of retail outlets.

We limit our sample to products that are sold in a specific unit size. Thus, we exclude product groups that are not suitable due to non-standard sizes. Examples are deli products, fresh vegetables, or fruits. Our analysis requires the identification of products a retailer offers within a week. Given that the scanner data only records instances of product sales per week, we have constrained our dataset to encompass primarily leading brands within each of the 1,100 product modules. We operationalize 'leading brands' as those constituting 80 percent of the sales revenue within their respective module. The reduction permits a more accurate estimation of retailer stock assortments on a weekly basis.

Given that also the price of a product is only observed in weeks with positive sales, we impute missing pricing following the approaches of [Hitsch et al., 2021](#); [Moshary et al., 2023](#) or [Shapiro et al. \(2021\)](#). For a discussion on the imputation approach and implication, see [Appendix A](#). For the estimation of price and size elasticities of demand, we further only consider food, drugstores, and mass merchandise chains. The final sample and summary statistics are illustrated in [Table A.1](#).

## 2.1 Identification of Product Size Change

A key challenge in our research framework is the accurate identification of products undergoing product size reduction or increases. We approach this process from the perspective of a regular consumer who visits a store and may not notice when a familiar product has been replaced by a similar item with a smaller or larger size. Our goal is to systematically identify each instance within a store where a product is substituted by an equivalent product of a different size.

The substitution is essential since product assortment expansions have been prevalent over the past decade (Neiman and Vavra, 2023). When identifying products that have decreased or increased in size, we maintain a neutral stance regarding the underlying cause. These variations may result from manufacturers altering products—introducing new sizes and discontinuing old ones—or from retailers modifying their assortment to include different sizes from the same manufacturer. We explore these different scenarios in detail in Section 4.

Our identification process is as follows. First, we classify products as equivalent if they share the same brand, brand description, and UPC (Universal Product Code) description, requiring that these attributes be consistently reported within the same store. Equivalent products that change in size only differ in the UPC itself, in addition to the reported size. A detailed justification for using UPC changes as indicators of product size changes, and why ignoring size changes of products with the same UPCs does not undermine our analysis, is provided in Online Appendix C. Second, we establish that the two products are in substitution; that is, when the old product is removed from the store’s inventory, it is replaced by a new product of a smaller or larger size. This substitution is not temporary but permanent. We anticipate some heterogeneity among stores—some may allow an overlap period to sell off old stock, while others may experience a temporary gap between the discontinuation of the old product and the introduction of the new one. Therefore, our third criterion is a maximum of either an eight-week overlap or an eight-week gap between the discontinuation of the old product and the introduction of the new one. Finally, we also require that the size changes are in a specific range, with an increase

of at most 33.33% and a decrease of at most 25%.<sup>2</sup>

Our method could mistakenly classify a product as equivalent when size changes coincide with rebranding or package redesigns that do not alter the brand or UPC description. To reduce such errors and validate our methodology, we employ a UPC lookup database (<https://www.upcitemdb.com/>) for a visual inspection to accurately identify packaging and product details before and after size changes. Despite limitations in tracking older, discontinued products, the inspection allowed us to validate over 800,000 out of 1,300,000 instances of size reduction in inspected groups as identical products, supporting our analysis's reliability. The similarities in price adjustments and size reduction patterns between the overall data and the subset with confirmed identical products post-reduction further reassure us of our study's validity. Appendix B.1 details the visual inspection approach and results. Additionally, we use Nielsen's household scanner data to assess whether households consistently purchase the same products before and after a change in package size (for details, see Appendix B.2). We document a consistent buying pattern among panelists, which reassures us that products experiencing size changes are, in most instances, identical in every aspect apart from size.

In Figure 1, we present an overview of product size variations across different product groups between 2010 and 2020. Subfigure 1a illustrates the count of unique products undergoing at least one size change, while Subfigure 1b details the frequency of these size alterations, counting each instance of increase or decrease at the store level.

A consistent trend observed in both subfigures is the predominance of product size reductions over increases. Notably, the instances of size decreases are significantly more frequent than those of increases. This pattern of size reduction being more common than size expansion is evident across almost all product groups.

The product categories of candies and snacks are notable for their frequent size variations, both in terms of decreases and increases. Additionally, it is worth mentioning that size changes are also frequently observed in product groups such as hair care and

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<sup>2</sup>We adjust the percentage decrease and increase to maintain equal relative changes between the maximally shrunk product and the old product, and between the old product and the maximally enlarged product. If we consider a 25%-change in both directions, the number of shrunk compared to increased products rises. The other results are stable.

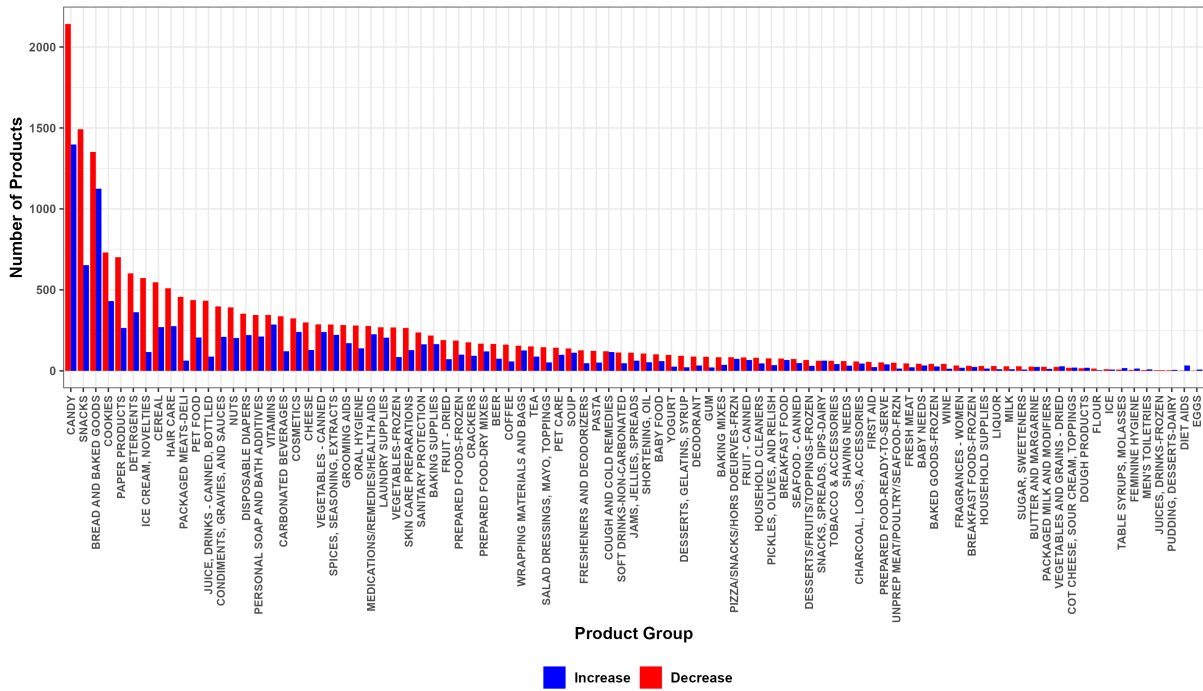
cosmetics, where changes in product size tend not to impact consumer usage patterns directly. Finally, there is substantial heterogeneity across product groups—with some product categories, such as milk or wine, where size changes rarely occur.

Additionally, we present a timeline analysis of product size changes from 2010 to 2020 in Figure 2, featuring weekly observations in both subfigures. Subfigure 2a illustrates the weekly count of unique products that either increase or decrease in size. In contrast, Subfigure 2b details the weekly total of size change occurrences across all stores.

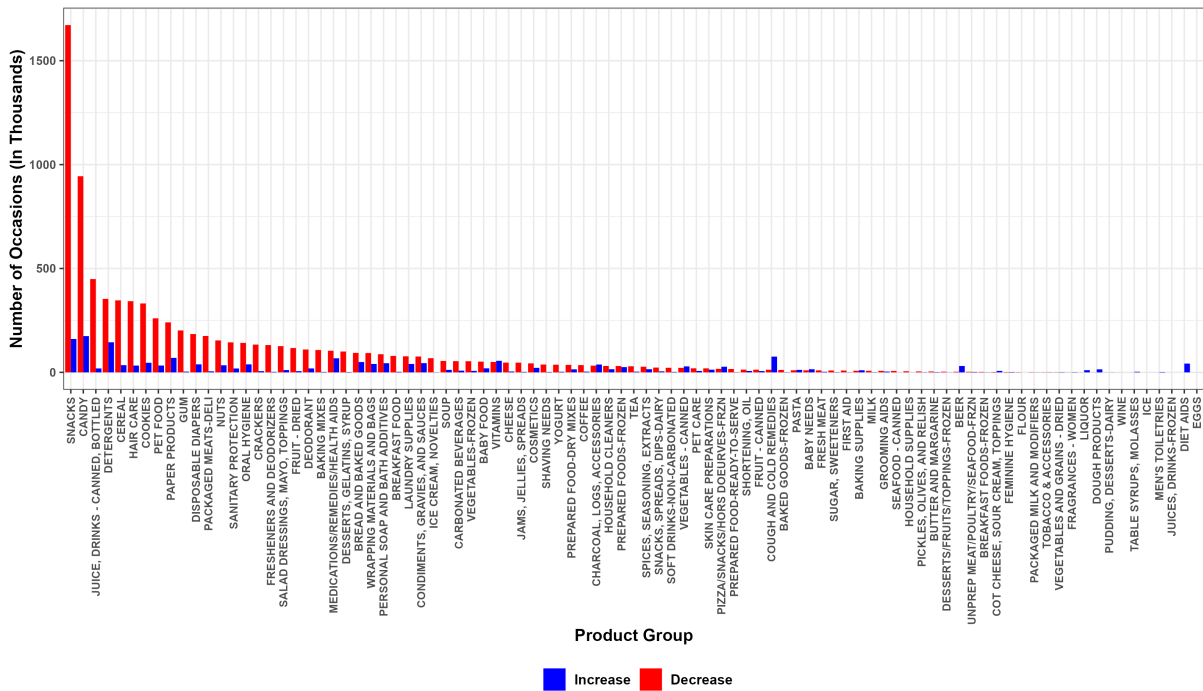
A consistent observation is that product size increases, both at the individual product level and in terms of occurrences, are more frequent than decreases. Throughout the decade from 2010 to 2020, product size changes have been a continuous trend, indicating that these changes are not a recent phenomenon but have been occurring since the early 2010s.

We also note a slight seasonal pattern, with product size changes being more common at the start of each year. This pattern is particularly apparent for the number of occasions across stores and shows some irregularities across years. Additionally, we observe a correlation between product size decreases and increases over time. This relationship may be linked to the infrequent adjustments in stores' product assortments, indicating that periods marked by significant product size reductions also tend to experience more occurrences of size increases, though to a lesser extent.

Figure 1: Overview of Product Size Changes



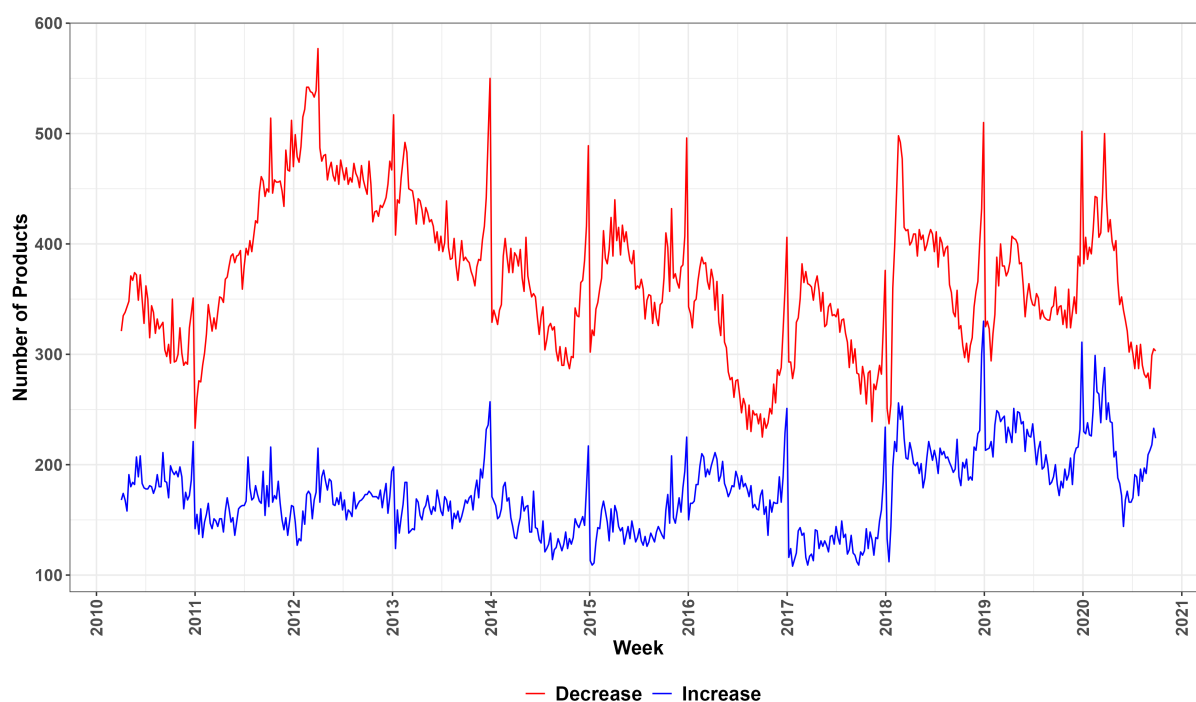
(a) Number of Products



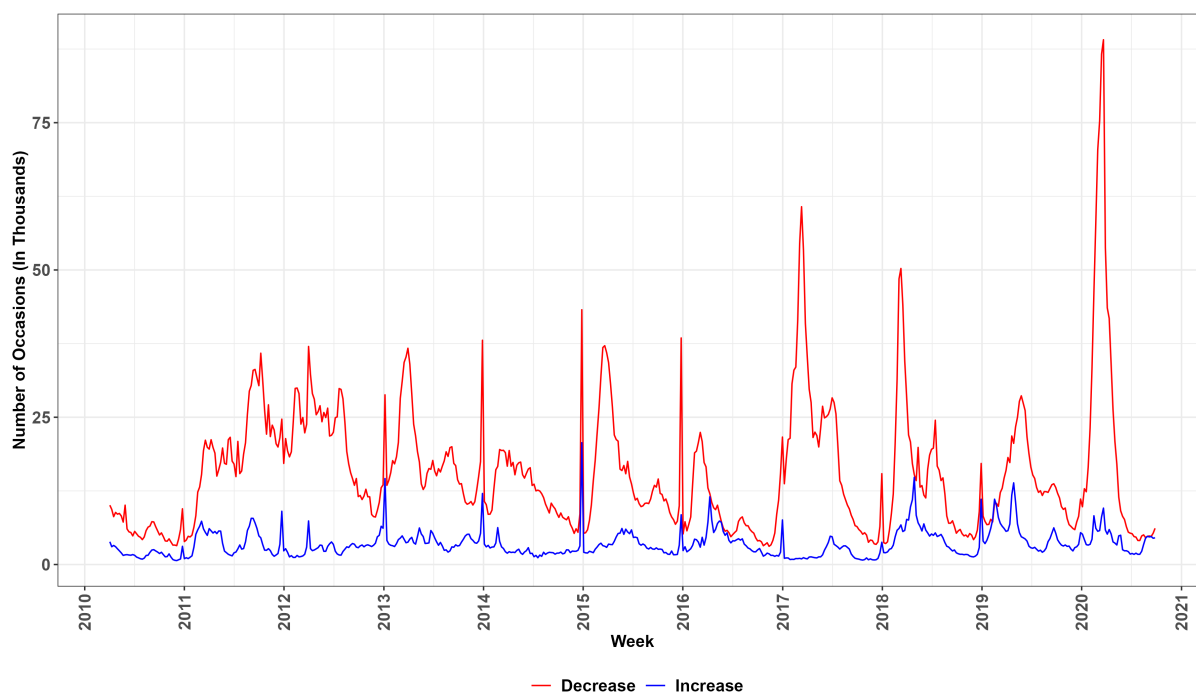
(b) Number of Occasions Across Stores

Notes: This figures illustrates the trends in product size changes across various product groups between 2010 and 2020. In Subfigure 1a, we display the total number of product size changes, counting each product once regardless of the number of stores affected. This contrasts with Subfigure 1b, which considers each instance of a size change within an individual store as a separate occurrence. In both subfigures, blue bars represent an increase in product size, while red bars denote decreases. Note that for a size change to be included, it must occur in an individual store where the new product size replaces the old one permanently, not just temporarily. Additionally, the size changes fall within specific parameters: increases are capped at 25%, and decreases at a maximum of 33.33%.

Figure 2: Timeline of Product Size Changes



(a) Number of Products



(b) Number of Occasions Across Stores

Notes: The figures provide a detailed timeline of product size changes from 2010 to 2020. In Subfigure 2a, we depict the trends in weekly product size changes, where each product is counted once, irrespective of the number of stores experiencing the change. In contrast, Subfigure 2b offers a different perspective by accounting for each size change event as a distinct occurrence within individual stores. Throughout both subfigures, blue lines represent increases in product size, and red lines indicate decreases. This dual approach allows for a comprehensive understanding of the frequency and distribution of product size alterations over the decade.

### 3 Insights into Product Size Changes

In this section, we analyze product size changes, examining how these variations differ across product categories, over time, and in their effects on prices, price per volume, and sales. When analyzing these dimensions, we distinguish between the characteristics of product size increases and decreases.

We begin our analysis by examining the temporal trends in product size changes across various product categories from 2011 to 2019, as illustrated in Figure 4. Subfigure 3a represents each product category in a separate row. The color intensity indicates the proportion of sales impacted by size reductions to total sales within each category in any given week across all stores. We categorize all sales in a specific store a year before and after a product size decrease as impacted by size reductions. The proportion is then equal to the ratio of all impacted sales and the rolling sum of sales for all products in that category within the same two-year span. Consequently, we exclude 2010 and 2020 due to the inability to calculate a two-year rolling sum. A darker shade signifies a larger percentage of category sales impacted by size reductions. Similarly, Subfigure 3b depicts the trends of product size increases, with darker shades of red denoting a higher fraction of sales affected by size increases.

It is noteworthy that the overall impact of size changes on sales is relatively modest. For product size decreases, the maximum proportion of affected sales in a week is 5.2%, with a sales-weighted average of 0.005% across all categories and time. In contrast, for size increases, the peak is 2.5%, and the weighted average is merely 0.001%. Two key observations emerge from this analysis. Firstly, there is significant variation in the frequency and timing of product size adjustments across different categories. These adjustments do not transpire within a brief interval; instead, we observe ongoing size reductions in various categories and stores. These reductions in individual product categories are not synchronized across stores but occur progressively over several months. Secondly, the modifications in product size, encompassing both increases and decreases, are not restricted to a specific time frame. Our research suggests that, although infrequent, these fluctuations



are evident across most product categories and persist throughout the entire study period.

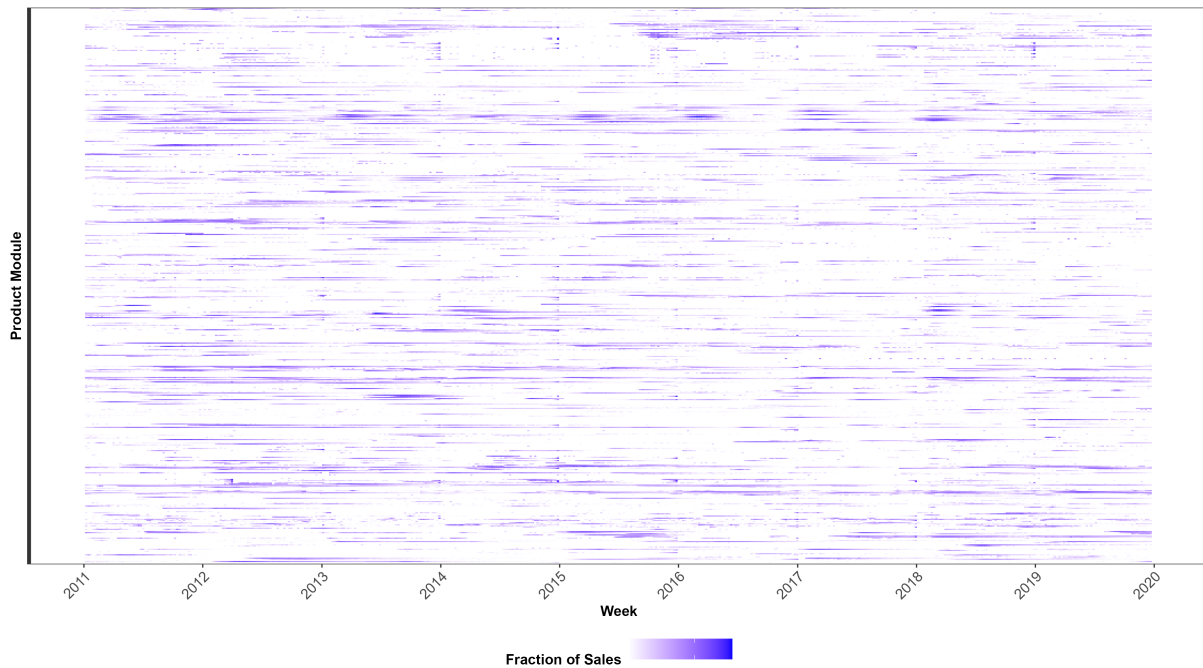
In our next analysis, depicted in Figure 4, we explore the relationship between product price changes and product size alterations. Subfigure 4a focuses on cases of product size reductions, while Subfigure 4b examines instances of size increases. In both cases, we consolidate data from individual product modules into broader product group categories. In the aggregation, we compute the weighted average of price changes and size alterations, using the sales volume of each module within a group as the weight. We measure price changes at the store level, assessing the year before and after any given price alteration.

In these subfigures, the blue line represents a linear weighted regression of product groups, with the weighting based on the sales volume of each group across all years. The red line denotes a 45-degree reference line. This line represents an equitable price adjustment, where the size change is proportional to the price change. Points above this line indicate scenarios where the price per unit volume has increased, while those below imply a decrease in price per volume.

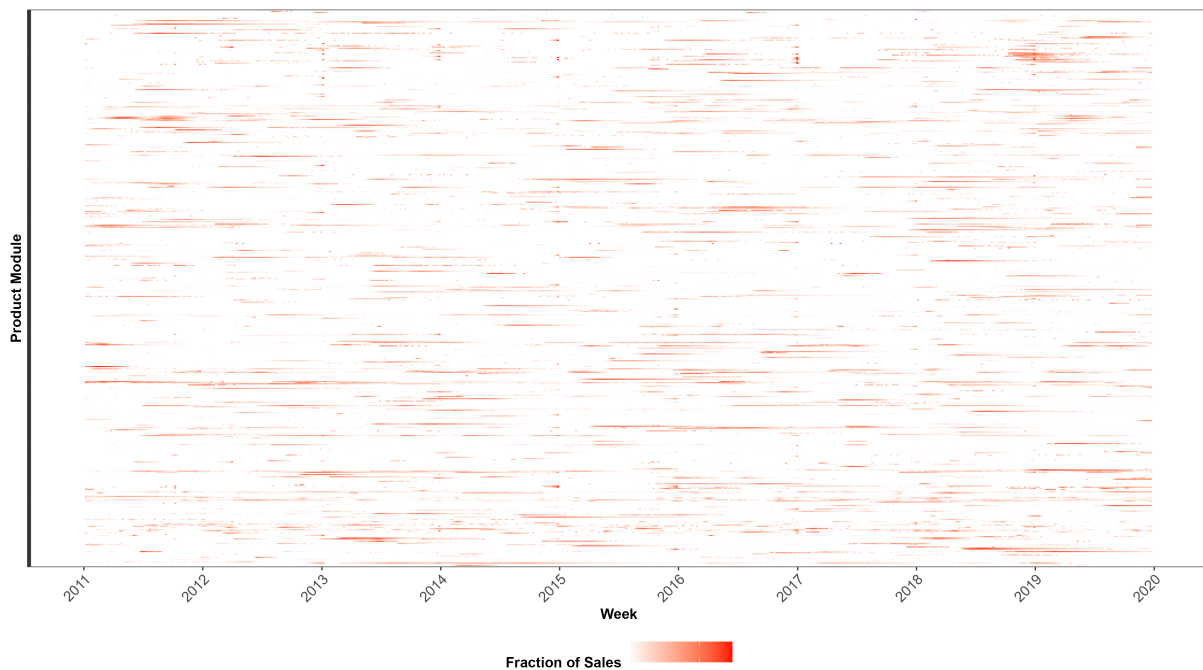
Figure 4 reveals how product size changes interact with price adjustments, particularly highlighting the differences between size increases and decreases. Price changes tend to be more modest when product sizes decrease compared to when they increase. Most product groups exhibit minimal changes in price following a size reduction, hovering near zero. Conversely, size increases often coincide with price changes. As these price hikes are typically lower than accompanying size increases, this pattern benefits consumers on average through lower prices per volume. This beneficial pattern is not observable for cases of size decreases. Figure 5 shows that for all product groups except liquor, the average price per volume increases when product sizes decrease. Conversely, changes in price per volume following a product size increase exhibit more heterogeneity across various product groups; however, prices per volume slightly decrease on average.

In sum, our analysis suggests that retailers or manufacturers often reduce product sizes while maintaining similar pricing levels, effectively increasing the price per unit volume. Conversely, when product size increases occur, prices tend to rise. However, this price hike is typically not enough to offset the size change, resulting in a lower price per volume.

Figure 3: Timing of Product Size Changes in Product Groups



(a) Product Size Decreases



(b) Product Size Increases

Notes: The figures presented herein offer insights into the timing of product size variations across different product modules. Specifically, Subfigure 3a illustrates the instances of product size reductions, whereas Subfigure 3b focuses on the occurrences of product size expansions. In these visualizations, each row is dedicated to a distinct product module. The intensity of blue or red hues within these rows represents the proportion of sales impacted by changes in product size, either through decrease or increase, respectively. This proportion, termed as the 'Fraction of Sales' is calculated using a moving average approach. It encompasses the sales of products that underwent size changes from one year prior to one year post-change. This figure is then compared to the aggregate sales of all products within the same module over the two-year period, across all stores. Note that due to the specifics of this moving average calculation, data from the years 2010 and 2021 are excluded from the analysis.

Our analysis proceeds with a descriptive analysis of the impact of product size changes on purchased volumes and sales. In Subfigures 6a and 6b, we illustrate changes in purchased absolute volumes before and after product size adjustments, for decreases and increases respectively. Notably, there is a discernible heterogeneity across product groups in response to size decreases. While some groups exhibit an uptick in purchased volume, others show a decline. On average, however, a reduction in product size is associated with a slight decrease in purchased volume. Conversely, when product sizes increase, the purchased absolute volume rises across the vast majority of product groups, indicating that consumers do not perfectly adjust their purchasing behavior to maintain the same level of absolute consumption in both scenarios of size decreases and increases.

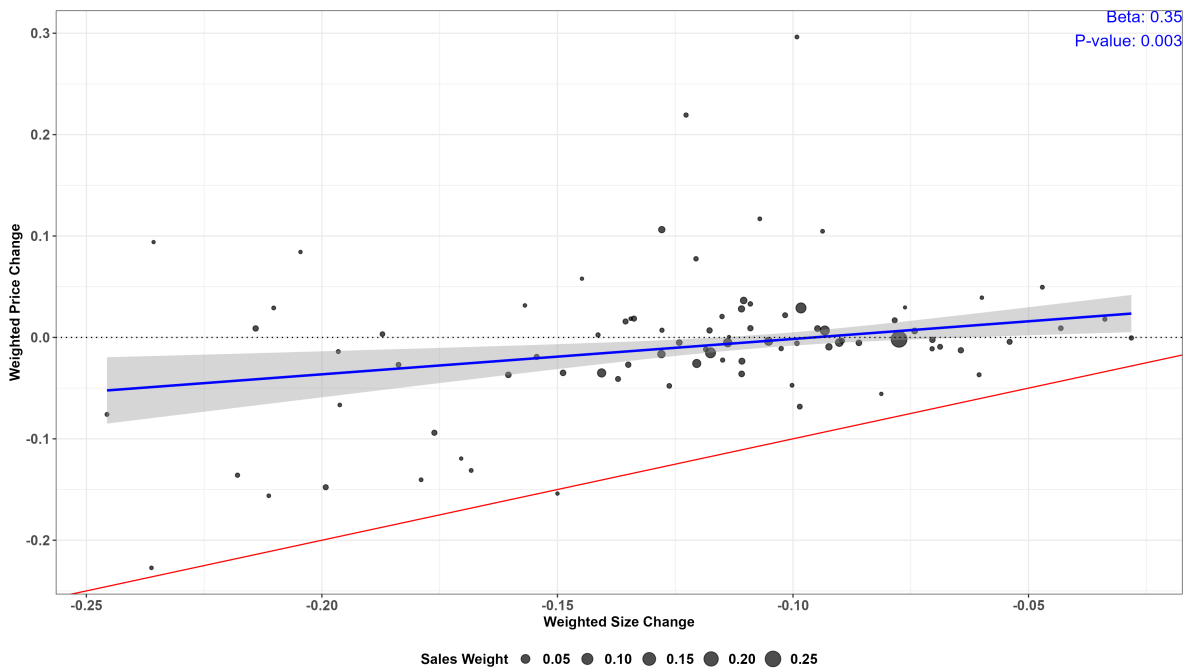
Subfigures 6c and 6d further explore the effects on stores' sales. Here, the trend is somewhat consistent for both size decreases and increases: most product categories experience an uptick in sales. These findings suggest that, on average, consumers are spending more on these products and that retailers and/or manufacturers successfully leverage product-downsizing and upsizing strategies to boost revenue.

## 4 Manufacturer or Store-Level Size Changes

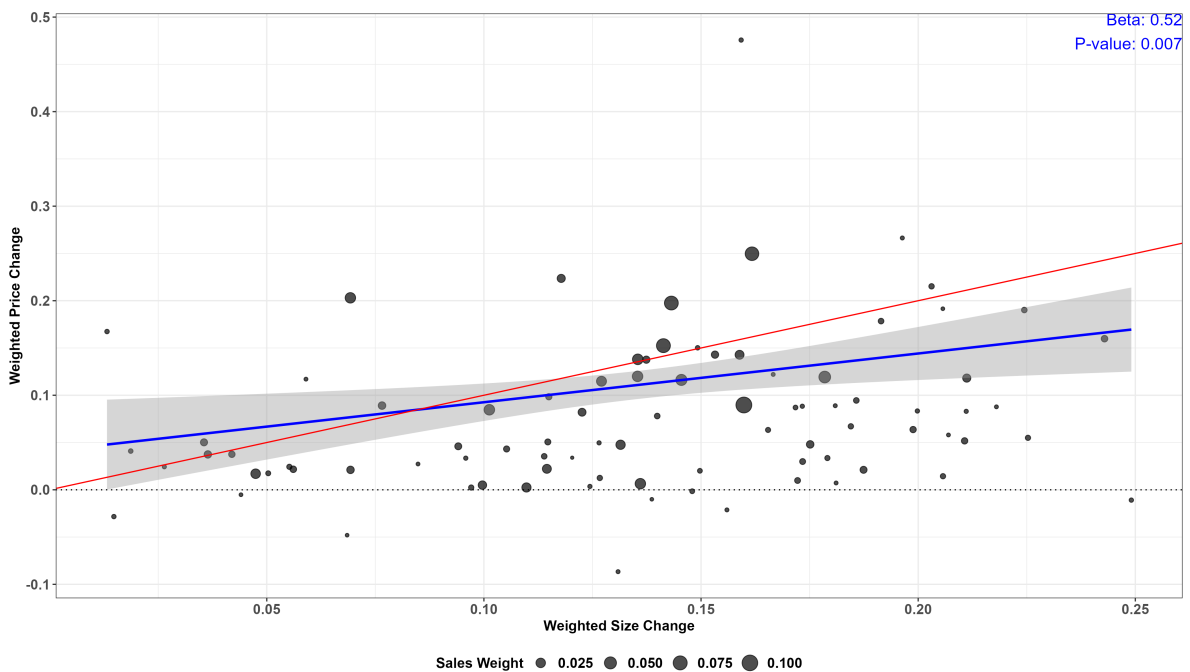
In this section, we explore who is primarily accountable for the observed changes in product sizes. Generally, either retailers or manufacturers might instigate size reductions or expansions. Recent media focus has largely been on manufacturer-led size alterations. Retailers, notably, have been pointing fingers at manufacturers for supplying smaller products, as highlighted in various reports ([The Associated Press, 2022](#)). Some retailers in other countries have even taken steps to transparently inform consumers about size reductions in products ([BBC News, 2023](#); [The Korea Times, 2023](#)).

However, it is also conceivable that retailers play a role in size changes. Manufacturers often provide several size variations of the same product. Retailers may choose to stock different sizes or select a particular size for their stores. Consequently, product size shifts at the store level could reflect retail decisions rather than manufacturing changes.

Figure 4: Price and Size Changes, Overview



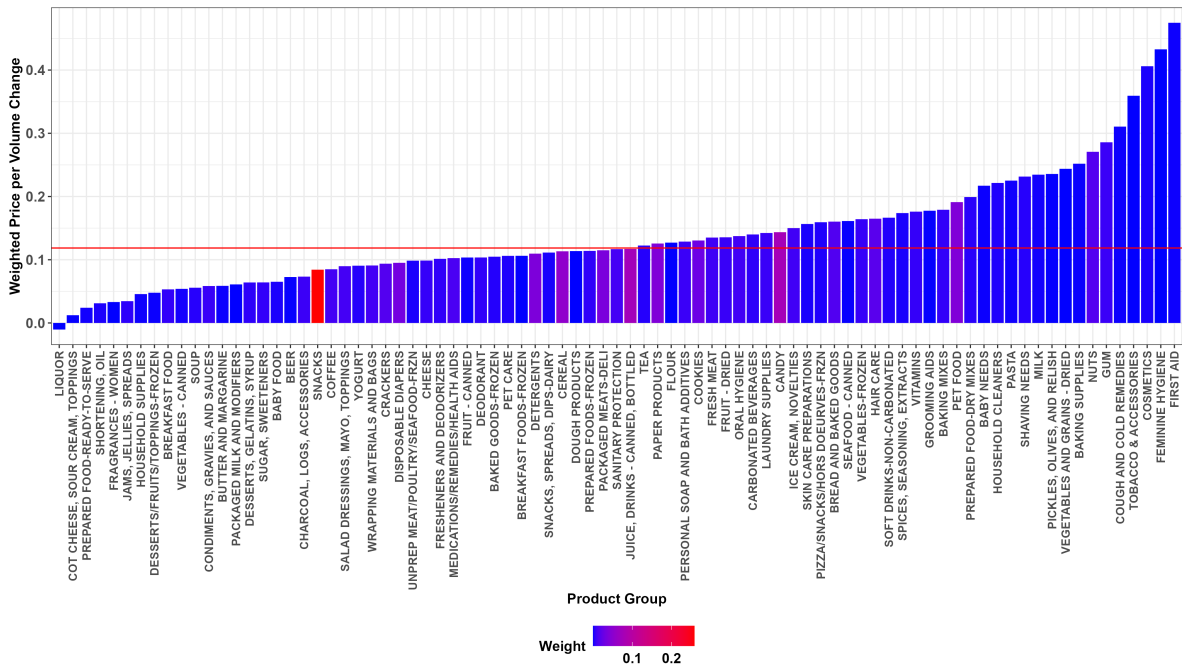
(a) Product Size Decreases



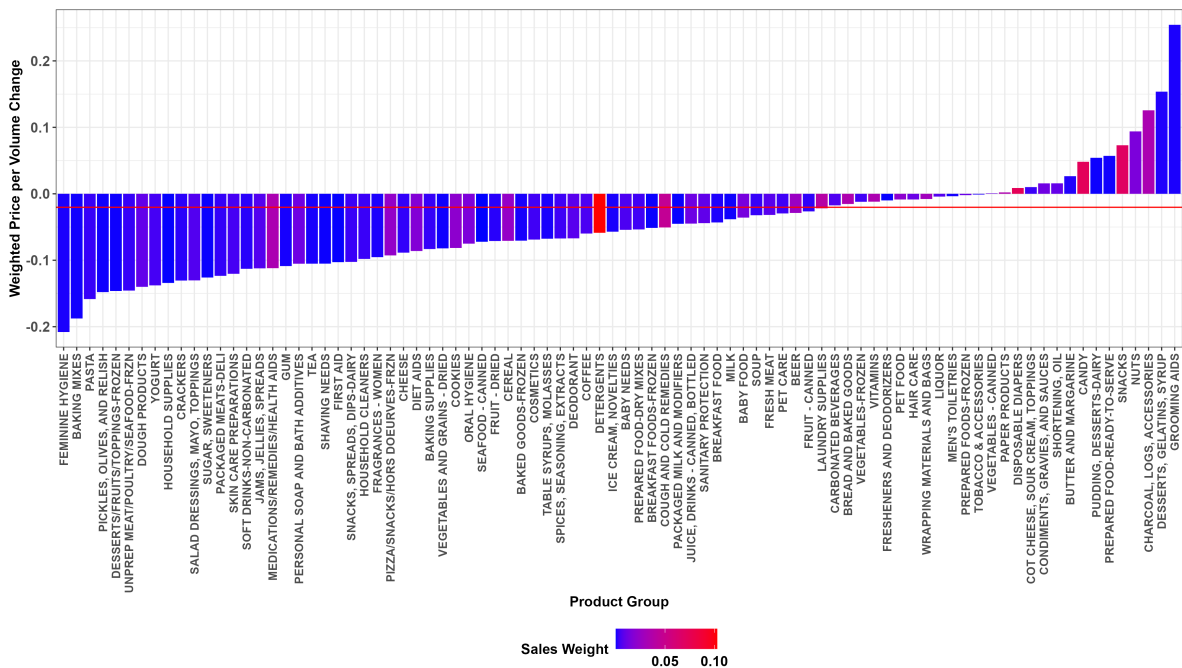
(b) Product Size Increases

Notes: The figures present an examination of how product size changes correlate with price adjustments. The analysis is divided into two parts: Subfigure 4a investigates product size reductions, and Subfigure 4b assesses size increases. For both scenarios, the data is aggregated from individual modules to product groups. Weighted average price and size changes are calculated using sales volume of the products as a weighting factor. Weighted average price changes are analyzed at the store level by comparing prices a year before and after the change. The figure features a blue line that depicts a linear weighted regression, where weights are based on sales of products that underwent size changes within their respective groups. The coefficients and p-values of these regressions are displayed in the upper right corner of each subfigure. Additionally, a red line is included to provide a baseline for proportional price-size adjustments.

Figure 5: Price per Volume, Overview



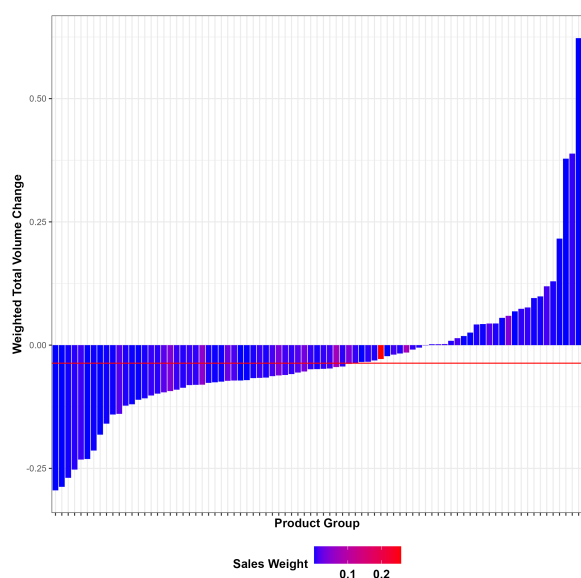
(a) Price per Volume, Product Size Decreases



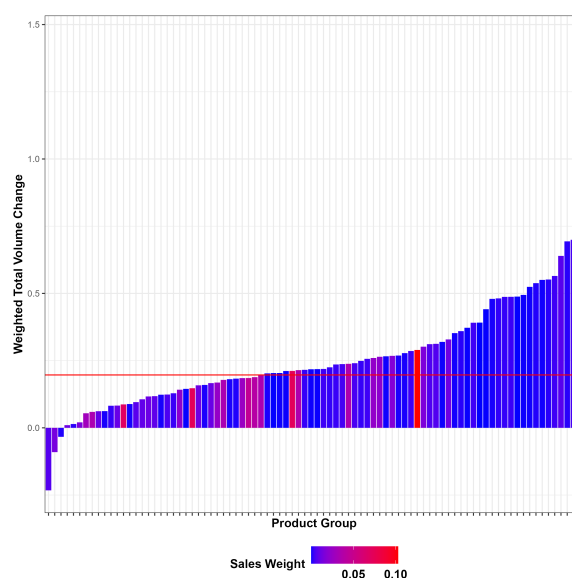
(b) Product Size Decreases, Product Size Increases

Notes: The figure presents an examination of how product size changes affect prices per volume. The analysis is divided into two parts: Subfigure 5a investigates product size reductions, and Subfigure 5b assesses size increases. For both scenarios, the data is aggregated from individual modules to product groups. Weighted average price per volume changes are calculated using sales volume of the products as a weighting factor. Note that prices per volume are prices divided by the size of a product using product group-specific measurements. The analysis compares these metrics from the year preceding to the year following a product size change. The color intensity of each bar in the figure corresponds to the sales weight of the product group, with deeper shades of red indicating higher sales volumes within that group. The red line shows the weighted average price per volume changes across all product groups.

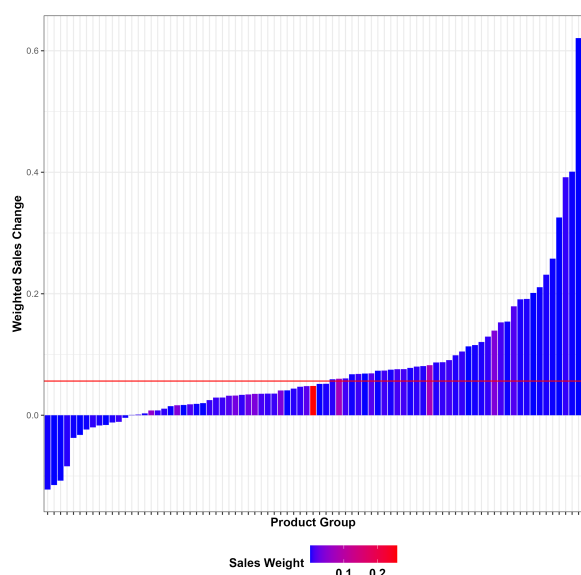
Figure 6: Volume Purchased and Sales across Product Groups



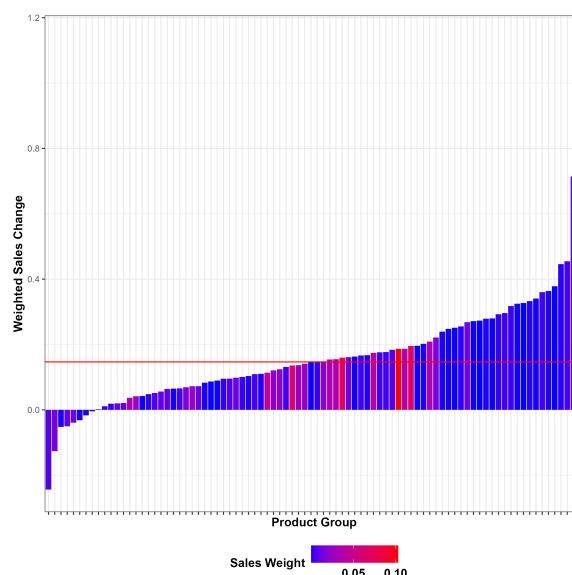
(a) Purchased Volume, Product Size Decrease



(b) Purchased Volume, Product Size Increase



(c) Sales, Product Size Decrease



(d) Sales, Product Size Increase

Notes: The figures show the changes of purchased volume and sales of products that decrease or increase in size across product groups. Each bar corresponds to one product group. Subfigure 6a considers the dynamics of purchased volumes following product size reductions, while Subfigure 6b focuses on the effects of size increases. Changes are measured on the product level and compare volumes measured in module-specific units (e.g., ounces) from the year before to the year after the product size change. The analysis employs an aggregation approach, consolidating data from individual products into product groups, considering their weights in sales. Similarly, Subfigure 6c and 6d analyze the corresponding changes in sales, adopting the same methodological framework. In these subfigures, the intensity of color in each bar graphically represents the sales weight of the product group, where richer red hues signify higher sales volumes of a group. A distinct red line across the figures denotes the aggregated weighted changes in volume or sales across all product groups.

We will next examine both manufacturer- and retailer-induced size changes. Generally, we argue that a size change observed nationally is attributed to manufacturers, while those observed only at the store level are retailer-induced. As explained in section 2.1, we define size changes based on exits and entries on the store level. The definition of exits and entries on the store level and the corresponding definitions of size changes remain unchanged. Next, we identify if a store-level size change is likely due to a manufacturer or a retailer.

Identifying manufacture-induced shrinking requires multiple assumptions. We never observe a coordinated size change across all stores for two reasons. First, we observe residual sales of all products even when the product is unavailable in nearly all US stores. Second, we often observe size changes on a store level preceding a more coordinated change in size nationwide. To tackle this challenge, we follow a two-step procedure: First, we define a manufacture-induced exit date as the date when the sales of the older version of a size-changing product drop permanently to less than 5 percent of the weekly national average of sales.<sup>3</sup> Second, as retailers may shrink their product actively way before the manufacturer-induced exit rate, we solely characterize store-level size changes as manufacturer-induced if the size change happens within 52 weeks before the estimated manufacturer-induced exit date.

On the other hand, a retailer-induced size change is identified if sales exceed the 5th percentile in the remaining stores in at least the following 52 weeks. This approach is designed to be robust against small retailers continuing to sell old stock (thereby inflating the prevalence of retailer-induced size changes) while avoiding the overestimation of manufacturer-induced changes by attributing every store-level variation to a decision by the manufacturer.

To clarify our methodology for distinguishing between retailer- and manufacturer-induced size changes, we present a visual illustration in Figure 7. Specifically, we focus on the top 100 products experiencing size reductions based on sales and observe a manufacturer-induced exit rate within our sample period.<sup>4</sup> In the figure, these products

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<sup>3</sup>In detail, we require four consecutive weeks of national sales that are lower than 5 percent of the national sales level.

<sup>4</sup>A similar analysis is conducted for size increases, yielding comparable results across all aspects.



are arranged by their sales volume, beginning with the highest. We highlight the initial observed size reduction event in red, followed by the estimated exit point – the moment when sales fall below 5 percent of the national average across all weeks in our data on a permanent basis.

The example of top-selling products that decrease in size reveals considerable variability in the time span between the first size reduction and the eventual national exit, with some products showing a shorter duration and others spanning several years. To discern whether the size reductions for each product are predominantly manufacturer-induced, we use a light blue highlight for products where the majority of size reductions occurred within a year prior to the national exit. Notably, our findings suggest that only about 10 percent of the products predominantly exhibit manufacturer-induced size reductions.

In Figure 8, we present an analysis comparing the sales volume associated with retailer versus manufacturer-induced size changes. Subfigure 8a illustrates the sales volume of products experiencing size decreases, while Subfigure 8b focuses on size increases. The sales size for both manufacturer and retailer-induced changes is represented as a two-year moving sum.

Consistent with the patterns identified in Figure 2, we find that product size decreases are more prevalent in terms of both frequency and sales volume. While manufacturer-induced size changes generally show lower sales volumes compared to those initiated by retailers, there appears to be a notable correlation between the two.

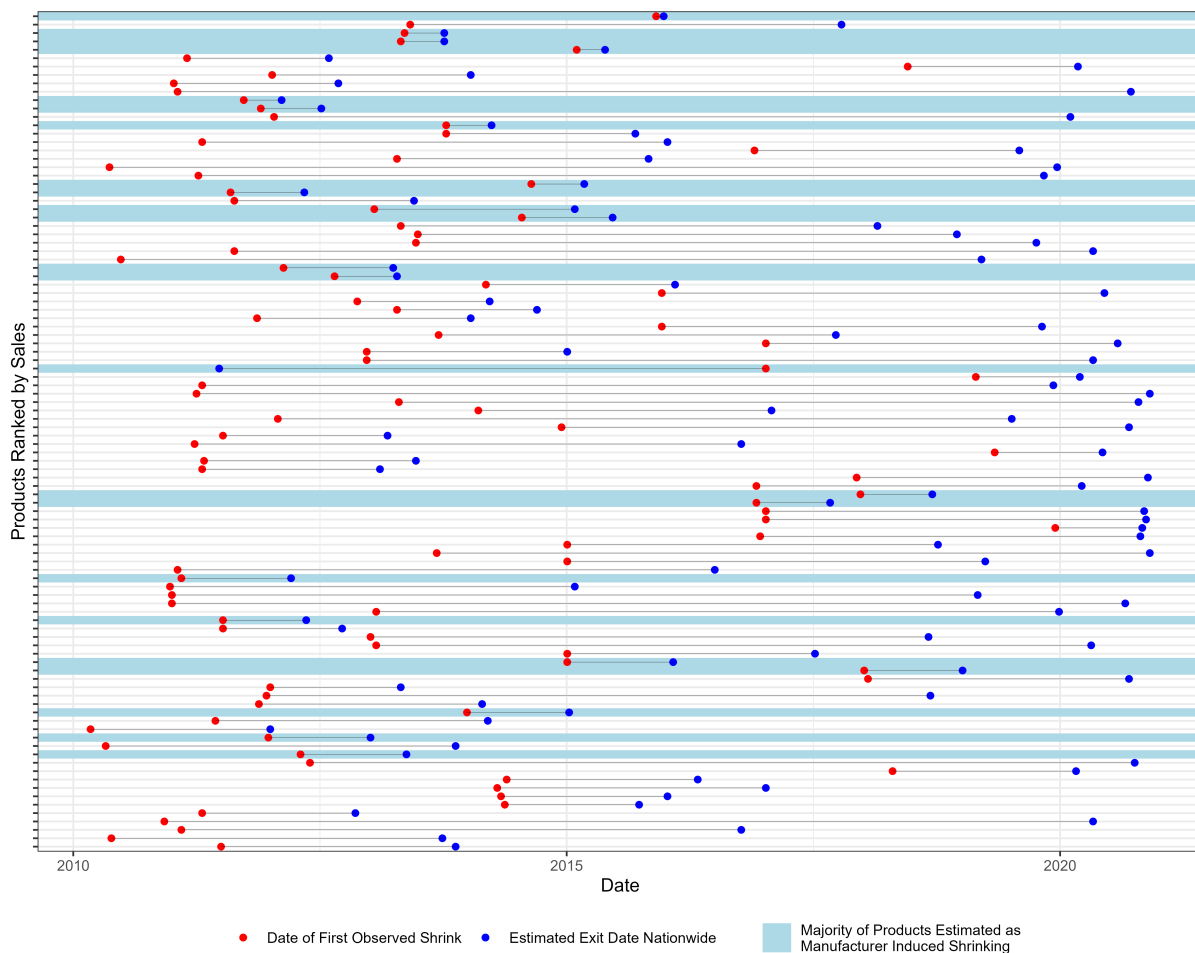
## 5 An Empirical Model of Consumer Responses

### 5.1 Empirical Strategy

In this section, we move to evaluating consumer responses to product price and size changes. In order to evaluate whether consumers react differently to unit price changes than to price changes due to package size, we estimate elasticities of demand for each

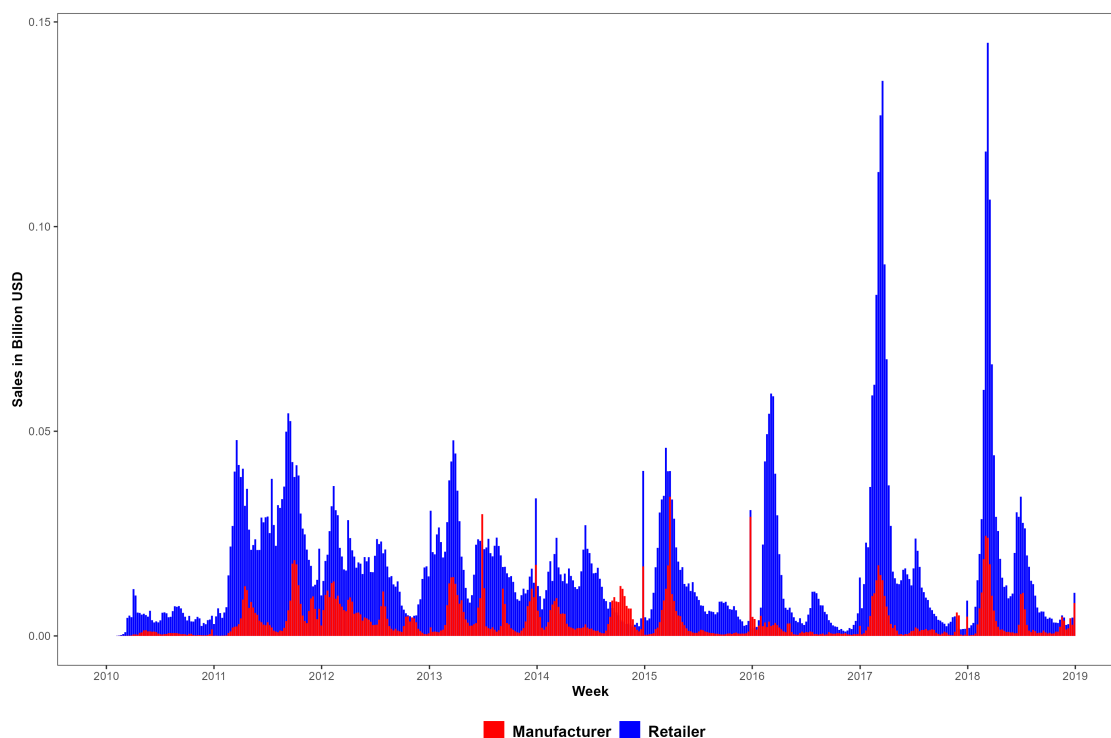


Figure 7: Example Retailer- vs. Manufacturer-Induced Size Decrease

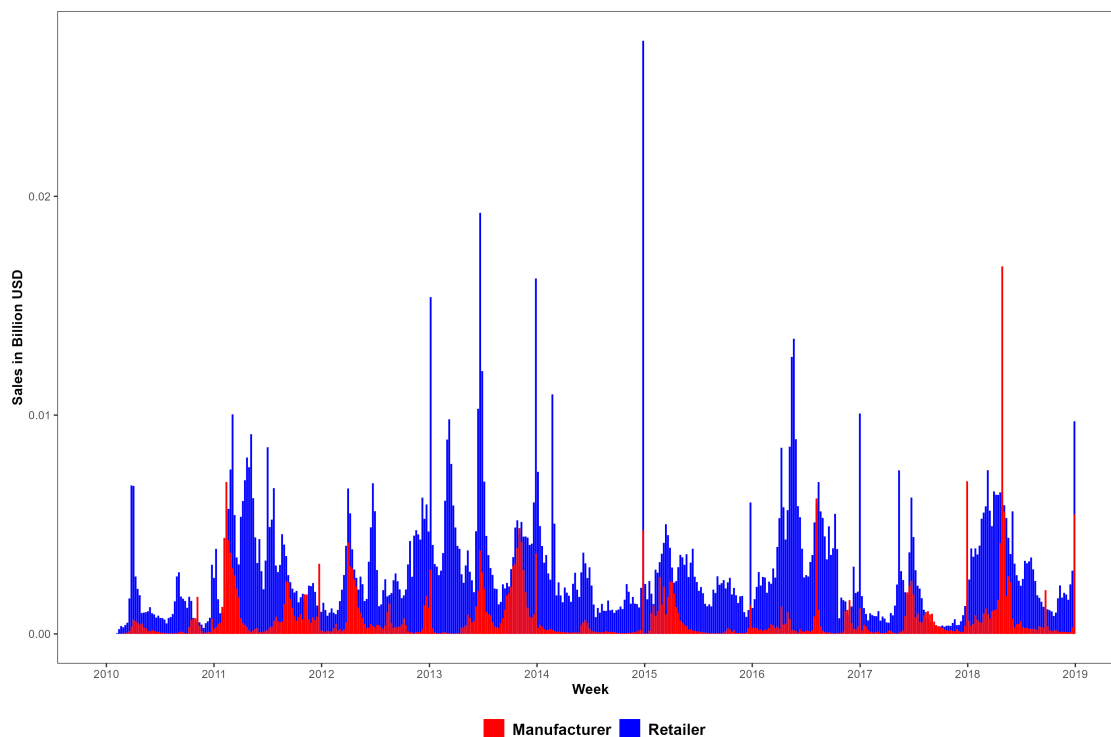


*Notes: This figure visually represents the leading 100 products by sales volume that have undergone size reductions on the store level, and there exists a date we define as manufacturer-induced exit date, meaning the sales of the older version of a size-changing product drop permanently to less than 5 percent of the weekly national average of sales. Products are ordered according to their sales, starting with the highest. Key events are marked: initial size reduction occurrences are indicated in red, and the estimated exit point—defined as the moment when a product’s sales consistently fall below 5 percent of the national average across the full sample period—is shown in blue. Products where the majority of size reductions are identified as manufacturer-induced, occurring predominantly within a year prior to the national exit, are highlighted in light blue.*

Figure 8: Sales Volume of Retailer- vs. Manufacturer-Induced Size Changes



(a) Product Size Decreases



(b) Product Size Increases

*Notes: This figure delineates the scale of product size alterations instigated by both manufacturers and retailers. Subfigure 8a focuses on product size decreases, while Subfigure 8b examines instances of product size increases. Sales volumes are calculated at the product level for each week, represented as a cumulative sum over two years. Note that data from the year 2020 is excluded from this analysis. Our current methodology for differentiating between manufacturer and retailer-induced size changes is not applicable to periods shorter than 52 weeks prior to the last date in the sample.*

store-product pair. We distinguish between price elasticity  $\eta_P$  and product size elasticity  $\eta_L$ . As our benchmark, we estimate the response of weekly log quantity,  $\log(x(p_{t,s,i}))$ , to the weekly log unit price and the weekly log product size of a product within a store  $s$ , allowing for store-product fixed effects,  $\alpha_{s,i}$ , and week fixed effects,  $\gamma_t$ :

$$\log(x(p_{t,s,i})) = \eta_p \log(p_{t,s,i}) + \eta_l \log(l_{t,s,i}) + \alpha_{s,i} + \gamma_t + \epsilon_{t,s,i}, \quad (1)$$

where  $P_{t,s,i}$  and  $L_{t,s,i}$  denote the weekly unit price and weekly package size of product  $i$  in store  $s$ . We define a product as in previous sections, i.e., having identical brand, UPC description and brand description. Our primary interest lies in the comparative analysis of elasticities. The implicit assumption allowing for meaningful comparison of the two elasticities in our benchmark model is that product size only affects demand through its effect on price per volume. If only the price per volume matters to consumers, we would expect that the two elasticities equate for fully attentive consumers, i.e., consumers' demand reacts to a percentage change in the unit price in the same way as to a percentage change in price per volume due to product size changes.

In our estimations, we selectively focus on products that experienced a variation in product size across at least one store within the U.S. across the observation period. By focusing on these products, we ensure a comparable set of products and computational feasibility. Yet, we still have a diverse set of observations, not subject to product size changes, that allow for meaningful time-fixed effects. The robustness of using different time-fixed effects reassures us that the results are not driven by the data set restriction. We estimate equation 1 separately for each product module and then aggregate it to the product group level by weighting it by total sales within each product module.<sup>5</sup>

A concern challenging the validity of our estimation approach is that prices and sizes are correlated to unobserved local demand shocks. To tackle endogeneity concerns, we follow [DellaVigna and Gentzkow \(2019\)](#) and instrument the weekly price and the weekly

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<sup>5</sup>We chose this approach because computational constraints did not allow us to run the regression for entire product groups or all products simultaneously. Weighted coefficients of smaller product groups are similar to coefficients of a regression using all products within the respective group.

product size in-store  $s$  with the average of prices and product sizes across other stores in  $s$ 's chain that is located outside the respective store's Designated Market Area (DMA). This instrument approach where prices in other markets are used as instruments is common in economics, following Hausman (1996) and Nevo (2001). The key assumption here is that the timing of chain-level sales is unrelated to local demand shocks after controlling for time-fixed effects. DellaVigna and Gentzkow (2019) shows that prices and stores' assortments are very similar within chains, but different between chains. These findings imply that chains do not account for local demand conditions when setting prices or product assortment, making our instrument approach convincing with respect to both price and product size. In contrast, to our benchmark model, DellaVigna and Gentzkow (2019) use store-product-week-of-year and store-product-year fixed effects. The qualitative results remain robust when using these alternative fixed effects. Moreover, product size changes, especially when initiated by manufacturers, are a long-term strategy that is not directly influenced by local demand shocks, which suggests that our fixed effects adequately capture relevant local demand variations. Focusing on manufacturer-induced shrinkflation, our findings remain robust, providing further support for this view.

While the estimation of model 1 allows us to estimate price and quantity elasticities of demand, we do not evaluate how the sensitivity of consumers differs when products are de- or increasing in size. Thus, we extend our main model and differential elasticities between products that decrease and increase in size. In detail, consider the following model which is a direct extension of model 1:

$$\begin{aligned} \log(x(p_{t,s,i})) = & \eta_p \log(p_{t,s,i}) + \eta_l \log(l_{t,s,i}) + \\ & \beta_p \log(p_{t,s,i}) \times \mathbf{I}(\text{Shrink}_{i,s} = 1) + \beta_l \log(l_{t,s,i}) \times \mathbf{I}(\text{Shrink}_{i,s} = 1) + \\ & \alpha_{s,i} + \gamma_t + \epsilon_{t,s,i}, \end{aligned} \tag{2}$$

where the key differences are the interaction terms of  $\log(p_{t,s,i})$  and  $\log(l_{t,s,i})$  with  $\mathbf{I}(\text{Shrink}_{i,s} = 1)$ , which is a dummy variable that takes the value one if the specific product has been

decreasing in size. As a result,  $\beta_p$  shows how price elasticities of that product that decrease in size differ from the general price elasticity of demand. Further,  $\beta_l$  shows how the size elasticity differs when considering products that decrease in size.

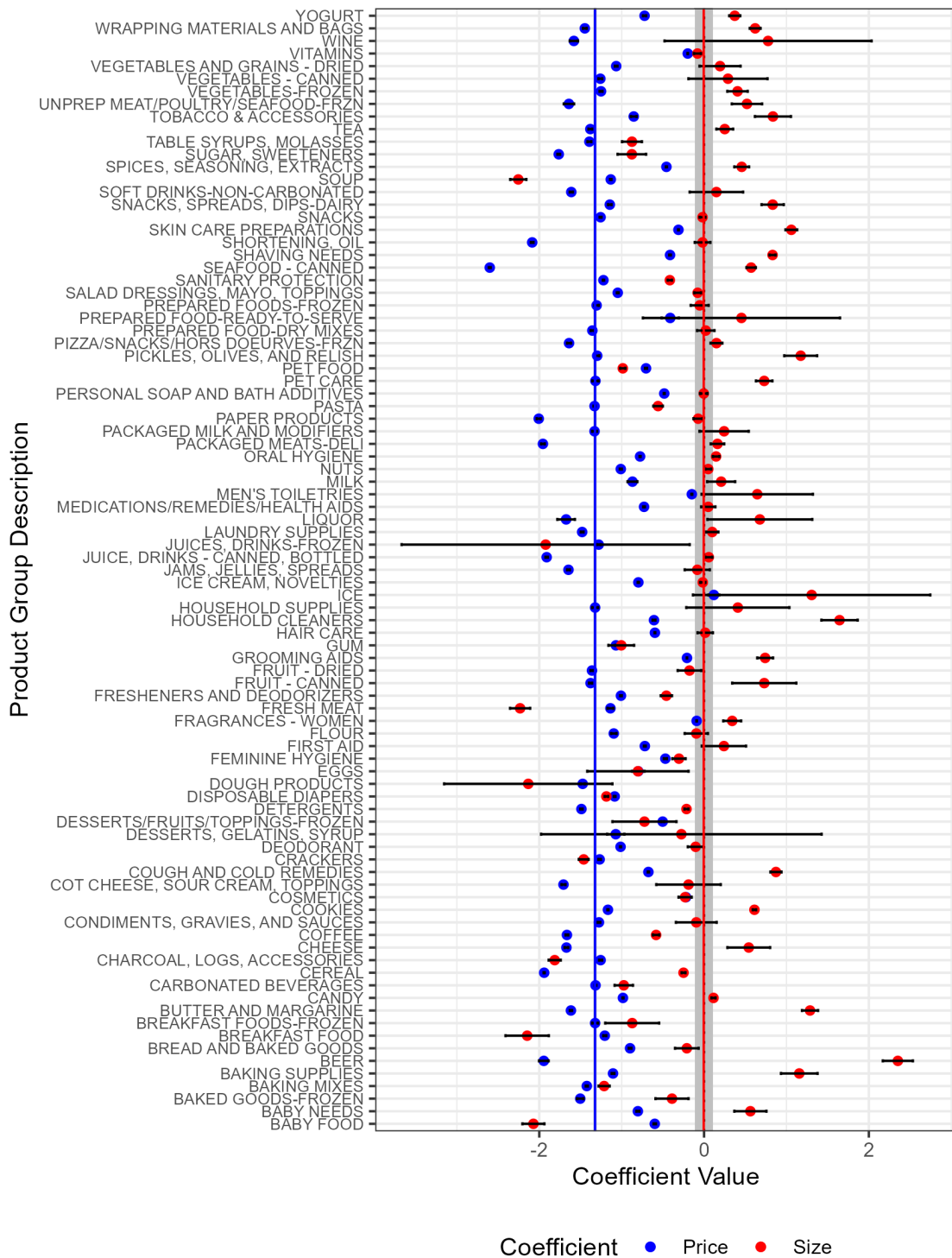
## 5.2 Results

Figure 9 presents the estimates aggregated by product group. The response to unit price changes appears more pronounced than to package size changes. The average estimated unit price elasticity, weighted by total sales across all product groups, which is illustrated by the solid blue line, is equal to -1.32. The average elasticity for product size, illustrated by the solid red line, is 0.004. Thus, on average, a 1 percent increase in price would reduce sales by 1.32 percent, while a 1 percent increase in size would increase sales by 0.004 percent. The difference between price and quantity elasticities suggests consumers are less responsive to the price-per-volume changes resulting from product size variations than to unit price changes. Such a tendency offers profit-maximizing firms an opportunity to capitalize on potential consumer underreactions to these changes by decreasing product sizes.

Second, Figure 10 presents the results for the instrument variable regression. The first stages of the IV regressions are very strong in most cases, with coefficients close to 1 for most product modules. Now, the price elasticity estimate of the weighted average is -1.95, and the estimate of the package size elasticity is 0.76. In contrast to the results from Figure 9, the package size elasticity is statistically different from zero when aggregating all product groups. While estimated elasticities increase in absolute size, the IV regression results produce a consistent picture. Consumers tend to underreact to price changes due to package size changes relative to unit price changes.

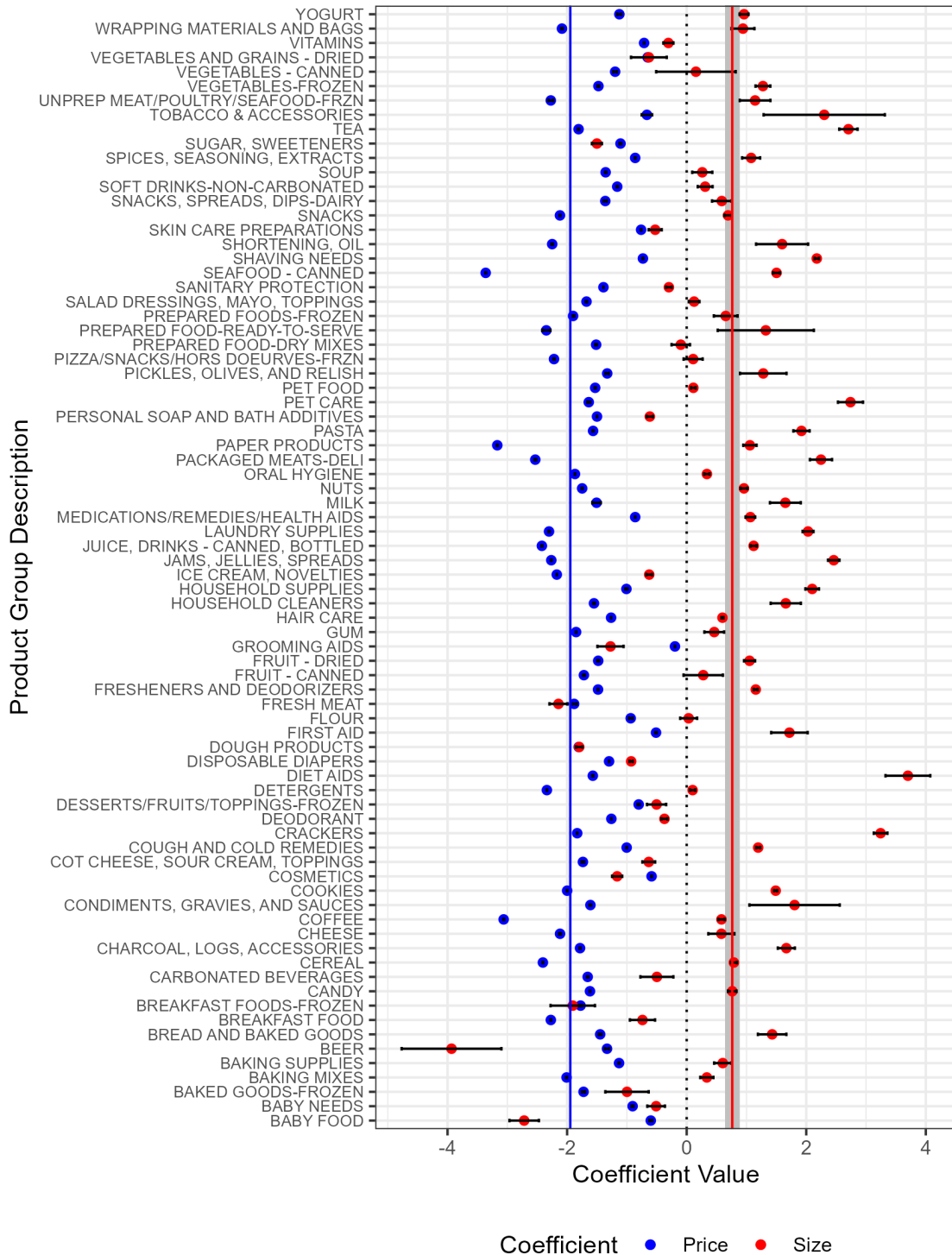
Our findings also reveal significant heterogeneity in elasticities across different product groups. The variation is more pronounced for product size elasticities, which can be partly attributable to considerably smaller variations in product size compared to unit price. Negative product size elasticities, indicating that demand is increasing for smaller

Figure 9: Estimated Unit Price and Package Size Elasticities for Different Product Groups



Notes: This graph presents the estimated unit price elasticities (in blue) and package size elasticities (in red) and corresponding 95% confidence intervals in different product groups, according to equation 1. The coefficients, therefore, refer to  $\hat{\eta}_p$  and  $\hat{\eta}_i$  in model 1. The coefficients in each group refer to the sales-weighted average of estimated elasticities across all product modules within one product group. The solid blue line (red line) illustrates the sales-weighted average unit price (package size) elasticity across all product groups. Error bars denote the 95% confidence intervals of the weighted coefficients. We exclude those product modules that do not allow inference due to extremely large standard errors that lead to rejecting the hypothesis that the point estimates are equal to  $\leq -5$  or  $\geq 5$ .

Figure 10: Estimated Unit Price and Package Size Elasticities for Different Product Groups, IV Regression



Notes: This graph presents the estimated unit price elasticities (in blue) and package size elasticities (in red) and corresponding 95% confidence intervals in different product groups, using an instrument variable approach. The coefficients, therefore, refer to  $\hat{\eta}_p$  and  $\hat{\eta}_l$  in model 1. We instrument the weekly price and the weekly package size in store  $s$  with the average of prices and package sizes across other stores in  $s$ 's chain that are located outside the respective store's DMA. The coefficients in each group refer to the sales-weighted average of estimated elasticities across all product modules within one product group. The solid blue line (red line) illustrates the sales-weighted average unit price (package size) elasticity across all product groups. We exclude those product modules that do not allow inference due to extremely large standard errors in the first or second stage of the instrumental variable regression that lead to rejecting the hypothesis that the point estimates are equal to  $\leq -5$  or  $\geq 5$ .

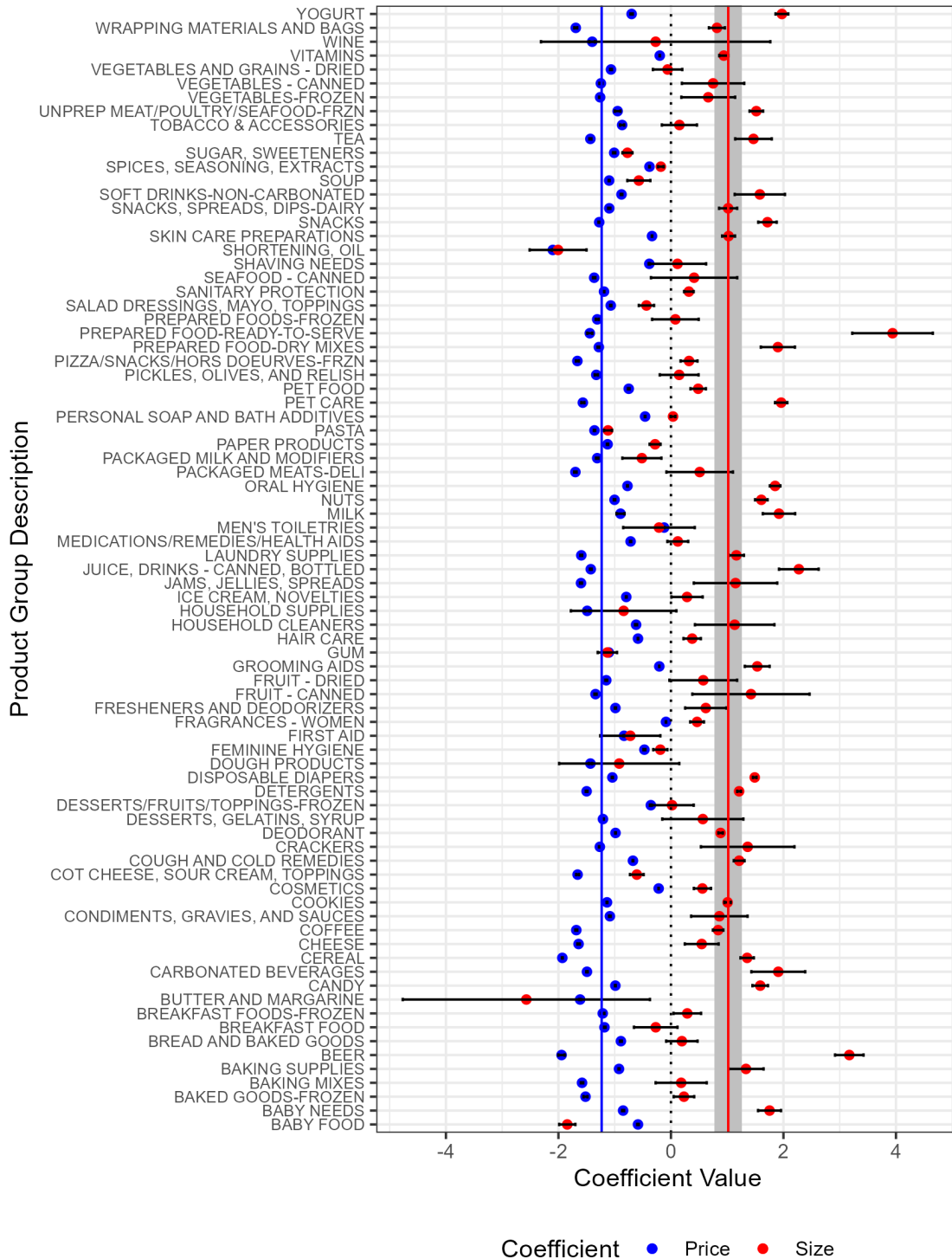
product sizes, are more prevalent for food and drink product groups, such as fresh meat, carbonated beverages or soup. This tendency could be related to consumers exhibiting a preference for product size, e.g., because of stockpiling constraints and healthier eating habits for some product categories. We expect this to be less relevant for the size elasticity in product groups that are more durable and where "one" product is typically connected to multiple uses, such as laundry supplies, toiletries, or hair care. In most of these groups, size elasticities are close to zero, which is in line with the idea that consumers are not attentive to product size changes. In the subsequent analyses, we further try to disentangle preference from price effects related to product size changes.

We start by investigating if elasticities vary between products that have shrunk and those that have increased in size. For this purpose, we interact the logarithm of prices and product size with a dummy variable indicating whether a product decreased in size at the store-product level. Additionally, we also interact the dummy variable with the week-fixed effects to account for diverging time trends for both subgroups. Figure 11 illustrates the elasticities for non-shrunk products, and Figure 12 presents the average interaction term's coefficients.

Estimating the price and package size elasticities for non-shrinking products gives weighted average estimates of -1.23 and 1.02, respectively. Thus, for nonshrinking products, the reaction to price changes is slightly stronger than for size changes. Moving to Figure 12, the average coefficient of the price interaction term is close to zero (-0.02), indicating no significant difference in unit price elasticities between products that decrease in size and those that do not. Secondly, the interaction effect for size changes is -1.15, suggesting that consumers react less to size changes when related to product size reductions. The weighted average coefficient of the size interaction term is of similar magnitude to the size elasticity of nonshrinking products, implying that the size elasticity of products size decreases is close to zero. The higher size elasticities for increased products aligns with the idea that retailers make size increases more salient, leading to more pronounced consumer reactions. Conversely, the near-zero average size elasticity for shrunk products suggests that product size decreases tend to be hidden.

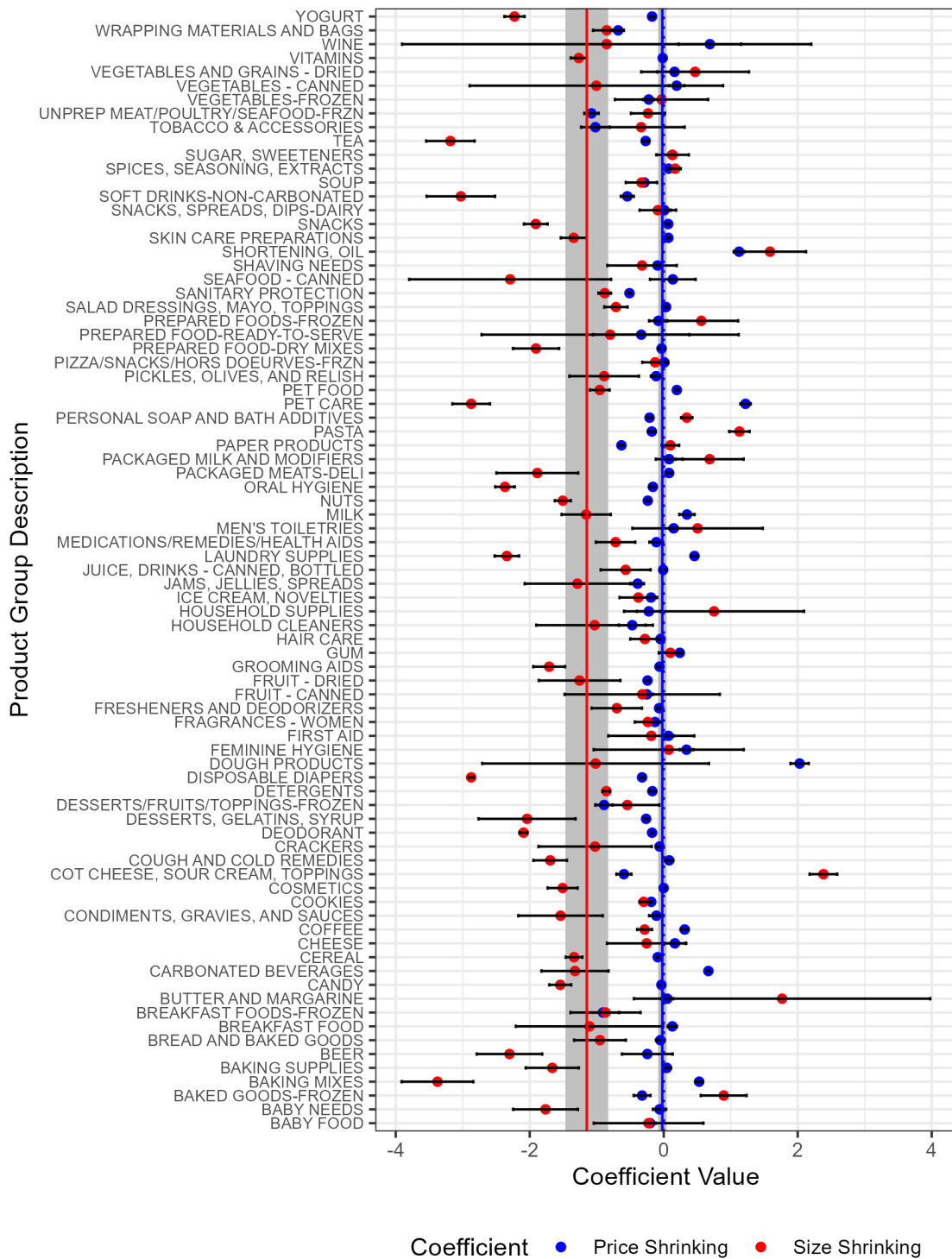


Figure 11: Estimated Unit Price and Package Size Elasticities for Different Product Groups



Notes: This graph presents the estimated unit price elasticities (in blue) and package size elasticities (in red) and corresponding 95% confidence intervals in different product groups for products that do not decrease in size. The coefficients, therefore, refer to  $\hat{\eta}_p$  and  $\hat{\eta}_l$  in model 2. The coefficients in each group refer to the sales-weighted average of estimated elasticities across all product modules within one product group. The solid blue line (red line) illustrates the sales-weighted average unit price (package size) elasticity across all product groups. Error bars denote the 95% confidence intervals of the weighted coefficients. We exclude those product modules that do not allow inference due to extremely large standard errors that lead to rejecting the hypothesis that the point estimates are equal to  $\leq -5$  or  $\geq 5$ .

Figure 12: Estimated Interaction Terms for Shrinking Products Across Different Product Groups



Notes: This graph presents the estimated interaction terms of equation 2. In detail, we show the differences for unit price elasticities (in blue), package size elasticities (in red), and corresponding 95% confidence intervals in different product groups for products that decrease in size. The coefficients, therefore, refer to  $\hat{\beta}_p$  and  $\hat{\beta}_l$  in model 2. The coefficients in each group refer to the sales-weighted average of estimated elasticities across all product modules within one product group. The solid blue line (red line) illustrates the sales-weighted average unit price (package size) elasticity across all product groups. We exclude those product modules that do not allow inference due to extremely large standard errors that lead to rejecting the hypothesis that the point estimates are equal to  $\leq -5$  or  $\geq 5$ .

## 6 Discussion

This study shows that shrinkflation is widespread in the U.S. retail market, subtly increasing the price per volume for various products. Product size decreases occur significantly more often than increases, and product downsizing usually happens without equivalent price reductions. In comparison, product size increases are correlated with increases in prices. Our findings reveal that both retailers and manufacturers strategically use product size changes to boost their revenues. Using a regression framework and instrumental variable approach, we show that consumers exhibit more sensitivity to price adjustments than to changes in product size. Additionally, the sensitivity to size changes is lower when product size decreases compared to product size increases.

The diverging responsiveness to price and size changes aligns with the idea that consumers are inattentive to non-salient or hidden attributes, as numerous studies demonstrate (DellaVigna, 2009). For instance, in a seminal paper on tax salience, Chetty et al. (2009) show that consumers react less to non-salient taxes not included in posted prices than to similar salient price changes.<sup>6</sup> This reasoning implies our results may be driven by inattentive consumers who react less to changes in price per volume attributable to size changes as they are typically less salient than direct changes to posted unit prices.

The underreaction to non-salient price attributes incentivizes profit-maximizing firms to hide or obfuscate relevant price attributes. Numerous examples exist of firms strategically hiding or obfuscating relevant prices to exploit consumers' underreactions. Examples of such practices include add-on pricing (e.g., Ellison, 2005; Gabaix and Laibson, 2006), hidden shipping and handling costs (e.g., Hossain and Morgan, 2006; Brown et al., 2010) and strategic price complexity (Carlin, 2009). According to models exploring optimal obfuscation behavior and market outcomes (e.g. Gabaix and Laibson, 2006; Ellison and Wolitzky, 2012; Janssen and Kasinger, 2024), price obfuscation decreases the price sensitivity of behavioral consumers, allowing firms to limit competitive pressure and boost their margins and revenues by obfuscating prices. Following this logic, our findings suggest shrinkflation as an effective strategy for retailers and manufacturers to increase prices

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<sup>6</sup>Other examples on the tax salience effect include Finkelstein (2009), Sallee (2011), Goldin and Homonoff (2013), Feldman and Ruffle (2015) and Taubinsky and Rees-Jones (2018).

obfuscated and non-saliently. This idea is supported by the result that for non-shrunk products, where firms typically have no incentive to hide those price changes as they benefit consumers, size and price elasticities are similar.

While beneficial for firms, the resulting increase in profits and revenues often comes at the expense of (inattentive) consumers. Consequently, policymakers may want to regulate shrinkflation behavior to protect consumers. Banning product size changes is, however, impractical and may limit beneficial size changes. A more viable policy could involve making size changes more salient and transparent—for instance, mandating that retailers display prices per volume or clearly communicate any changes in product sizes to consumers. The regulation would, therefore, follow the warning labels that we observe in French supermarkets (Vidalon, 2023). Importantly, the policy should not be solely tailored to manufacturer-induced product size decreases, given our findings that retailer-driven size changes are also common.

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# Online Appendix

## A Price Imputation

In the RMS retail scanner data, price information is only available for weeks when a product is sold. This leads to missing price observations, especially for smaller products with rare sales. We use the price imputation algorithm developed by [Hitsch et al. \(2021\)](#) to overcome this issue. The algorithm works by identifying base prices and promoted prices. It does so by examining the typical price pattern at the store level, where base prices are stable for some time, followed by shorter periods of promoted prices. The algorithm can fill in missing price data, ensuring a more accurate representation of the full price spectrum for these products. It assumes that weeks with no sales are periods when prices are non-promoted. The algorithm imputes prices if, for the last observed (base) price, i.e. the reference price, there is another observed price (close enough to the reference price) within a 12-week window. If this is the case, prices that are missing between these two observed prices will be set equal to the reference price, assuming that the reference price is correct and stable within the specified window. As a result, the price in a respective period can still be missing if there is no observed price within 12 weeks from the last observed price. For more details see the online appendix of [Hitsch et al. \(2021\)](#)

We only consider products, as defined by their UPC, that experienced either a product size increase or decrease in at least one store within the U.S. across the observation period. Table [A.1](#) compares aggregated summary statistics of the original movement files with those of the imputed dataset. Through the price imputation algorithm, we increase the number of observations from near 18 billion to 25 billion observations, implying that around 30% of the observations in the final data set are imputed. A ratio very similar than in [Hitsch et al. \(2021\)](#). Unsurprisingly, the average units and value of purchase are both lower in the imputed dataset as it now includes zero quantity observations. Similarly, it is sensible that the average price is slightly higher in the imputed data set, given that lower prices are positively associated with quantity.

Table A.1: Summary statistics for the original and the imputed scanner data

	Original data	Imputed data
Average price	3.93	4.50
Average sales value of a purchase	20.96	14.17
Average size of purchased product	23.60	25.55
Average units of a purchase	7.85	5.04
Total observations	17,795,385,427	25,392,165,898

## B Are Products Identical?

### B.1 Visual Inspection

In our primary analysis, we focus on identifying products that exhibit decreasing or increasing trends. This is achieved by examining products from the same brands and analyzing UPC descriptions that are substituted at the store level with either a smaller or larger equivalent. However, this approach is not without its risks, particularly in terms of potentially mislabeling certain products. For instance, it's possible that a product is replaced by another version that is not only different in size but also distinct in its marketing approach. Consider a scenario where a product undergoes a rebranding or packaging overhaul. While our experience suggests that such concurrent changes are common, we acknowledge this limitation and address it by implementing several robustness checks in the subsequent sections of our study.

In the first robustness check, we examine each individual UPC associated with products that have demonstrated either a decrease or increase in size. This involves a detailed comparison of packaging to ascertain whether the products in question are truly identical. Given the sheer volume of products across all modules, manual verification for each is impractical. Therefore, we have chosen to concentrate on specific modules where changes in product size are most commonly observed: Candy, Snacks, Detergents, Hair Care, and Cereals.

For each product within these modules, we utilize a UPC lookup database (accessible at <https://www.upcitemdb.com/>) to accurately determine the packaging of each product both prior to and following any changes in size. However, it's important to note that this database has its limitations, particularly concerning products that were phased out more than a few years ago and are no longer on the market. Consequently, we rely on a subset of products with confirmed size changes as a representative sample to demonstrate the validity of our analysis. The remaining products may still be valid product size changes, but we are not able to confirm the changes visually.

In this analysis, we present a detailed comparison between the complete collection of products that have undergone size reduction and those specifically verified as identical despite this decrease. The relevant statistics for the product group of snacks are detailed in Table B.1.<sup>7</sup> Our focus centers on key aspects such as variations in product size, price dynamics, and sales trends before and after the size reduction event.

In over 800,000 instances, we have been able to confirm that the size reduction corresponds to identical products. This figure stands in comparison to the 1,320,041 size reduction events reported in the main study. Each observation here represents a sin-

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<sup>7</sup>We also show corresponding statistics for the product group of hair-care and detergent in Table B.2 and B.3. Results are comparable.

gle instance of size reduction within a store, suggesting that a large proportion of these reductions are indeed with the same product.

It is also important to note that the unconfirmed observations do not necessarily imply inaccuracies or different products. In these cases, the issue often lies in the insufficient clarity to definitively confirm the product's identity.

When analyzing both sets of products against our selected metrics, only slight differences emerge. Crucially, trends in size reduction, price adjustments, and sales fluctuations are remarkably similar across the general range of products and those where the identity post-reduction has been confirmed. This uniformity leads us to conclude that, apart from the change in size, the products remain essentially identical in other respects. This insight offers a valuable perspective into the market dynamics associated with changes in product size.

Table B.1: Comparison of Products That Are Confirmed by Visual Inspection in the Product Group of Snacks

	All	Confirmed
Number of Observations	1,320,041	800,658
Avg Size Before Decrease	7.59 (3.98)	7.79 (3.65)
Avg Size After Decrease	7.06 (3.73)	7.29 (3.45)
Avg Price Before Decrease	2.57 (1.14)	2.64 (1.14)
Avg Price After Decrease	2.56 (1.14)	2.63 (1.15)
Avg Price per Volume Before Decrease	3.84 (6.68)	3.96 (6.95)
Avg Price per Volume After Decrease	3.51 (5.95)	3.6 (6.16)
Avg Weekly Units in Store Sold Before Decrease	9.63 (13.97)	10.06 (14.92)
Avg Weekly Units in Store Sold After Decrease	9.67 (14.34)	10.12 (15.23)
Avg Weekly Sales in Store Sold Before Decrease	22.73 (34.08)	24.35 (37.14)
Avg Weekly Sales in Store Sold After Decrease	23.11 (35.57)	24.63 (38.28)

*Notes: This table presents a comparative analysis of products within the snack subsegments, focusing on those that underwent a size reduction. It differentiates between products confirmed to be identical despite the size decrease and their counterparts in terms of pricing adjustments. The confirmation is based on individual UPC lookups and visual inspection of the package. Key metrics such as changes in size, price fluctuations, and sales variations before and after the size reduction event are examined. The dataset encompasses the entire range of products, offering insights into the typical market behavior surrounding size and price modifications in this category. Standard deviations are indicated in parentheses to provide a statistical perspective on the data's variability.*

Table B.2: Comparison of Products That Are Confirmed by Visual Inspection in the Product Group of Hair Care

	All	Confirmed
Number of Observations	325,286	283,199
Avg Size Before Decrease	16.53 (7.42)	16.25 (7.14)
Avg Size After Decrease	14.62 (6.33)	14.39 (6.15)
Avg Price Before Decrease	4.12 (1.63)	3.97 (1.41)
Avg Price After Decrease	4.23 (1.67)	4.13 (1.57)
Avg Price per Volume Before Decrease	6.03 (14.7)	6.22 (15.02)
Avg Price per Volume After Decrease	7.03 (20.62)	7.35 (21.36)
Avg Weekly Units in Store Sold Before Decrease	1.81 (1.22)	1.8 (1.14)
Avg Weekly Units in Store Sold After Decrease	1.79 (1.28)	1.77 (1.23)
Avg Weekly Sales in Store Sold Before Decrease	7.2 (7.18)	6.78 (5.54)
Avg Weekly Sales in Store Sold After Decrease	7.25 (7.28)	6.92 (6.26)

*Notes: This table presents a comparative analysis of products within the hair-care subsegments, focusing on those that underwent a size reduction. It differentiates between products confirmed to be identical despite the size decrease and their counterparts in terms of pricing adjustments. The confirmation is based on individual UPC lookups and visual inspection of the package. Key metrics such as changes in size, price fluctuations, and sales variations before and after the size reduction event are examined. The dataset encompasses the entire range of products, offering insights into the typical market behavior surrounding size and price modifications in this category. Standard deviations are indicated in parentheses to provide a statistical perspective on the data's variability.*

Table B.3: Comparison of Products That Are Confirmed by Visual Inspection in the Product Group of Detergents

	All	Confirmed
Number of Observations	344,696	223,040
Avg Size Before Decrease	36.75	33.84
	(32.93)	(30.28)
Avg Size After Decrease	32.25	29.69
	(28.9)	(25.83)
Avg Price Before Decrease	4.54	4.25
	(3.84)	(3.47)
Avg Price After Decrease	4.35	4.06
	(3.62)	(3.23)
Avg Price per Volume Before Decrease	12.81	13.36
	(33.42)	(35.68)
Avg Price per Volume After Decrease	11.3	11.54
	(25.36)	(27.22)
Avg Weekly Units in Store Sold Before Decrease	4.86	5.35
	(6.38)	(6.96)
Avg Weekly Units in Store Sold After Decrease	4.76	5.22
	(6.1)	(6.6)
Avg Weekly Sales in Store Sold Before Decrease	15.59	16.17
	(31.17)	(19.51)
Avg Weekly Sales in Store Sold After Decrease	14.95	15.29
	(25.64)	(17.63)

*Notes: This table presents a comparative analysis of products within the detergent subsegments, focusing on those that underwent a size reduction. It differentiates between products confirmed to be identical despite the size decrease and their counterparts in terms of pricing adjustments. The confirmation is based on individual UPC lookups and visual inspection of the package. Key metrics such as changes in size, price fluctuations, and sales variations before and after the size reduction event are examined. The dataset encompasses the entire range of products, offering insights into the typical market behavior surrounding size and price modifications in this category. Standard deviations are indicated in parentheses to provide a statistical perspective on the data's variability.*

## B.2 Household Data

In our second robustness check, we employ Nielsen’s household scanner data to examine whether households consistently purchase identical products before and after a change in package size. Although there might be variations in consumer behavior, this pattern generally supports the accurate identification of products undergoing size changes. However, it is important to note that the Nielsen household scanner data is not perfectly suited for this analysis. Product size changes at the store-level are infrequently observed, and their occurrence is relatively rare compared to the number of households in the panel purchasing products within a specific segment. Consequently, our analysis is conducted on a small sample of observed households within a specific store.

We investigate each product size reduction recorded over the 10 years within our sample, focusing on households that purchased a product which decreased in size at least four times in independent shopping trips within one year before and after the size reduction. This criterion ensures that the analysis includes only households that regularly purchase the product, rather than those trying it incidentally without awareness of previous price changes, thereby precluding their purchase decisions from being influenced by size alterations.

Figure B.1 presents the findings, depicting the number of households that exclusively purchased the product either before, after, or both before and after the product size decrease. The data reveal that repeated purchases both before and after the size reduction are the most common. The frequencies of households that exclusively purchase the product either before or after the size decrease are relatively similar, with a marginal tendency towards more purchases before the size reduction.

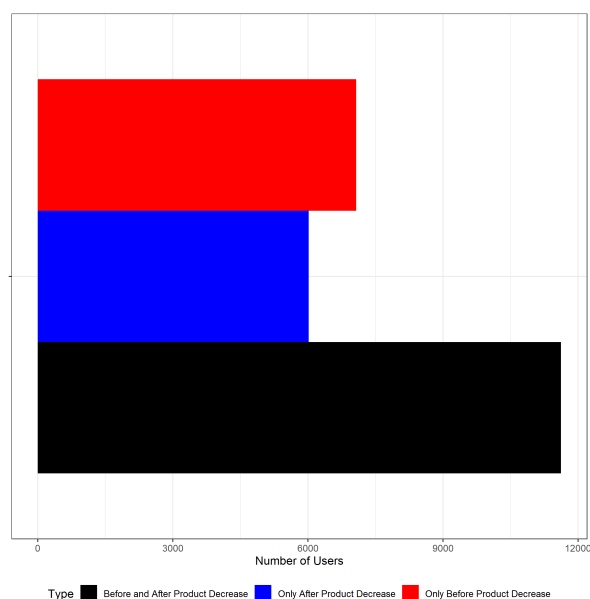
While this analysis does not provide in-depth insights into the household choices regarding product size changes—due to infrequent purchases and the limited number of households buying specific products that decrease in size—the summary statistics suggest a higher likelihood of households purchasing the product both before and after a size increase. This observation further corroborates our belief that the products undergoing size decreases are identical in all other dimensions besides size.

## C Shrinking a Product without changing the UPC

We primarily identify a product that is reducing in size at the store level using the following criteria: we notice a new UPC from the same brand entering the system. This new UPC, while having an identical brand and description to the previous UPC, is up to 25% smaller. Concurrently, the old UPC exits the system. However, our data source does not enable us to detect product shrinkage when a smaller product is substituted under the same UPC code. Since product details for a specific UPC are only updated at the start of the year, identifying the exact time of substitution for products with unchanged



Figure B.1: Repeated Purchases By Households



*Note: This graph shows the number of households purchasing products that decrease in size. Specifically, it includes households with at least four purchase occasions of products experiencing size decreases in the year prior and following the event of a decrease. The graph categorizes the households into three groups: those who only purchased the product before the size decrease (red), after the size decrease (blue), and both before and after the size decrease (black).*

UPC codes is not feasible.

In this section, we contend that neglecting size reductions of same UPC products does not compromise the integrity of our analysis for two primary reasons. First, it's important to recognize the prevalent practices among retailers and manufacturers. Most adhere to guidelines set forth by the Uniform Code Council, now recognized as GS1 US, the originators of the UPC system. The UPC is predominantly designed to identify individual consumer products at retail point-of-sale, serving as a distinct barcode predominantly utilized in North America for retail commodities.<sup>8</sup> As per the management standards stipulated by GS1, any alteration in net content mandates the introduction of a new GTIN, and consequently, a new UPC (GS1US, 2023). To verify the adherence of manufacturers to this practice, we explored popular consumer forums like <https://www.reddit.com/r/shrinkflation>. Here, consumers voluntarily report recent instances of product shrinkage. In the majority of these cases where UPC information was accessible, we observed modifications to the UPCs. However, it's crucial to highlight that there's no stringent legal mandate enforcing UPC alterations for every size change, which implies that some manufacturers might retain an unchanged UPC despite

<sup>8</sup>It's worth noting that the UPC is frequently used interchangeably with the GTIN (Global Shipment Identification Number). The GTIN varies in length, but the UPC-A barcode, the version most prevalent at points of sale and within our dataset, employs data from the GTIN-12 (?).

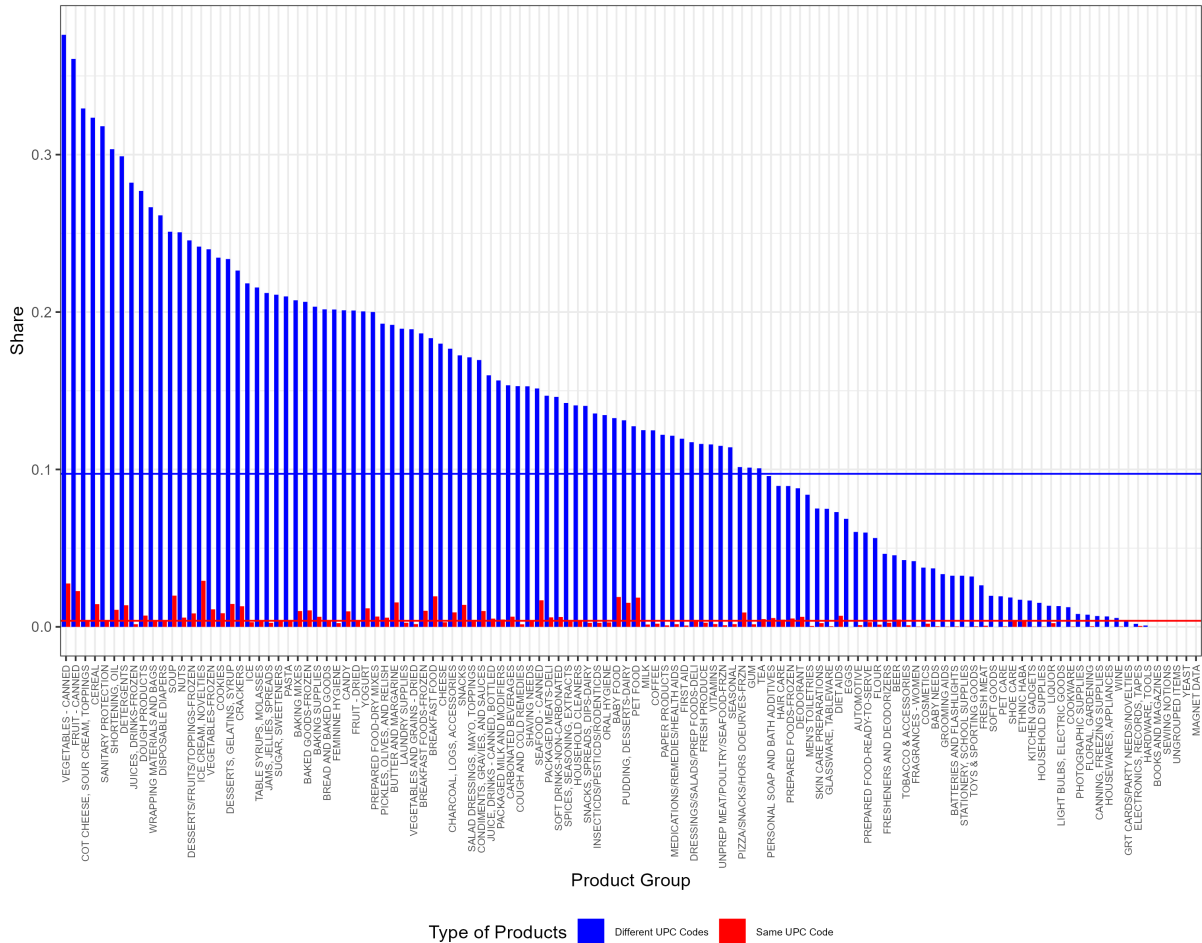
modifying product dimensions.

Secondly, we approach this from an empirical perspective. While our current methods do not permit us to pinpoint instances where products under the same UPC experience size reductions (given our inability to temporally and geographically trace the introduction of an identical UPC at the store-level), we can juxtapose the overall count of such UPCs exhibiting varied sizes against the tally of multiple UPCs manifesting similar size variations nationwide from 2010 to 2020. By contrasting the aggregate of products with unchanged versus altered UPCs that display size differences within a 25% range, we gain preliminary insight into the frequency of occurrences where products retain their original UPC despite size adjustments.

In Figure C.1, we present the proportion of products within each category that exhibit multiple size variations within a 25% range, while maintaining identical brand, brand description, and UPC description. We distinguish between products with differing UPCs (depicted in blue) and those with identical UPCs (depicted in red). On average, 9.7% of products display size variations alongside different UPCs, despite being marketed under the same brand with identical descriptions. By contrast, a mere 0.4% of products show size differences under the same UPC with the same brand and description. This marked discrepancy suggests that instances of product size changes without corresponding UPC updates are relatively rare. It reinforces our belief that the vast majority of manufacturers and retailers likely adhere to GS1's management standards when implementing product changes such as size reductions or substitutions.

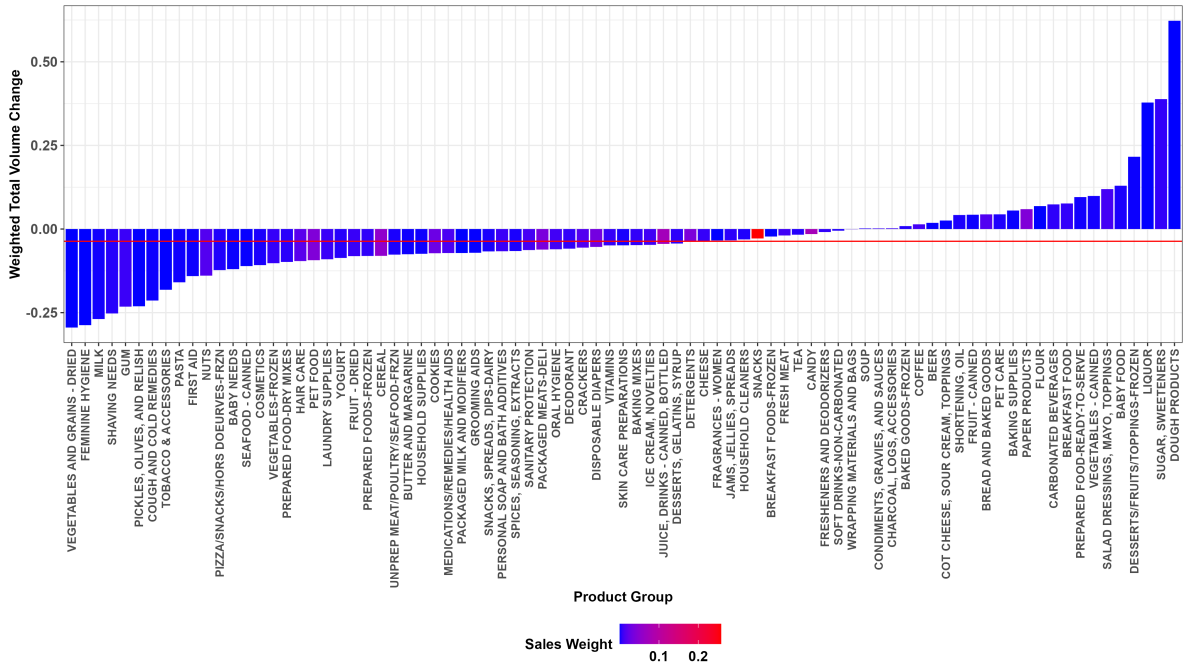
## D Additional Descriptive Statistics and Analyses

Figure C.1: Different Sized Products, Same and Different UPCs

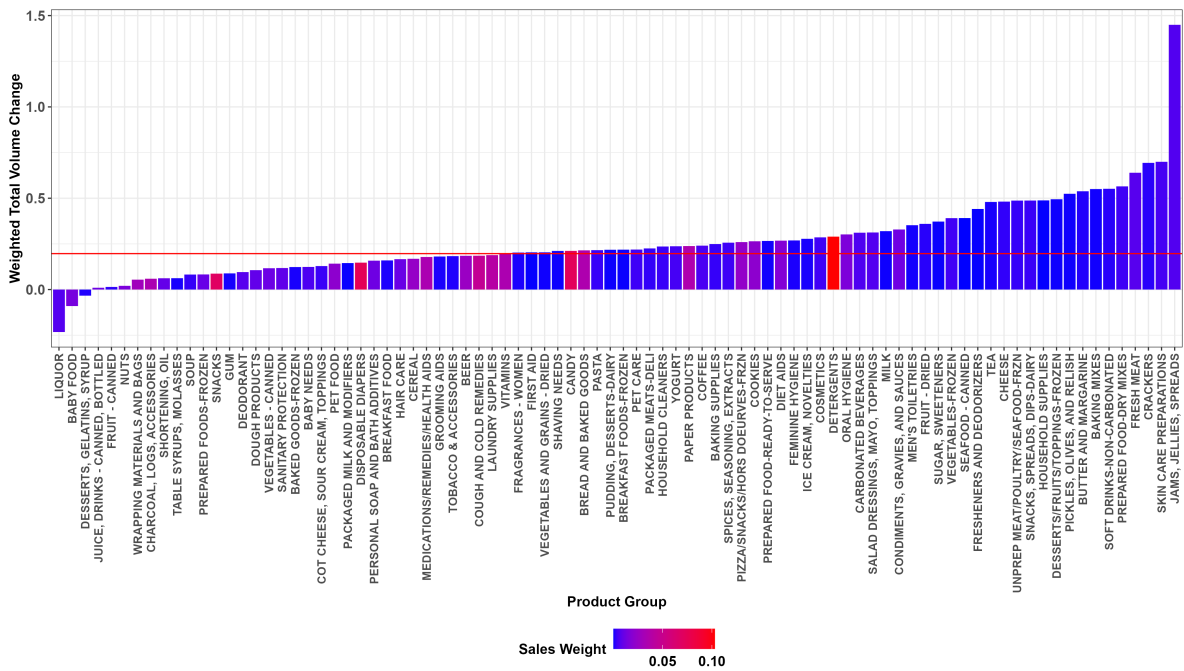


Notes: This graph illustrates the proportion of products that feature size variations within a 25% range, while retaining identical brand attributes and UPC descriptions. Each bar represents a distinct product category. The data is differentiated by products with variant UPCs (in blue) and those with consistent UPCs (in red). The solid blue and red lines indicate the average percentage of products with multiple sizes across all categories, corresponding to different and identical UPC scenarios, respectively.

Figure D.1: Changes of Volume Purchased across Product Groups



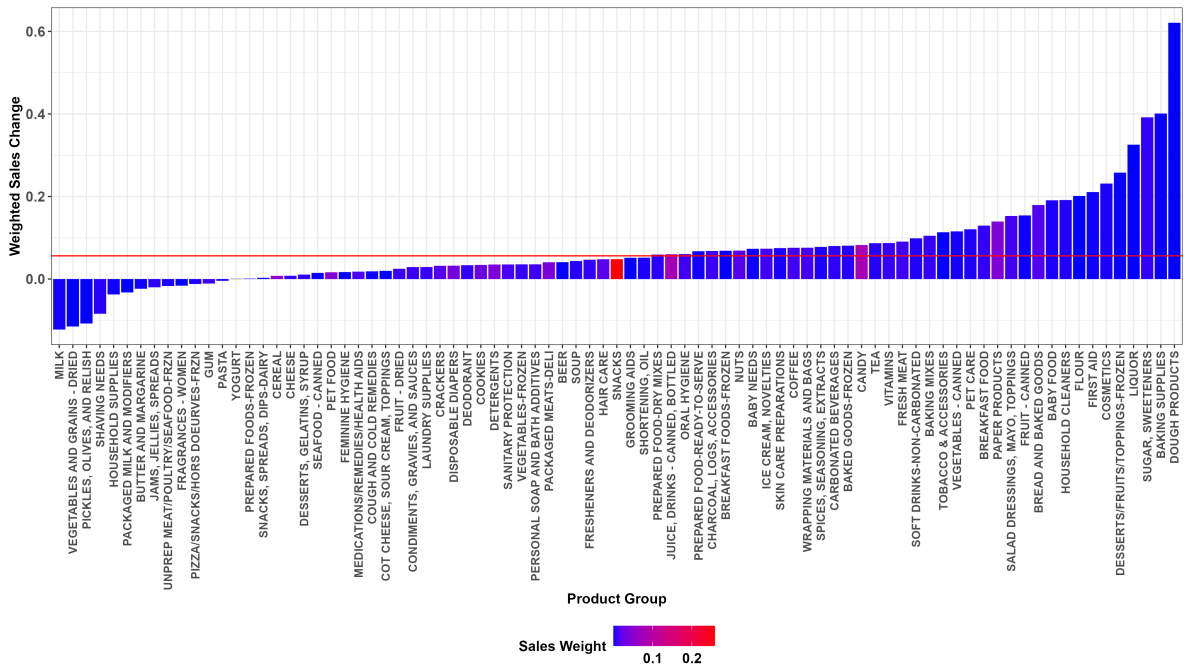
(a) Purchased Volume, Product Size Decrease



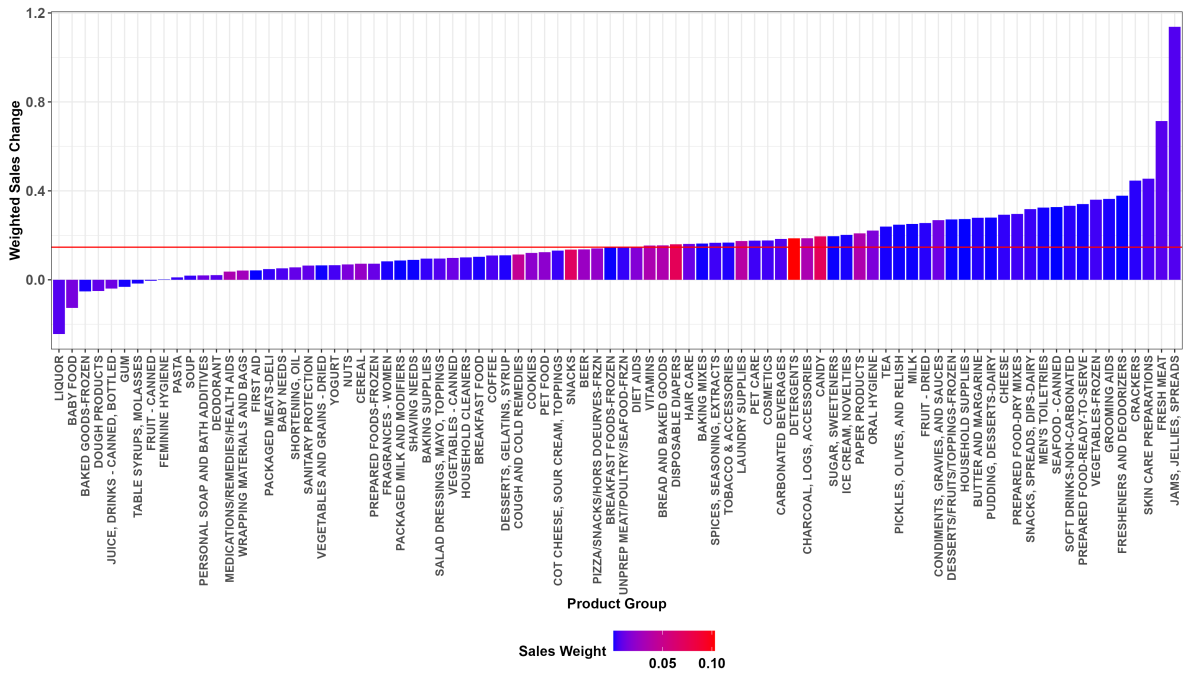
(b) Purchased Volume, Product Size Increase

Notes: This graph illustrates the purchased volume changes for product groups for product size decreases and product size increases. Subfigure D.1a investigates product size reductions, and Subfigure D.1b assesses size increases. For both scenarios, the data is aggregated from individual modules to product groups. Weighted average price per volume changes are calculated using sales volume of the products as a weighting factor. Changes in volume are measured on the product module level and considering the year before and after the product size change. The color intensity of each bar in the figure corresponds to the sales weight of the product group, with deeper shades of red indicating higher sales volumes within that group. The red line corresponds to the weighted average across all product modules.

Figure D.2: Changes of Sales across Product Groups



(a) Sales, Product Size Decrease



(b) Sales, Product Size Increase

Notes: This graph illustrates the sales changes for product groups for product size decreases and product size increases. Subfigure D.2b investigates product size reductions, and Subfigure D.2c assesses size increases. For both scenarios, the data is aggregated from individual modules to product groups. Weighted average price per volume changes are calculated using sales volume of the products as a weighting factor. Changes in sales are measured on the product module level and considering the year before and after the product size change. The color intensity of each bar in the figure corresponds to the sales weight of the product group, with deeper shades of red indicating higher sales volumes within that group. The red line corresponds to the weighted average across all product modules