Shrinkflation? Quantifying the impact of changes in package size on food inflation

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Abstract

The shrinkage of packaged food as a hidden source of inflation has received increased attention in recent years, particularly after the onset of COVID-19. Despite the media attention and many informal accounts of "shrinkflation" in specific food products, no attempt has been made to quantify the phenomenon on a large scale. In this paper, we pursue three objectives: a) to determine whether packaged food sizes have declined over time, b) to quantify the impact of changes in package size on inflation, and c) to explore the possible channels that explain the observed changes in package size. We find that the average size (measured in grams) of packaged food products (where a product is defined at the bar code level) has decreased by 7.24% between 2012 and 2021. To isolate the role of package size on food prices, we compute food inflation under the status quo and then compare it to a food inflation counterfactual where product size unaccounted for. Specifically, we apply hedonic methods to measure quality-adjusted food inflation in the US, where product size is one of several product characteristics that enter the hedonic function. Since consumers value larger packages, not adjusting for size changes produces a downward bias in inflation when products shrink. We find that annual inflation would be underestimated every year if the observed product shrinkage were not taken into account. In our calculation, this implies that the accumulated inflation in packaged food between 2012 and 2021 would be 3.9 percentage points lower had product sizes remained at 2012 levels. In our last analyses, we find that product shrinkage is significantly larger in: a) states without a unit pricing law, b) households at the top of the income distribution, c) retailers that do not specialize in bulk discounts, d) less bulky items, and e) sugary food categories. We argue that part of our results are consistent with product shrinkage driven by consumer inattention, while others are consistent with firms' strategies to segment the market or as reactions to recent calls for healthier diets.

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1 Introduction

Inflation has received increasing attention, especially after the onset of the COVID-19 pandemic. Increasing food prices have often been cited as a main driver of recent inflation (IMF, 2022). In 2022, food inflation in the United States registered a 9.9% annual rate, compared to 7% for all items in the economy.[1] Furthermore, food inflation is particularly salient. Food expenditures comprise 13% of household expenditures in the United States, making it the third largest expenditure category after housing (33%) and transportation (17%) (BLS, 2023). Another factor that makes food inflation particularly noticeable is that most people buy food on a daily basis (often multiple times a day).

In addition to the factors mentioned, food inflation (in particular packaged food) has recently received increased public scrutiny as a result of the so-called shrinkflation phenomenon: package shrinkage that is not accompanied by a price decrease. Traditional and social media, especially in the summer of 2022 (when inflation was at its highest), highlighted numerous examples of products that had shrunk in size while maintaining their original price.[2] Despite the broad attention that shrinkflation has received, to our knowledge, no attempts have been made to determine its existence and importance for the food industry at large. This paper aims to fill this void.

In this paper, we present what is to our knowledge the first attempt to quantify: a) the degree to which package sizes in the US food industry are changing over time and b) the role that package size changes have on food inflation. We carry out these empirical exercises at a large scale. That is, our objective is not to study or identify specific cases where shrinkflation has occurred (i.e., instances where a specific product has decreased in size but not in price). Instead, we are interested in understanding the market-wide evolution of package sizes in food manufacturing and the extent to which changes in the average package size among all products available in the market have impacted food inflation.

Our approach to quantifying inflation is based on hedonic methods. Hedonic methods model price as a function of product characteristics, making them well suited for the question at hand. Specifically, we argue that, since "more is better", consumers generally prefer larger package sizes, when other product characteristics (including price) are kept constant. This argument is analogous to the use of computer speed, fuel efficiency, and square footage in hedonic models of PCs, cars and housing (respectively).

The use of hedonic methods to calculate inflation measures is not new. The ideal scenario that would produce reliable inflation calculations is one in which the set of products and their characteristics remain constant over time. In the absence of this scenario (which is almost always the case in consumer goods), proper adjustments need to be made, since the observed price changes may be due to reasons unrelated to increases in the cost of living. Hedonic methods can produce this adjustment, in particular, when products experience substantial quality changes over time. For example, when calculating the price inflation of televisions

[1] Data retrieved from multiple BLS reports at https://www.bls.gov/cpi/tables/supplemental-files/.

[2] Many of these accounts are documented at www.consumerworld.org, an initiative led by consumer advocate Edgar Dworsky, who has received broad media coverage on the shrinkflation phenomenon.

between two periods, the BLS takes into account increases in screen size from one period to the next by incorporating a downward adjustment to the observed price change.[3] This adjustment, in turn, is a function of the empirical (i.e., hedonic) relationship between TV prices and screen size observed in the market (which is positive).

Intuitively, the approach attempts to make the items comparable over time: If TVs are getting larger over time, hedonic corrections help, in this example, prevent an upward bias in inflation.[4] We borrow from this insight and use hedonics to compute quality adjusted measures of food inflation, where product size is one of many attributes that enter the hedonic function. To isolate the role of product size on inflation, we perform a second inflation computation, this time removing product size from the hedonic function (and from the subsequent inflation correction). Importantly, as we later explain, our chosen method allows for product turnover (entry and exit - which is substantial in our data) to be accounted for in our inflation measurements.

We use barcode-level data from 2012-2021 for our empirical exercises. First, we quantify the average change in the size of packaged food products. Second, we calculate a quality-adjusted measure of packaged food inflation. Due to the nature of our data, we carry out these exercises at the annual level. We find that products have progressively shrunk over time, with the average product being 7.24% lighter in 2021 with respect to base year 2012.[5] Our inflation calculations indicate that product shrinkage has contributed to larger (or less negative - in years where deflation is registered) price changes in every year of our sample. In other words, food inflation has been higher than it would otherwise have been had the market not experienced a decrease in (average) package sizes. In our computations, this effect is substantial. Cumulative (quality-adjusted) inflation during the 2012-2021 period is estimated at 3.8%; however, this figure drops to -0.1% when product size is removed from hedonic adjustments.

In the last part of our analysis, we explore several mechanisms that could explain the observed product shrinkage. One mechanism is related to the notion that consumers may not easily recognize changes in product size. Specifically, we test whether product shrinkage is larger in situations where it is less likely to be noticed. First, we test whether product size reductions are more prominent in states that have adopted unit pricing regulation.[6] Second, we test whether shrinkage is greater in situations where search costs or inattention may be more pronounced. In this group of hypotheses, we consider whether the degree of

[3]The BLS makes hedonic adjustments for selected categories (electronics, apparel, appliances, and some technology services), but not for food. When one of the sampled products that enter the BLS calculations changes in size, the BLS takes this change into account by computing inflation on a per-unit (e.g., gram) basis. As we explain later, this correction implicitly assumes that the hedonic relationship between price and size is exactly equal to 1, which is not supported by the data. Moreover, the BLS correction is only applied to the small number of sampled products used by the BLS in its calculations; in contrast, our approach aims to adjust for product size changes for all packaged food products.

[4]See BLS (2020) for an expanded explanation and example of this type of correction.

[5]As we later explain, although the average product decreases in size, there is a large heterogeneity across the food categories included in our data, with one third of these categories registering an increase in average product size.

[6]Unit pricing laws mandate that retailers prominently display per-unit (i.e., per gram) prices so as to facilitate price comparisons across products. We provide details in Section 3.

product shrinkage varies by consumers' income, outlet type (e.g., convenience store versus bulk/discount retailer), and relative size of the product (with respect to others in the same food category). Finally, we consider the extent to which the dietary profile of products may be related to the observed shrinkage. Specifically, we look at whether product shrinkage may be more prominent in products that are known to be of lower dietary quality.

We find evidence that appears to support the notion that shrinkage may be more difficult for consumers to recognize in certain situations. Product shrinkage is *less* pronounced in states with unit pricing regulation (where price-per-unit comparisons are facilitated by regulation) and among low-income consumers (who are known to face lower search costs and to be more sensitive to per-unit prices). Furthermore, bulk discount retailers, where consumers' awareness of and attention to per-unit prices are likely to be higher, exhibit the opposite phenomenon (an increase in average package size), whereas all other outlet types (Convenience, Dollar, Grocery, and Mass merchandisers) exhibit product shrinkage.

We find that (except in the last year of the data) bulkier packages within a food category experience no product shrinkage whereas smaller versions shrink significantly over time; we interpret this evidence as consistent with two notions. On the one hand, smaller versions may be particularly valuable for consumers who want to experiment with a new product (Shoemaker and Shoaf, 1975), and therefore the sensitivity to size reductions is likely more limited. Alternatively, or in addition to, smaller versions may be associated with a more limited sensitivity to changes in product attributes because these products are purchased for convenience reasons (Gerstner and Hess, 1987) or because they are relatively unimportant in a household's total food budget. Finally, we find that product shrinkage in sugary product categories is significantly larger than in nonsugary categories and that this difference amplifies in 2015 and onward; although we cannot make any causal claims, we note that this timing coincides with the year in which sugar-sweetened beverage (SSB) taxes started to be rolled out in several US cities.

We state two caveats at the outset. First, our empirical approach is largely atheoretical. That is, the hedonic relationship between price and size is jointly explained by a combination of supply and demand factors that we cannot isolate (Rosen, 1974). Some of these factors could include second-degree price discrimination, technological and logistical changes, evolving consumers' preferences for product size and in their willingness to pay for convenience, etc. Second, different product categories face different market conditions, and as a result, the economic rationale for the observed changes in package size may vary from category to category. Thus, our study should be taken as an exploratory analysis of certain patterns that may be applicable, on average, to the entire packaged food industry. We leave market-specific questions to future research.

The rest of the paper is structured as follows. First, we review the related literature. Then, we present a methodology section, in which we explain both the conceptual framework of our approach and the econometric methods used. The results and conclusions follow in subsequent sections.

2 Literature

There are three strands of literature related to our work. The first consists of a group of studies related to the specific question of product "downsizing". A second group of studies focus on consumers' failure to recognize certain product attributes. The third strand is related to methodological issues in the calculation of inflation.

2.1 Downsizing

There are several studies that empirically evaluate a number of hypotheses when a reduction in package size is observed. As opposed to studying product downsizing at large scale (as we do in this paper), these studies focus on specific package size reductions in a given food category. Examples include the impact of smaller canned tuna and peanut butter packages on household purchases Çakır et al. (2021) and whether size reductions in certain ice cream products are related to a higher cost pass-through rate Çakır (2022). Yonezawa and Richards (2016) take a structural approach and study the strategic interaction among ready-to-eat cereal manufacturers when firms compete both in price and package size. The authors report that price and package size are strategic complements; this finding leads the authors to conclude that, since package shrinkage would intensify price competition, manufacturers may not find it in their best interest to reduce package size.

2.2 Consumer Inattention

More broadly, our study is related to a strand of work that analyzes the economic implications of consumers' failure to notice certain product attributes in their decision-making. This *consumer inattention* has been the focus of much behavioral work (see Gabaix, 2019 for a review). Some studies analyze questions related to consumer inattention in a context similar to ours. Çakır and Balagtas (2014) find that the demand elasticity with respect to package size is approximately 75% lower than the demand elasticity with respect to price, which may suggest that consumers are (relatively) inattentive to changes in package sizes. Kim (2022) report a similar finding: when faced with a given increase in the price per unit (that is, the price per fl oz) of milk, consumers prefer that this increase come from a reduction in package size rather than from an (equivalent) increase in package price.[7] A third paper adds direct evidence to these findings by specifically calculating a parameter of consumer inattention (Meeker, 2021). Meeker (2021) estimates that the overwhelming majority (97%) of consumers in the black pepper market do not notice at least one package size change (thereby making their choices suboptimal).[8]

A closely related literature looks at the question of whether it would be profitable for

[7] Kim (2022) provides a theoretical mechanism that explains the observed behavior.

[8] Beyond packaged food, there is empirical evidence of consumer inattention in other domains. Some examples include sales taxes (Chetty, Looney and Kroft, 2009), shipping costs (Brown, Hossain and Morgan, 2010), and fuel economy (Allcott, 2013).

firms' to purposefully make it harder for consumers to notice a product attribute. The intuition for why this channel is potentially likely is that if firms can increase the difficulty for consumers to notice an attribute (in our setting, a change in product size), the resulting higher search costs can lead to higher markups and prices (Ellison and Wolitzky, 2012).[9] This strategic *obfuscation* (Ellison and Ellison, 2005), has received some empirical support in food manufacturing (Richards et al., 2020).[10] Using case studies in coffee and soft drinks in Europe, Richards et al. (2020) find evidence consistent with the notion that retailers use smaller product sizes as a way to obfuscate consumers (and increase margins).

As we later explain, we draw from the insights in the consumer inattention and obfuscation literatures to propose and test some possible channels that could explain the observed average package size reductions.

2.3 Inflation calculation methodology

Inflation is measured through price indices, such as the consumer price index (or CPI). In this review, we focus our discussion on issues in price index calculation that overlap with our work. An important portion of the price index literature that is related to our paper is the push to improve measurement methods as richer data becomes more available. A key aspect in this call for superior inflation measurements is the incorporation of product quality in the calculation of price indices; see, for example, Boskin et al. (1996) and Shapiro and Wilcox (1996) for discussions of the implications of CPI mismeasurement when quality is omitted.[11]

Two approaches have been proposed to address the quality issue. The first is a demand-based approach where the object is to quantify price changes by computing (an approximation to) consumers' compensating variation from one period to the next (see, for example, Feenstra, 1996; Hausman, 2003). The demand-based approach is structural in nature, which requires the modeler to make assumptions such as the functional form of demand and to take a stance on firms' mode of competition. Recent demand-based applications, with datasets similar to those we employ in this paper, have recently been proposed (Redding and Weinstein, 2020; Ehrlich et al., 2023).

The second approach, which we use in this paper, is based on hedonics. The mechanics of the hedonic approach, already described in the Introduction, are fairly straightforward: if a product changes an attribute from period one to period two, the price level in period two should be adjusted appropriately to reflect the change in the attribute. [12] There have been extensive discussions as to whether either the demand-based approach or the hedonics

[9]A related approach is that of Gabaix and Laibson (2006), who show that firms' *attribute shrouding* may be a feasible equilibrium under certain conditions.

[10]See also Ellison and Ellison (2009) for an empirical study on computer memory modules.

[11]There are other concerns regarding biases in price index calculations. These include substitution across products (because of price, for instance) and outlets (towards low-price stores), and entry of new products (see, Hausman, 2003).

[12]Pakes (2003) provides an extensive discussion of the method, including its history, the connection with economic theory and an illustration.

approach is more appropriate.[13] While this debate is ongoing, there appears to be some evidence that, when using transaction-level data (as we do here in this paper), a hedonic approach may be potentially more robust (Cafarella et al., 2023).[14] More importantly, however, the hedonics approach is particularly suitable for our question at hand since hedonics explicitly model prices as a function of product attributes (which is our object of study) whereas the demand approach does not.

Specifically, we implement a hedonic approach for computing quality-adjusted inflation that accounts for product turnover and controls for time-varying unobservables. This approach was originally proposed by Erickson and Pakes (2011) and has been recently implemented for the computation of quality-adjusted inflation in an application that uses a level of data granularity similar to ours (Cafarella et al., 2023; Ehrlich et al., 2023). There are some differences between our work and these two recent applications. First, Cafarella et al. (2023) and Ehrlich et al. (2023) do not observe a detailed and well-defined set of product characteristics (which we do); instead, the authors rely on machine learning techniques to approximate the hedonic predictions. Second, both of these (closely related) studies use price per unit (i.e., package price / package size) as their object of study. This approach not only effectively ignores product size as an attribute to be included in the hedonic function but, as we explain in the next section, it implicitly imposes a hedonic coefficient of 1 on the package price/package size relationship.

3 Methodology

As is the norm in studies that use barcode-level data to compute price indices, we define a product as a distinct universal product code (UPC). One feature of our data is that, in addition to the product's price, it contains information on a large number of attributes (among which is *size*) for each UPC. Our overarching approach is to rely on these attributes to estimate a quality-adjusted price index that accounts, among several other attributes, for the role of product size.

Before proceeding to the methodological details of the price index we implement in our analysis, we first provide a discussion and some simple empirical relationships in our data that illustrate the importance of accounting for changes in product size in inflation calculations.

3.1 The role of product size on inflation

A main objective of price indices is to capture changes in the cost of living. To obtain a reliable measure of the change in the cost of living, the products used in the index construction should remain comparable over time. If products' characteristics change (e.g., there is an increase

[13] See, for example, the Winter 2003, *Journal of Economic Perspectives* edition for a discussion of these issues.

[14] The reason for this conclusion is that demand-based approaches appear to be sensitive to the assumptions regarding demand functional form and market structure (which are needed in this method).

in quality or a decrease in size), then price index changes cannot be ascribed to cost-of-living changes. The importance of product size as one of the attributes for which such type of adjustment should be performed is illustrated in the IMF's Consumer Price Index Manual (ILO, 2004, p. 29):[15]

"...most consumers are very unlikely to rate a refrigerator that has three times the capacity of a smaller one as being worth three times the price of the latter. Nevertheless, it is clearly possible to make some adjustment to the price of a new quality or different size to make it more comparable with the price of an old quality. There is considerable scope for the judicious, or common sense, application of relatively straightforward quality adjustments of this kind."

Government agencies have paid some attention to the changing nature of product attributes and their role in the construction of price indexes. In the U.S., for example, the BLS' CPI uses hedonic methods to adjust for quality changes in certain product categories, although food is not one of them.[16] We note that product size in food is a quality (vertical) attribute and therefore argue that product size should be amenable to the same type of hedonic corrections recommended, for instance, for the size of a refrigerator in the OECD example above.

We propose to use hedonic techniques to produce quality-adjusted packaged food price index, where product size is one of several product attributes that enter the hedonic function. We then compute a "partially" adjusted price index, where product size is intentionally removed from the hedonic function. One can think of this partially adjusted price index as a counterfactual that keeps (average) product size constant over time. To isolate the impact of product size changes on inflation, we compare the fully adjusted price index to the partially adjusted price index.

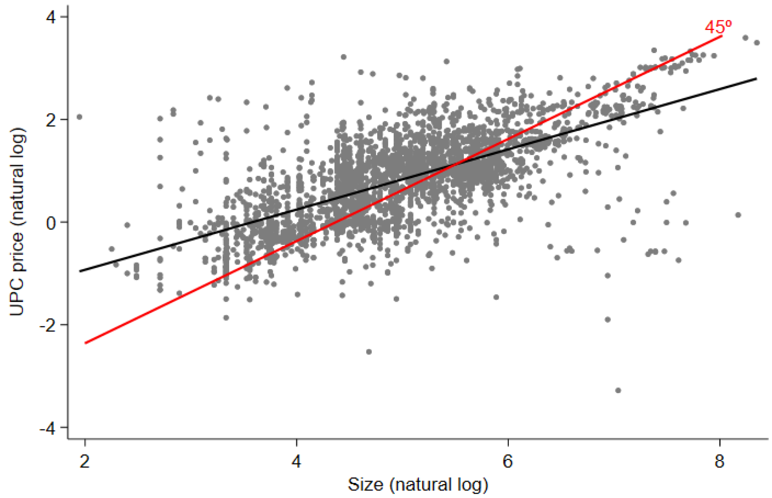
To visualize the importance of product size on prices in the hedonic functions we estimate, Figure 1 shows a scatter plot of the (log) relationship between "price per package" (PP) and package size (S), where a package is a distinct barcoded product. The figure illustrates the relationship for Chocolate Candy (one of the 2,092 product types in our data) in 2014. As can be seen, the raw correlation (black line), which can be interpreted as a first approximation to the hedonic $PP - Size$ relationship, is significantly flatter than a 45 degree line (red line), confirming the IMF's observation that product prices increase less than proportionally with size.[17]

[15]A similar statement can be found in the OECD's Handbook on price index adjustments (Triplett, 2004, p.30): *"Considering that the relation between size and price is seldom linear, it is a bit surprising that statistical agencies use predominantly the simple linear form of package size adjustment... When the price per gram falls as package size increases, [linear] package size adjustments bias the price index downward, because they over-adjust for the value of the larger package. Hedonic functions can be used to estimate a more appropriate package size adjustment."*

[16]The product categories where hedonic adjustments are made are apparel, appliances, telecommunication services and electronics.

[17]Strictly speaking, the term proportional refers to a linear relationship (not necessarily a 45 degree line) between two variables. However, for expositional ease, here we use the term "proportional" to denote a 1-to-1 relationship.

Figure 1: Illustration of Package Price (PP) v. $Size$ Relationship (Chocolate Candy, 2014)

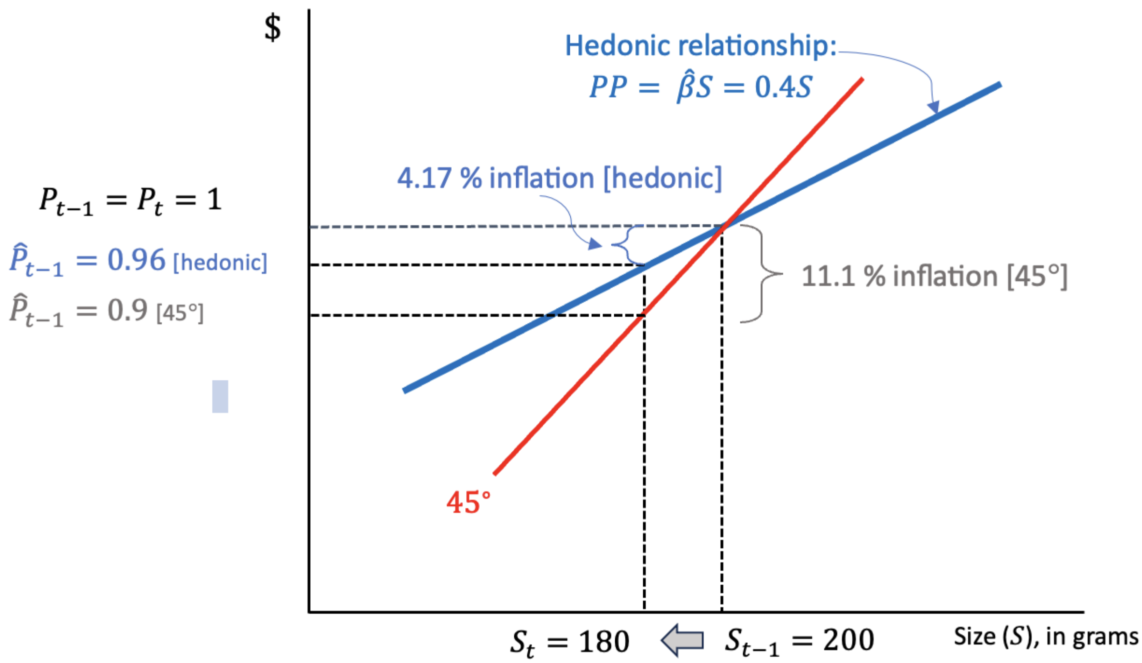


In our data, the less than proportional relationship between price and size seen in Figure 1 remains fairly stable when a rich set of other product characteristics are included, and it is always estimated to be less than one for all food categories.[18] When estimated for the entire packaged food industry, the hedonic regression reveals that a package that is twice as large is accompanied, on average, by a 43% higher package price .

Once the hedonic relationship is measured, the implementation of hedonic methods to compute a price index that accounts for changes in product size is straightforward. We illustrate the intuition of this process in Figure 2. The Figure shows that the price-size hedonic relationship has a slope of 0.4 (which is approximately what we observe in our data for the entire food industry). The x-axis indicates that product size has decreased by 10% from period t to period $t-1$ (from 200 gr to 180 gr), while product price has remained constant at $P_t = P_{t-1} = 1$. In this example, inflation would (incorrectly) be equal to zero if one did not account for the change in product size.

[18]The regression we run for this hedonic specification corresponds to equation 1, which we later discuss in more detail (i.e., the first stage in our two-stage hedonic model). When equation 1 is estimated separately for each of the 57 food categories in our data, the (log) hedonic coefficient between package price and size ranges from to 0.12 (baby food) to 0.71 (carbonated beverages).

Figure 2: Illustration of hedonic inflation correction



To obtain the "size-adjusted" inflation, one compares the current price, P_t with a counterfactual price for period $t-1$. This counterfactual price ($\hat{P}_{t-1}$) is obtained by moving along the hedonic line from period $t-1$, when size = 200 gr, to period t, when size = 180gr. In this illustration, the counterfactual generated by the hedonic line would be $\hat{P}_{t-1} = 0.96$ resulting in a size-adjusted inflation of 4.17% (i.e., $4.17\% = (\frac{1}{0.96} - 1) \times 100$).

For comparison purposes, Figure 2 shows the inflation that would be implied if one adjusted for size changes by computing inflation using per-unit prices (i.e., price per gram) instead of package prices. This correction is depicted by the 45-degree line: using per-unit prices to measure inflation amounts to imposing a 1-to-1 empirical relationship between package price and size (red line). In this example, such an adjustment would result in an inflation rate of 11.1% (i.e., $11.1\% = (\frac{1}{0.90} - 1) \times 100$), an inflation 2.66 times larger (i.e., $2.66 = 11.1/4.17$) than the one obtained via hedonic methods.[19] Interestingly, using the per-unit price as a way to account for product size changes has been used in both the inflation literature (e.g., Ehrlich et al., 2023) as well as statistical agencies such as the BLS in the US and the ONS in the UK.[20]

The extent to which product size will matter in inflation calculations depends on whether product sizes change significantly over time. To obtain a first glimpse of the changes in

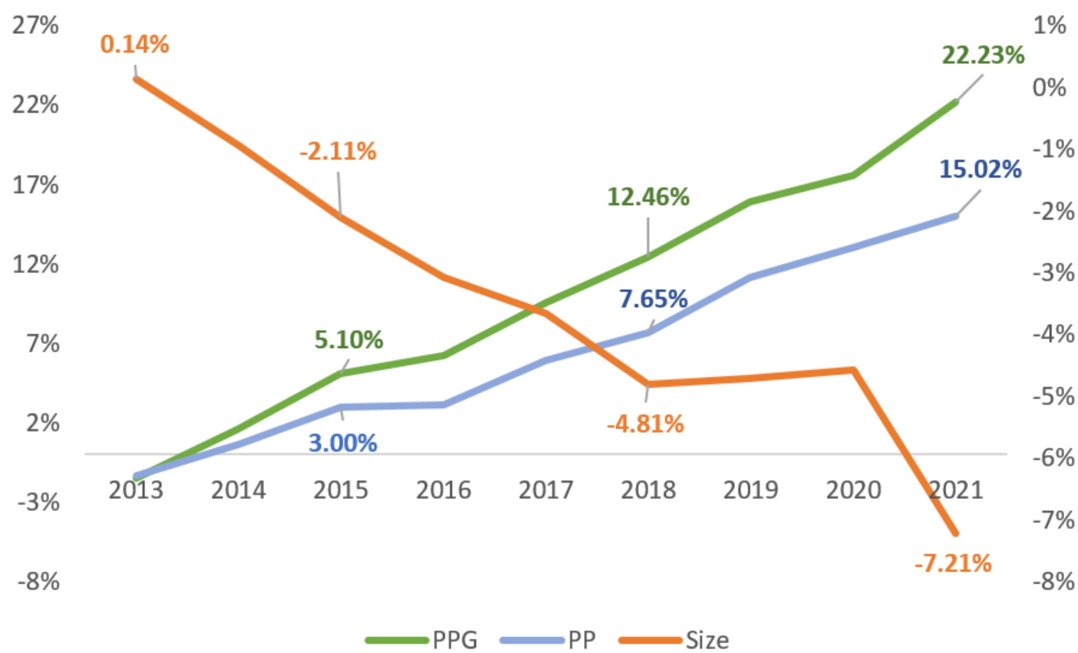
[19] Note that the bias implied by this correction would operate in the opposite direction in the case of product size increases. This is the bias that the OECD refers to in the quote shown in footnote 15.

[20] See BLS Handbook of Methods ("Direct Comparison" section) at: https://www.bls.gov/opub/hom/cpi/calculation.htm#direct-comparison. For the ONS, see https://www.ons.gov.uk/economy/inflationandpriceindices/articles/theimpactofshrinkflationoncpihuk/howmanyofourproductsaregettingsmaller. This approach is somewhat surprising given the calls by the IMF and the OECD (shown above) to treat product size as another attribute in the hedonic equation.

product size, we used our data to calculate the cumulative annual change in the average package size across all UPCs using 2012 as the base year.[21]

Figure 3 shows that the average package size in manufactured food has been declining with time: In 2021, the average weight of a UPC was 7.24% smaller with respect to 2012.[22] The figure also shows the cumulative change in the average package price (PP) and the average price per gram ($PPG = PP/Size$)). Although these are not proper inflation measures (an issue to which we turn next), one can see (the direction of) the impact that shrinking package sizes may be having on inflation: average price per gram grows at a faster pace than average package price.[23] Our inflation calculations, explained next, aim to capture this effect using appropriate price index methodology.

Figure 3: Accumulated change in average price per package (PP), average per unit price (PPG) and average size (gr) with respect to 2012, all manufactured food UPCs



3.2 Price Index Construction

We divide the methodology in two parts. The first explains the hedonics model and the second presents how the price index is constructed using the hedonic estimates.

[21]These averages are obtained from year fixed effect estimates in a regression that includes the log of the variable (price or size) as the dependent variable and 2,092 product type fixed effects as controls.

[22]Figure 3 shows results that use the main dataset (sales recorded at stores). Appendix Figure A1 shows results using an alternative dataset (sales recorded by households). We provide a description of these two datasets in Section 4.

[23]The difference between PP growth and PPG growth is exactly equal to size growth (or decline in this case).

3.2.1 Hedonics

To keep products comparable over time, traditional price indices are based on a matched-model methodology: prices of a basket of products in the current period are compared to their prices in the prior period. However, the application of a matched-model price index to transaction data is problematic due to the large turnover of products from one year to the next. For example, in our data 21.6% of products in a year disappear the following year. Similarly, 18.4% of products in a year were not present in the previous year.[24]

Hedonic methods are well suited to address product turnover issues in price index calculations. Specifically, the estimated hedonic function is used to generate a "counterfactual" price for products that lack an observation in the previous year (entering products) or in the following year (exiting products). Specifically, we use the approach implemented by Ehrlich et al. (2023), who suggest a way to implement the method proposed by Erickson and Pakes (2011) to transactional data.[25]

The method proposed by Erickson and Pakes (2011) controls for unobservable product characteristics using a two-step procedure. In the first step, a usual hedonic regression (price on observed product attributes) is estimated and its residual collected. The second step consists of a hedonic regression in price differences where the residual from the first step is included to control for unobservables that may be correlated with product attributes.

Formally, the first stage is given by:

$$lnp_{it} = h_t(Z_{it}) + \eta_{it} = \sum_{k=1}^{K} \alpha_{kt} z_{ikt} + \phi_i + \eta_{it} \tag{1}$$

where i and t index product and time (in our case UPC and year, respectively), p is the package (UPC) price, Z_{it} is a vector of K product characteristics ($Z_{it} = z_{i1t}, ..., z_{iKt}$), ϕ_i is a set of 2,092 product type fixed effects (see Section 4 for details), and η_{it} is the error term. We use a linear specification to approximate the time-varying hedonic function $h_t(Z_{it}) = \sum_{k=1}^{K} \alpha_{kt} z_{ikt}$;[26] in a robustness check we verify that our results are robust to a more flexible quadratic specification. In the presence of unobserved product attributes for product i, η_{it}, the error term can be written $\eta_{it} = \gamma_{it} + \epsilon_{it}$; where γ_{it} captures the market valuation of product i's unobserved characteristics and ϵ_{it} is an idiosyncratic component. Equation 1 is estimated via OLS and the resulting residual $\hat{\eta}_{it}$ is collected.

In a second step, the products that appear in both periods t and $t+1$ are used to estimate the following equation via OLS:

[24] These figures correspond to the average of exit and entry rates across all ten years in our sample.

[25] Erickson and Pakes (2011) use their procedure to "fill in" for future prices of exiting products but not for past prices of entering products. Ehrlich et al. (2023) extend this methodology to include entering products.

[26] We follow the suggested practice of estimating a hedonic function in each time period, which captures varying market environment factors such as consumers' valuations and supply-side factors. (Pakes, 2003); in equation 1 this is reflected by the t subscript in the α coefficients.

$$\Delta lnp_{it} = \tilde{h}_{t+1}(Z_{it+1}) + \hat{\eta}_{it} + \nu_{it+1} = \sum_{k=1}^{K} \beta_{kt+1} z_{ikt+1} + \hat{\eta}_{it} + \phi_i + \nu_{it+1} \tag{2}$$

where $\Delta lnp_{it} = lnp_{it+1} - lnp_{it}$. The hedonic coefficients from equation 2 are then used to fill in for the "missing" *change* in log prices either with respect to the prior period (in the case of product entrants) or with respect to the next period (in the case of product exits).[27] This two-step approach serves to control for unobservable product characteristics that may bias the hedonic coefficients. It does so in two ways. First, since equation 2 is specified in differences, it removes any time-invariant product-specific unobservables that may bias the hedonic coefficients (i.e., the time-invariant portion of γ_{it}). Second, the inclusion of $\hat{\eta}_{it}$ in the second stage, serves as a control for time-variant product unosbervables that can can be correlated with product attributes.

Equations 1 and 2 are estimated using the entire pool of UPCs in the sample. In a robustness check, we verify that our conclusions remain unchanged when we allow the hedonic estimation to vary by food category.

3.2.2 Price Index

We follow the common practice in the literature and calculate a price index based on the geometric mean of "price relatives". A price relative is given by the ratio of a product's price between two periods: $\frac{p_{t+1}}{p_t}$. Specifically, we employ the Tornqvist index:

$$\Phi_{t,t+1} = \prod_{i \in \mathbf{CEX}} \left(\frac{p_{it+1}}{p_{it}} \right)^{\left(\frac{s_{it+1} + s_{it}}{2} \right)} \tag{3}$$

where **CEX** contains the set of continuing products present in the t and $t+1$ periods (**C**), the set of products that enter the market in $t+1$ (**E**), and the set of products that exit between t and $t+1$ (**X**); s_k is product i's expenditure market share. Equation 3 is expressed in log form as:

$$ln\Phi_{t,t+1} = \sum_{i \in \mathbf{CEX}} \frac{s_{it+1} + s_{it}}{2} ln \left(\frac{p_{it+1}}{p_{it}} \right) \tag{4}$$

Typically, the Tornqvist index in equation 4 is estimated using only the set of continuing products, since these are the only products for which there is price information in both time periods. Although this is practical, when there is significant product turnover, the index does not capture the impact of changes in market-wide product quality (or product attributes) available to consumers, nor does it capture the importance (i.e., expenditure shares) of these

[27]A product that exits in period $t+1$ has a predicted price change, $\Delta \widehat{lnp_{it}} = \sum_{k=1}^{K} \hat{\beta}_{kt+1} z_{ikt} + \hat{\eta}_{it}$. A similar procedure is used for a product that enters in $t+1$, with the caveat that this product does not have an estimated $\hat{\eta}$ in period t; we follow Ehrlich et al. (2023) and assign $\hat{\eta} = 0$ in these cases.

products. We use the hedonic estimates to address this issue. Specifically, we compute a slightly different version of equation 4:

$$ln\hat{\Phi}_{t,t+1} = \sum_{i \in \mathbf{CEX}} \frac{s_{it+1} + s_{it}}{2} \Delta \widehat{lnp_{it}} \tag{5}$$

where $\Delta\widehat{lnp_{it}} = (\widehat{lnp_{it+1} - lnp_{it}}) = ln\widehat{\left(\frac{p_{it+1}}{p_{it}}\right)}$ is estimated via equation 2. We follow the literature and implement a fully-imputed price index, which means that the estimate $\Delta\widehat{lnp_{it}}$ in 5 is applied to all products (i.e., those that need imputation, **E** and **X**, as well as those that do not, **C**).[28]

Isolating the role of product size

To isolate the impact of product size on inflation, we estimate the hedonic model, and subsequent price index, twice. In the first estimation, we include product size in the set of product characteristics, Z_{kt}, that enter equations 1 and 2 and use the results to compute the price index in equation 5. The second estimation proceeds in a similar fashion, except that product size is removed from equations 1 and 2. Because the hedonic equation projects prices onto product attributes, the omission of one attribute effectively imposes the restriction that product size does not matter in the formation of prices. More importantly for our purposes, this second estimation effectively produces a counterfactual price index in which average product size is held constant. Thus, the difference between the two price indices can be interpreted as the impact of product size (changes) on inflation: if product size is an important determinant of prices, omitting it from the hedonic model will produce a consistent bias in the index.

3.3 Other details

In addition to the price index, we report results that quantify how average package size evolves over time for different n subsets of the data. These results are based on the following specification:

$$lnSize_{it} = \delta + \sum_{c=1}^{n} \sum_{t=2013}^{2020} \tau_{ct} year_t \times Subset_c + \phi_i + \epsilon_{it} \tag{6}$$

where c indexes the different subsets of data, $Subset_c$ is an indicator variable for subset c, and ϕ_i is a set of fixed effects for 2,092 product types (e.g., within the yogurt category there are dozens of product types, such as “Greek Yogurt”, “Kefir Yougurt”, etc. - see Section 4 and Appendix Table A2 for more details) which control for heterogeneity across

[28] See Erickson and Pakes (2011), Bajari et al. (2023), Ehrlich et al. (2023). As noted by Ehrlich et al. (2023), an advantage of full imputation is that the price index is less subject to chain drift.

food products. In the results, we report the cumulative percentage change in product size in year t and subset c with respect to base year ($\%\Delta \hat{Size}^{c}_{it}$), which is given by $exp(\hat{\tau}_{ct}) - 1$.

We slice the data in different ways to create different subsets. In the first, we separate products into 57 food categories to investigate heterogeneity if product size changes. Then, we generate subsets of data based on particular hypotheses (or "channels") about the factors that may drive product shrinkage. Every hypothesis, which we describe in Section 5.3, has its own set of channels (and data subsets). For all these regressions, we cluster standard errors at the food category (FC) level (57 clusters).

4 Data

Our data come from Circana (formerly Information Resources Inc - IRI) through a licensed use agreement with the United States Department of Agriculture (USDA). Circana specializes in providing detailed and comprehensive *product* and *sales* information for each UPC. The Circana data set that we use in this paper combines two types of information.

First, Circana provides detailed *product* information for each UPC on an annual basis. In addition to many descriptive details about the product (name of the product, manufacturer, branded/private label), Circana provides details of each product as stated in the nutrition facts panel (NFP). Aside from nutrition information (e.g. saturated fat, sodium), which is important for the estimation of the hedonic regression, of particular value for our work is the information on product weight. Specifically, the information provided by Circana is standardized across all UPCs in a single metric measure: grams.[29] In this paper we refer to the variable $Size$ as the weight of the product (in grams).

The database provides additional product information (beyond the NFP) that is either provided by the manufacturer or extracted from the product packaging. In addition to the brand name (and manufacturer), these additional data contain information on claims made by the manufacturer (non-GMO, organic, gluten-free, sugar-free, etc.). We include these variables in the hedonic regression.

To be more precise, the vector of product characteristics Z_{it} that enters the hedonic equations 1 and 2 contains the following variables: Size (in logs), protein, fiber, saturated fat, sodium, sugar, organic, natural, without growth hormone, GMO, gluten-free, without preservatives, no sodium, no sugar, vegetarian. Protein, fiber, saturated fat, and sugar are measured in grams per UPC while sodium is measured in miligrams per UPC. The remaining variables take a value of one if the package displays the claim (e.g., 1 if there is a "gluten-free" claim and 0 otherwise).

[29]More specifically, the database reports two separate variables that allow the computation of total grams per UPC: grams per serving and number of servings. This is a superior measure of the weight of the product compared to that available in other scanner databases. In our experience, the unit of measurement reported in commonly used scanner databases (i.e. Nielsen) varies widely (e.g. liquids are measured in fluid ounces, meat is measured in pounds, sliced bread in pieces, etc.) making weight comparisons of the type we pursue here unfeasible (unless meticulous work is done; see Cengiz and Rojas (2024)). Another advantage of the weight variable is that it does not include the packaging weight, which could otherwise cloud our interpretations.

Another important piece of information provided by Circana is product categorizations. There are different levels of aggregation for food categories. We make use of two. The first are what we call "food categories" (FC) and correspond to the same categories used by the BLS in their sampling of items to generate packaged food inflation measures. There is a total of 57 FC (see the Appendix Table A1 for a list).[30] As stated earlier, we use these categories to analyze the heterogeneity of the results and to cluster standard errors.

The second categorization, which corresponds to the lowest level of aggregation provided by Circana, is called "food type". There exist 2,092 food types. Due to space constraints, we do not list all food types, but display a selection of food types in the Appendix (Table A2) for illustration. We use food-type fixed effects in all our regressions, including hedonic equations 1 and 2, to control for (unobserved) heterogeneity across products.

Second, we rely on Circana's *sales* data base to obtain product prices. Our main analyses are based on store-level data obtained from approximately 70,000 stores. These data come at the store-week-UPC level. We aggregate these data up to the UPC-year level to match the frequency of product information (reported at the annual level).[31] In other words, the unit of analysis is the average nationwide price of a UPC in a year across all stores in the sample.[32]

For certain analyses (robustness checks and to investigate certain mechanisms that may be driving product shrinkage), we employ Circana's household panel database. This data contains purchase information (price and volume) from store visits ("trips") made by approximately 60,000 households per year. One of these analyses looks at whether households with different income levels are exposed to different rates of product shrinkage. The household panel includes the price and volume of each UPC purchased by a household on each shopping trip. Circana provides detailed socioeconomic and demographic information for each household in each year, including annual household income. Our analysis of product shrinkage by income focuses on four brackets: <\$25k; \$25k-\$50k; \$50k-\$70k; >\$70k.[33] To calculate the price of a product in a year, we identify all shopping trips in all households in which a UPC was purchased and calculate the average price paid for the package (UPC) over the aggregate volume purchased by the entire panel in a year.

We use all years in the data set: 2012 through 2021. The original IRI dataset contains approximately 375,000 UPCs of packaged food per year, of which we use approximately 58% (the remaining 42% do not contain the detailed product information we need to perform the hedonic analysis). The usable set of UPCs comprises 83% of all sales of packaged food in the

[30] The BLS computes the CPI by selecting and tracking the price of a representative item in a given category. There are 243 categories. The BLS calls the 243 categories "entry-level items" or ELI. Of these, 71 are food, of which 57 correspond to packaged food. See `https://www.bls.gov/cpi/additional-resources/entry-level-item-descriptions.htm)`

[31] A subset of retailers report data to Circana at the "retail marketing area" (RMA); this means that these data have been aggregated across the retailer's stores in that RMA. In these cases, we treat each RMA as a different store.

[32] An advantage of computing a CPI at the annual level is that it is subject to significantly smaller (or minimal) chain drift (Ivancic, Diewert and Fox, 2011).

[33] The original dataset contains eleven income categories; to make the analysis parsimonious, we collapse these categories into four brackets, as suggested Allcott et al. (2019)

database.[34]

A note on defining a product at the UPC level

Defining a product at the UPC level is appropriate for a couple of reasons. First, the industry has adopted the standard of using a new UPC whenever a sufficiently "different" product (e.g. a significantly different size of the same brand) is introduced. To be clear, this is not to say that continuing UPCs do not experience reformulation. In our data, continuing UPCs sometimes (although not often) change some attributes. However, when they do, they remain largely the same product (e.g., a zero-calorie soft drink UPC may vary somewhat in its formulation over time; for example, fewer calories and a slightly smaller bottle).

Second, barcode reuse (use of a deprecated UPC by another entirely different product) is extremely rare (and, in fact, currently banned) in food retailing because it causes large logistical problems for manufacturers and retailers.[35] This gives us confidence that UPCs observed from one year to the next correspond essentially to the same product (with some reasonable variation in product attributes).

5 Results

5.1 Price Index

Our main result is the annual price index given in equation 5, which is constructed using the hedonic estimates from equations 1 and 2. Figure 4 reports the annual inflation rate implied by the price index. The figure shows that including package size in the hedonic model results in a higher (or less negative) annual inflation rate, a result that is consistent with the negative average package size trend shown in Figure 3.[36]

This persistent difference generates a substantial gap at the accumulated level. Figure 5 shows that the accumulated inflation between 2012 and 2021 is 3.8% when size is taken into account but -0.1% when it is not. Another way of interpreting this counterfactual is that 2012-2021 inflation would be 3.9% lower had package sizes remained at the level seen in 2012. Similar results are obtained if the analysis is carried out with the household panel data

[34] Circana has recently made available data for 2022, but for reasons unknown to us, the product attribute information is either missing or unreliable for this year. Therefore, we do not include this year in the analysis.

[35] The GTIN Management Standard Rules effectively ban UPC recycling from 2018 onward. The GTIN rules prior to 2018 were also very strict: Manufacturers were allowed to reuse UPCs only if a minimum of 4 years had elapsed since a UPC had been discontinued. We have verified the (near) inexistence of UPC reuse in the data by performing a text analysis that compares product descriptions of a given UPC over time. We find that less than 1.5% of the cases could be considered as UPC reusage (cosine similarity measure less than 70%).

[36] These quality-adjusted inflation rates are comparable to those reported by Ehrlich et al. (2023), for the years when the span of their data overlaps with ours (i.e., 2012-2015). Also, our quality-adjusted inflation measure closely tracks the movements in the food-at-home CPI reported by the BLS (see Appendix Figure A3).

(see Appendix Figures A2 and A4), and with more flexible hedonic specifications (quadratic specification for package size or with a food category-specific specification; See Appendix Figures A5 and A6).

Figure 4: Quality-adjusted annual inflation rate, packaged food

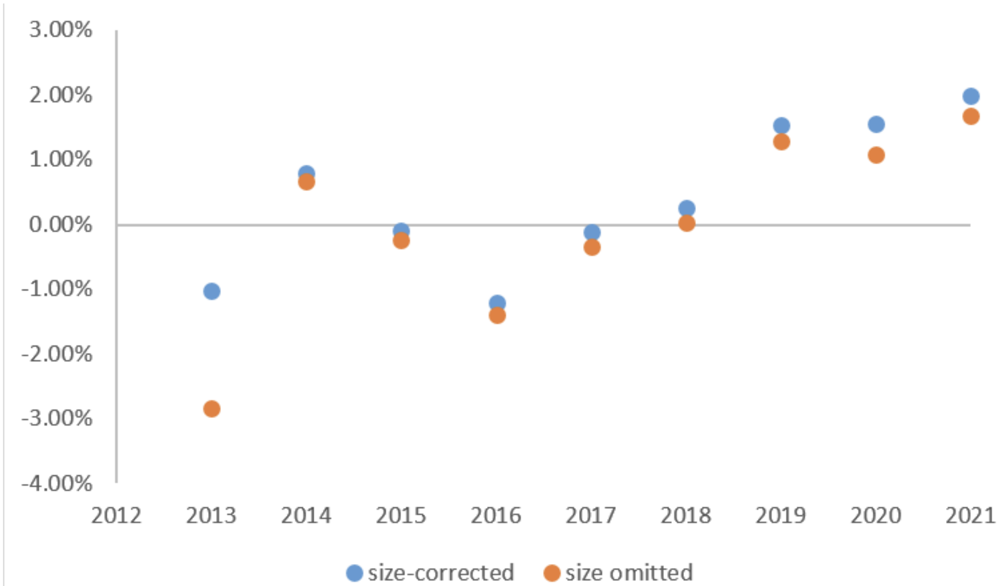
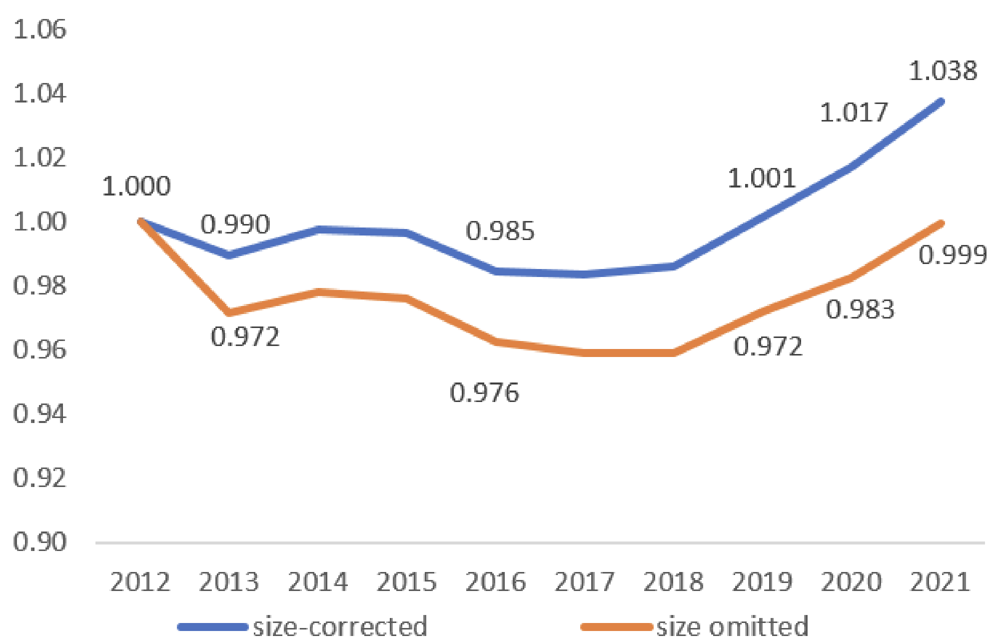


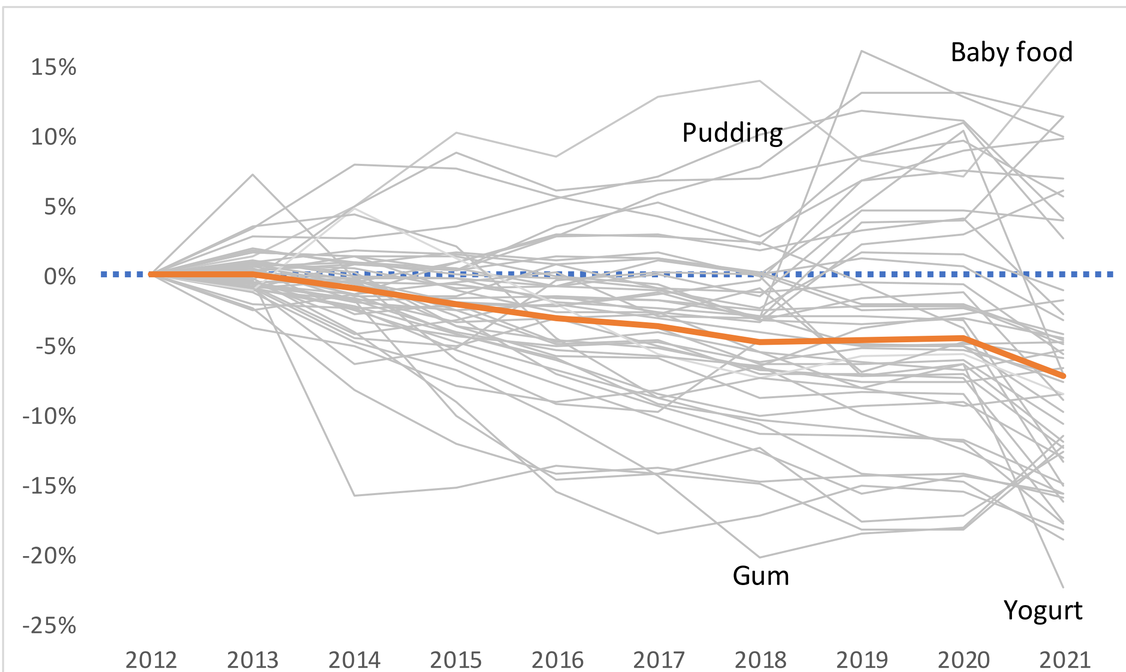
Figure 5: Chained (quality-adjusted) price index, packaged food



5.2 Product size changes

To better understand the types of products driving the decline in average package sizes, we use equation 6 to calculate the cumulative growth in average package size in each of the 57 food categories. Figure 6 reports the results. There is significant heterogeneity between food categories, with most registering a downward trend. Tables 1 and 2 show, respectively, the top 10 categories that experienced the largest accumulated change between 2012 and 2021, together with each category's expenditure share. Shrinkage has been more heavily concentrated in food categories that represent a larger share of food expenditure: the top 10 food categories that experience product shrinkage comprise 35.7% of all food expenditures, while the top 10 food categories that experience product enlargements comprise 13.7% of food expenditures.

Figure 6: Accumulated change in average product size, by food category



Note: Orange line depicts the overall average shown in Figure 3.

5.3 Mechanisms

In this section, we explore some possible mechanisms that may contribute to the observed downward trend in average product sizes.

Table 1: Food Categories with largest average package size declines

	Food Category	2012-21 Shrinkage	% Expenditures
1	YOGURT	-22.5%	2.3%
2	PACKAGED MEATS-DELI	-19.0%	5.5%
3	BREAD AND BAKED GOODS	-18.3%	5.7%
4	MILK	-17.8%	3.9%
5	TEA	-17.8%	1.1%
6	PIZZA/SNACKS/HORS D'OEUVRES-FRZN	-16.3%	1.6%
7	SOUP	-15.9%	2.0%
8	SNACKS	-15.8%	5.5%
9	COT CHEESE, SOUR CREAM, TOPPINGS	-15.7%	6.5%
10	BUTTER AND MARGARINE	-15.2%	1.6%

Note: % expenditures calculated using aggregate 2012-2021 data.

Table 2: Food Categories with largest average package size increases

	Food Category	2012-21 Enlargement	% Expenditures
1	ICE CREAM, NOVELTIES	15.6%	2.9%
2	BABY FOOD	15.6%	0.2%
3	VEGETABLES-CANNED	15.6%	1.9%
4	PASTA	11.5%	0.7%
5	PACKAGED MILK AND MODIFIERS	11.4%	1.0%
6	VEGETABLES-FROZEN	9.9%	2.0%
7	PICKLES, OLIVES, AND RELISH	9.8%	0.7%
8	BREAKFAST FOODS-FROZEN	7.0%	0.8%
9	CEREAL	6.1%	3.3%
10	DESSERTS/FRUITS/TOPPINGS-FROZEN	5.7%	0.2%

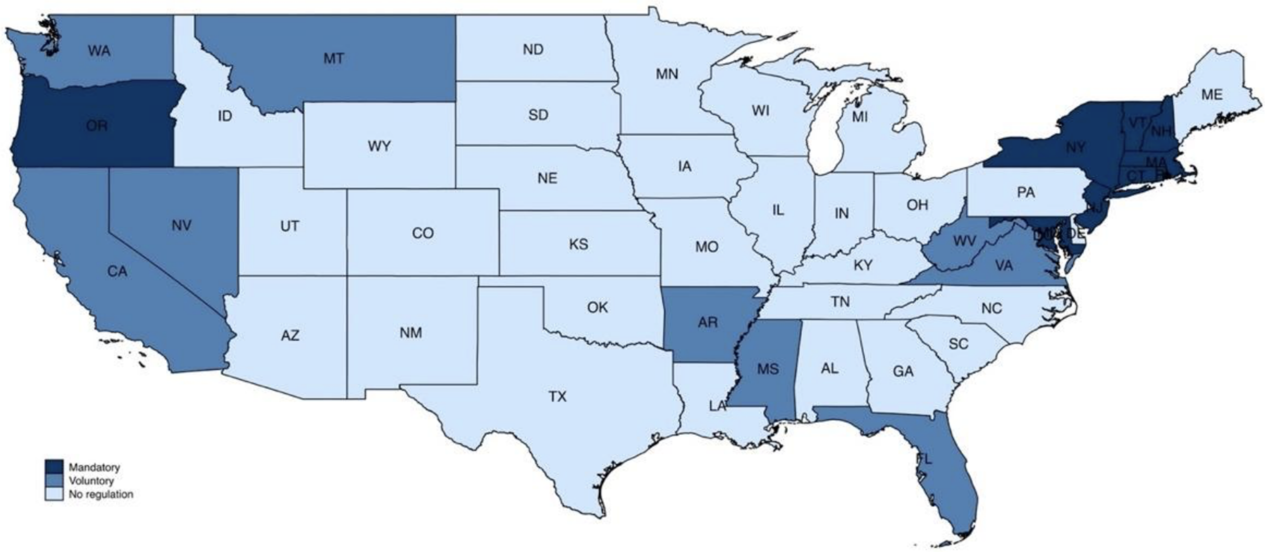
Note: % expenditures calculated using aggregate 2012-2021 data.

Consumer obfuscation

We posit that product shrinkage may be partially driven by the relative shrouded nature of product size as an attribute. If product size is more difficult to notice (than, say, price), then there can be an opportunity for firms to exploit consumers' relative difficulty to notice changes in product size (Ellison and Ellison, 2005, 2009). This type of "obfuscation" increases search costs that can result in higher markups and prices (Ellison and Wolitzky, 2012).

To probe this mechanism, we make use of variation in unit pricing laws (UPL) across states. Unit pricing laws were instituted in several states in the 1970s with the purpose of helping consumers make product assessments and price comparisons more easily. In states where UPLs are mandated, retailers must prominently display the per-unit price in the immediacy of the package price. Furthermore, the unit of measurement in any given product category must be the same (for example, oz) to facilitate price comparisons. Figure 7 shows the states where unit price regulation is mandatory, voluntary, or nonexistent.

Figure 7: Unit Price Regulation in the US



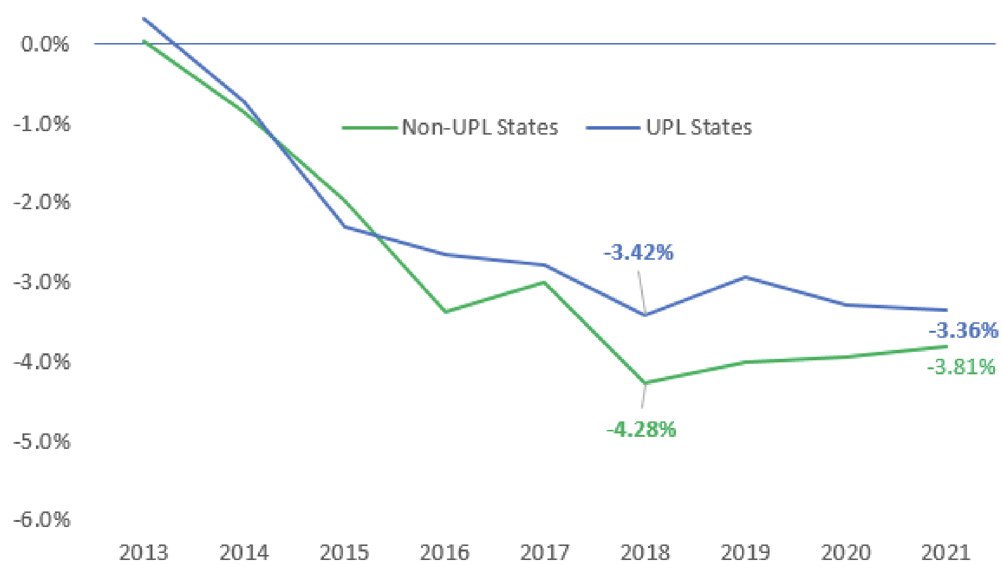
Mandatory: CT, MA, MD, NH, NJ, NY, OR, RI, VT. Voluntary: AR, CA, FL, MS, MT, NV, VA, WA, WV.
Source: National Institute of Standards and Technology

To test whether product shrinkage differs between UPL and non-UPL states, we compare the average package size in UPCs available in UPL states to the average package size of UPCs in non-UPL states. Specifically, we estimate equation 6, where our two subsets are UPCs in UPL states and UPCs in non-UPL states. In addition to product-type fixed effects, we add state fixed effects to control for time-invariant unobservables specific to each state. To produce a cleaner comparison, we restrict the non-UPL states to those that share a border with UPL states.

We show the results of this regression visually in Figure 8.[37] The results indicate that product sizes decrease in both types of states. However, the average product size is consistently smaller (except in one year) in states that lack UPL regulation; this pattern is consistent with the purpose of UPL laws, which was to help consumers realize and avoid packages that are too costly (on a per unit basis). Importantly, starting in 2016, the rate of product shrinkage in non-UPL states *accelerates* with respect to UPL states, a result consistent with the notion that product shrinkage may play an obfuscation role among consumers.

[37] Appendix Table A7 reports the results from the household panel data.

Figure 8: Accumulated average package size change, by UPL regulation



Note: UPL v. non-UPL difference is statistically significant at the 95% level for all years, except 2014 and 2017.

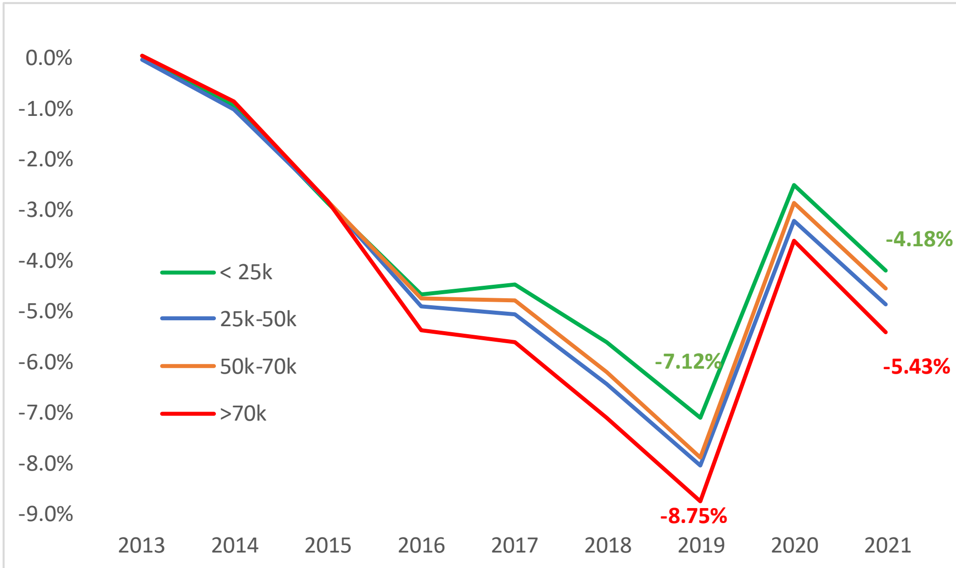
Inattention

The idea here is that certain consumers may not pay attention to product sizes (or product size reductions) in certain situations. This, in turn, can lead to firms exploiting this limited reaction to package sizes by shrinking package sizes more heavily in certain situations. The types of channel that we have in mind in this set are similar in spirit to the UPL test. We posit that the level of inattention is related to the search cost associated with finding package size information. This search cost can vary by consumers, outlet types, or products.

High-income consumers, who arguably have a greater opportunity cost of time, may face a higher search cost. We use the household panel data to test whether product shrinkage is more pronounced among high-income consumers versus low-income consumers. Specifically, we estimate equation 6 to estimate how the cumulative average change in product size differs across the four income bins (Section 4).[38] Figure 9 shows the results. Product shrinkage starts out to be similar across all income brackets in the 2012-5 period, but starting in 2016 larger income brackets start to experience larger shrinkage rates, a pattern that is consistent with the inattention hypothesis. In 2021, the top income bracket registers an accumulated package shrinkage rate that is approximately 30% larger than the rate observed in the bottom income bracket (i.e., -5.43% v. -4.18%).

[38]To do this, we create four sets of UPC-year observations, each containing all UPCs purchased by households in an income bin.

Figure 9: Accumulated average package size change, by household income



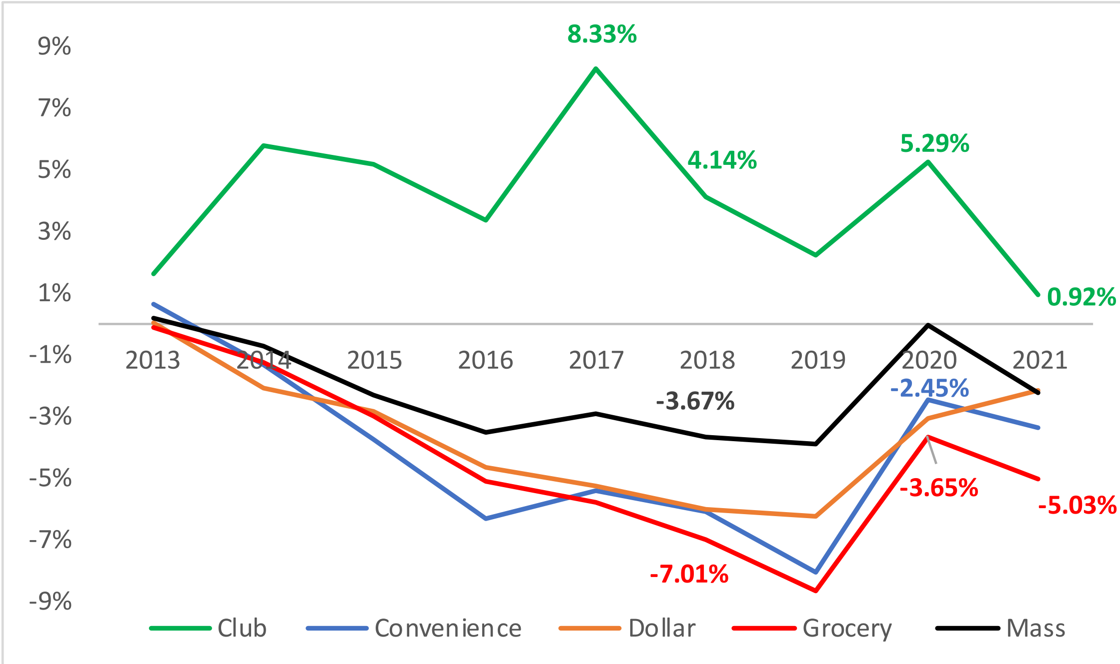
Note: The difference between the bottom bracket (<\$25k) and top bracket (>\$70k) is statistically significant at the 95% level in all years in the 2016-2021 period. The same holds when comparing the second and third income brackets with either the top or the bottom bracket.

A second channel is related to the type of outlet. A consumer making a quick purchase at a convenience store may not have time to shop around for (or is simply inattentive to) a more economical package size than when purchasing an entire week's worth of groceries at the supermarket. Thus, a plausible hypothesis is that the product product shrinkage rate is more pronounced at stores where consumers may be less likely to pay attention to product sizes. We estimate equation 6 by slicing the data into six subsets of UPCs, each corresponding to the products that are sold in club stores (e.g., warehouse outlets), convenience stores, dollar stores, grocery stores, mass merchandisers, and a residual group (other).[39] We note that we carry out this exercise with the household panel data (instead of the store data) because the store data in the Circana database contains a less comprehensive set of outlet types.[40]

[39]Our mass merchandisers category combines the "Mass" and "Supercenter" outlets in the original data. Our other category combines the "Drug" and "All other" categories in the original data.

[40]Specifically, Circana contains limited or no information (in certain years) for Club retailers.

Figure 10: Accumulated average package size change, by type of outlet



Note: The difference between Club and all the other outlets is always statistically significant at a 95% confidence level (except for 2013). Mass is statistically different than: Grocery for 2016-21; Convenience for 2015-19; and Dollar 2017-2020.

Figure 10 shows the results. The most striking result is that the products in the Club outlets show a growth in package size, while all other outlets display varying degrees of product shrinkage (with respect to 2012 levels). Club outlets are popular among consumers looking to obtain a significant discount on the per-unit price of staple products. Therefore, these consumers are arguably much more likely to pay close attention to package sizes.

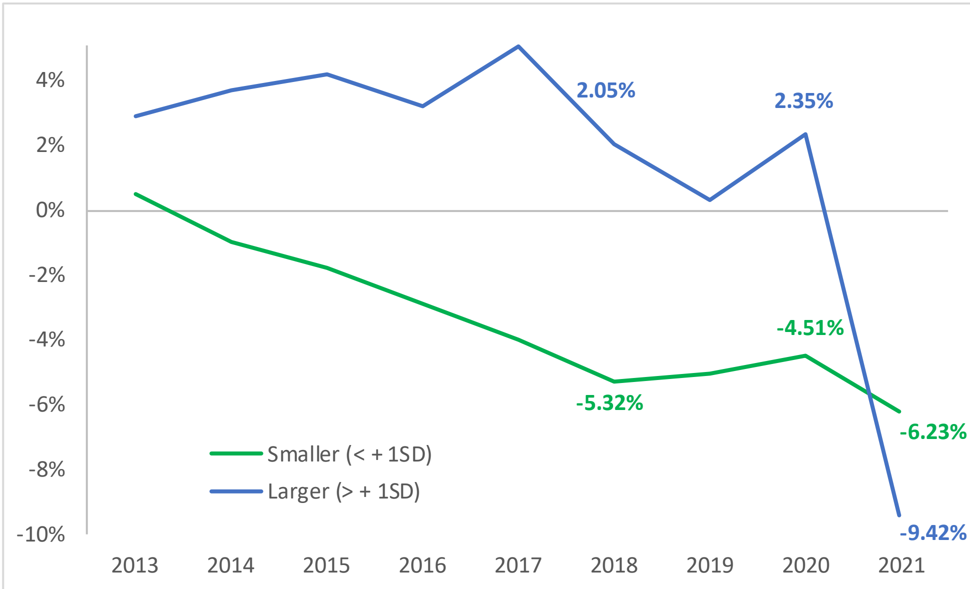
A related mechanism is that consumers may be less attentive (or sensitive) to package size reductions due to convenience or budgetary reasons. Certain consumers may prefer smaller package sizes because they are convenient (e.g., a quick on-the-go purchase), storage space at home is limited, budget constraints, or because smaller versions allow consumers to experiment with newer products (Shoemaker and Shoaf, 1975; Koenigsberg, Kohli and Montoya, 2010). To test for channel, we compare whether relatively bulkier products (within a product type) experience different rates of shrinkage than smaller products.

To do this, we use the distribution of package sizes within each of the product types to rank products from heaviest to lightest. We then divide products into two groups: those that are one standard deviation above the mean ("larger") and the rest ("smaller"). Figure 11 shows the results of applying equation 6 to these two subsets of products.[41] We observe that in all but one year (2021), product shrinkage is driven by lighter products, while heavier products grow in size. The year 2021 is a notable exception, where bulky products register

[41] Appendix Table A8 shows the results for the household panel data.

a dramatic rate of product shrinkage, surpassing that of the lighter set of products.

Figure 11: Accumulated average package size change, by bulkiness of product



Note: the difference between the two lines is statistically significant at the 95% confidence level in all years.

Dietary quality

Concerns about high levels of added sugar content in manufactured food have been voiced for years. In some cases, this has led to interventions aimed at curbing sugar consumption (e.g., sugar-sweetened beverage, aka SBS, taxes). Furthermore, there is growing evidence that companies may be reformulating their products, both in nutrient content and in packaging, in response to recent policy concerns and increasing consumer awareness of unhealthy eating (Dickson, Gehrsitz and Kemp, 2023; Keller and Guyt, 2023; Rojas and Cengiz, 2024). Therefore, we conjecture that one of the reasons for the observed reductions in package size may be driven by higher rates of product shrinkage in "unhealthier" product categories.

To investigate this association, we divide products into two groups. The first group, which we call "sugary", contains products in food categories known for their high sugar content.[42] The second group contains all other products, which we call "other".[43] Figure 12 shows the results.[44] As conjectured, sugary products not only show higher levels of shrinkage, but the rate of product size reduction accelerates starting in 2016 with a pronounced decline in 2021. Between 2012 and 2021, the average product in a category of sugary foods had

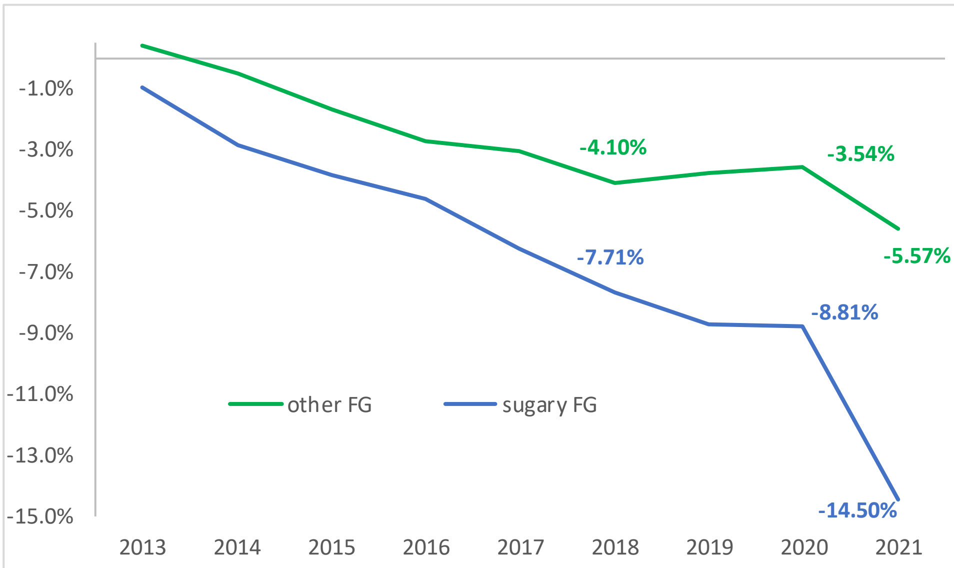
[42]These categories are: desserts/fruits/toppings-frozen; desserts, gelatins, syrup; candy; ice cream, novelties; juice, drinks - canned, bottled; carbonated beverages; and cookies.

[43]We also experimented with other dimensions of healthfulness (e.g., sodium, saturated fat, etc.) as well as with a holistic measure (a healthfulness index for each product, as reported in Allcott et al. (2019)). The results reported on sugary/other products generated the largest and most significant results.

[44]Appendix Table A9 shows the results for the household panel data.

shrunk 2.6 times more than the average product in other categories (-14.5% vs. -5.57%). It is interesting to note that, although we cannot make any causal claims, the acceleration in product shrinkage in sugary categories starts shortly after the first SSB tax took effect in Berkeley, California (2015).[45]

Figure 12: Accumulated average package size change, by sugary v. non-sugary food category



Note: the difference between the two lines is statistically significant at the 95% in all years.

6 Conclusion

We report a generalized pattern of product shrinkage in manufactured food in the United States between 2012 and 2021. We then compute the impact that product size reductions have had on manufactured food inflation and find that prices would have been generally lower had average package size remained unchanged over time. However, the magnitude of product shrinkage between 2012 and 2021 (which we estimate to be on average 7.24%) is larger than its contribution to quality-adjusted 2012-2021 inflation (which we estimate to be 3.9%). This finding suggests that smaller package sizes have been accompanied by higher levels of product quality.

As stated in the Introduction, the across-industry nature of our work, while informative, is not conducive to definite or conclusive answers about the reasons for package shrinkage. Despite this limitation, we provide suggestive evidence that package size reductions have may respond to a variety of factors including consumers' difficulty in assessing product sizes, consumer inattention, firms' product differentiation strategies, and policy-driven food refor-

[45]Another regulatory change that coincides with this timing is the FDA's 2016 rule to standardize serving sizes. However, a determination (or conjecture) of how or whether this rule may have modified firms' incentives to alter package sizes in a given direction is not clear, nor has it, to our knowledge, been studied.

mulation. Future work focusing on specific categories with notorious package size changes would be particularly valuable to shed more definite light on the mechanisms behind such changes.

From a policy perspective, our findings about lower levels of product shrinkage in UPL states suggest that regulation that improves consumers' assessment and knowledge about product sizes can help consumers make more optimal choices and limit the effect of product shrinkage on inflation. However, some of our findings do not necessarily cast product shrinkage as having a negative impact on consumers (or society). For instance, the extent to which the observed product size reductions respond to firms' greater efforts to engage in second-degree price discrimination may constitute a welfare-improving mechanism.

Similarly, product size reductions in unhealthy product categories (such as sugary products) that result in higher per-unit prices may provide some of the same (dis)incentives that policies to induce healthier eating (e.g., sugary-beverage taxes) pursue. More broadly, our research raises the interesting question of whether recent policy efforts to improve diets, as well as greater consumer awareness for healthier eating, have played a role in firms' decisions to reduce package sizes. Future work in this area, which is largely non-existent,[46] is particularly promising.

[46] A notable exception in this direction is Barahona, Otero and Otero (2023)

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Appendix A: Tables

Table A1: Food Categories

	Food Category		Food Category (cont'd)
1	BABY FOOD	30	JUICE, DRINKS - CANNED, BOTTLED
2	BAKED GOODS-FROZEN	31	JUICES, DRINKS - FROZEN
3	BAKING MIXES	32	MILK
4	BAKING SUPPLIES	33	NUTS
5	BREAD AND BAKED GOODS	34	PACKAGED MEATS - DELI
6	BREAKFAST FOOD	35	PACKAGED MILK AND MODIFIERS
7	BREAKFAST FOODS-FROZEN	36	PASTA
8	BUTTER AND MARGARINE	37	PICKLES, OLIVES, AND RELISH
9	CANDY	38	PIZZA/SNACKS/HORS DOEURVES-FRZN
10	CARBONATED BEVERAGES	39	PREPARED FOOD - DRY MIXES
11	CEREAL	40	PREPARED FOOD-READY-TO-SERVE
12	CHEESE	41	PREPARED FOODS-FROZEN
13	COFFEE	42	PUDDING, DESSERTS-DAIRY
14	CONDIMENTS, GRAVIES AND SAUCES	43	SALAD DRESSINGS, MAYO, TOPPINGS
15	COOKIES	44	SEAFOOD-CANNED
16	COTCHEESE, SOURCREAM, TOPPINGS	45	SHORTENING, OIL
17	CRACKERS	46	SNACKS
18	DESSERTS, GELATINS, SYRUP	47	SOFT DRINKS-NON-CARBONATED
19	DESSERTS/FRUITS/TOPPINGS-FRZN	48	SOUP
20	DOUGH PRODUCTS	49	SPICES, SEASONING EXTRACTS
21	DRESSING/SALAD/PREPFOODS-DELI	50	SUGAR, SWEETENERS
22	EGGS	51	TABLE SYRUPS, MOLASSES
23	FLOUR	52	TEA
24	FRESH PRODUCE	53	UNPREP. MEAT/POULTRY/SEAFOOD-FRZN
25	FRUIT CANNED	54	VEGETABLES - CANNED
26	FRUIT - DRIED	55	VEGETABLES AND GRAINS - DRIED
27	GUM	56	VEGETABLES -FROZEN
28	ICE CREAM, NOVELTIES	57	YOGURT
29	JAMS, JELLIES, SPREADS		

Table A2: Examples of Product Types in Selected Food Categories

Food Category (examples)	Product Types (examples)
MILK:	Almond Milk
	Buttermilk
	Coconut Milk
	Condensed Milk
	Coffee Creamer
	Eggnog
	Dairy Smoothie
	Half & Half
	Milk
	Whipping Cream
BAKING MIXES:	Baking Mix
	Belgium Waffle Mix
	Bread Machine Mix
	Brownie Mix
	Cake & Cooke Mix
	Cheesecake Mix
	Cookie Mix
	Cornbread Mix
	Cupcake Mix
	Crepe Mix
	Dumpling Mix
	Falafel Mix
	Muffin Mix
	Pancake Mix
	Pie Crust
SOUP:	Boullion
	Broth
	Consomme
	Japanese Noodle Soup Mix
	Noodle Soup Mix
	Ramen Noodle Soup Mix
	Soup
	Soup Mix
	Soup Stock

Appendix B: Figures

Figure A1: Accumulated change in average price per package (PP), average per unit price (PPG) and average size (gr) with respect to 2012, all manufactured food UPCs - Household Panel

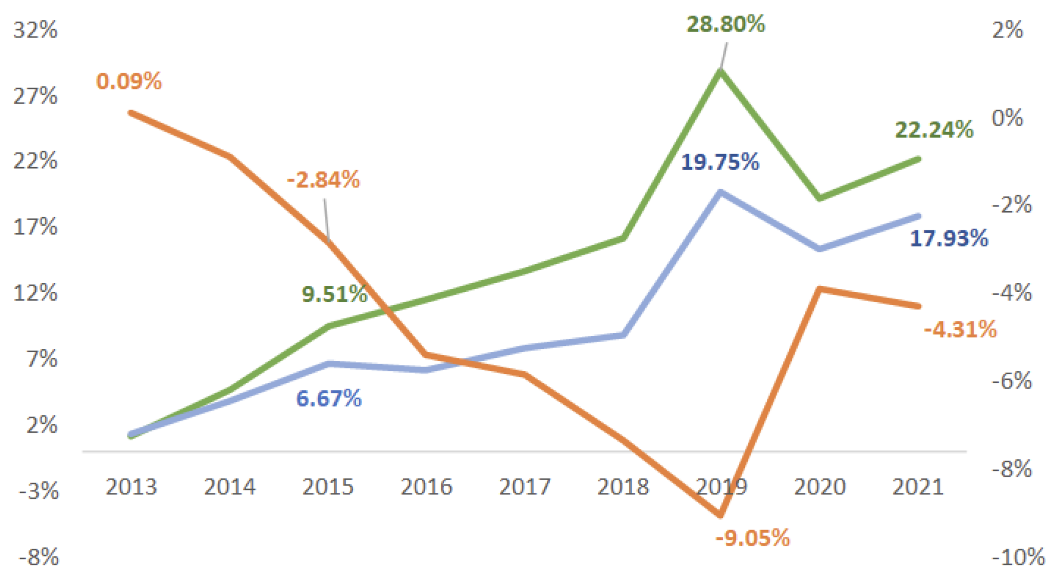


Figure A2: Quality-adjusted annual inflation rate, packaged food - Household Panel

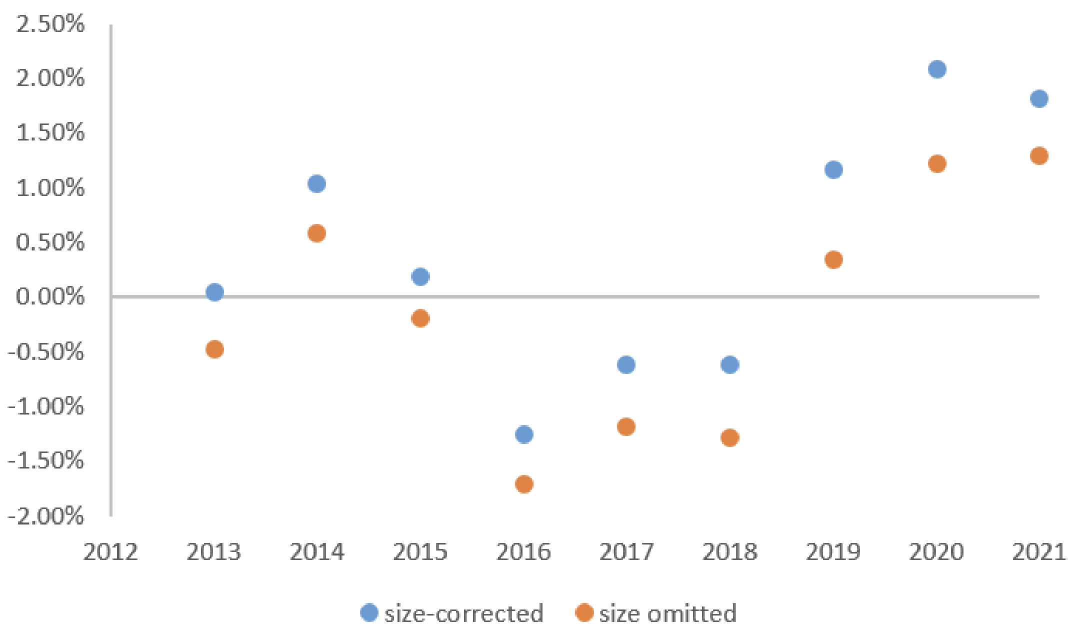


Figure A3: Food at Home Annual Inflation (from BLS' CPI) v. Quality-Adjusted Inflation (this paper)

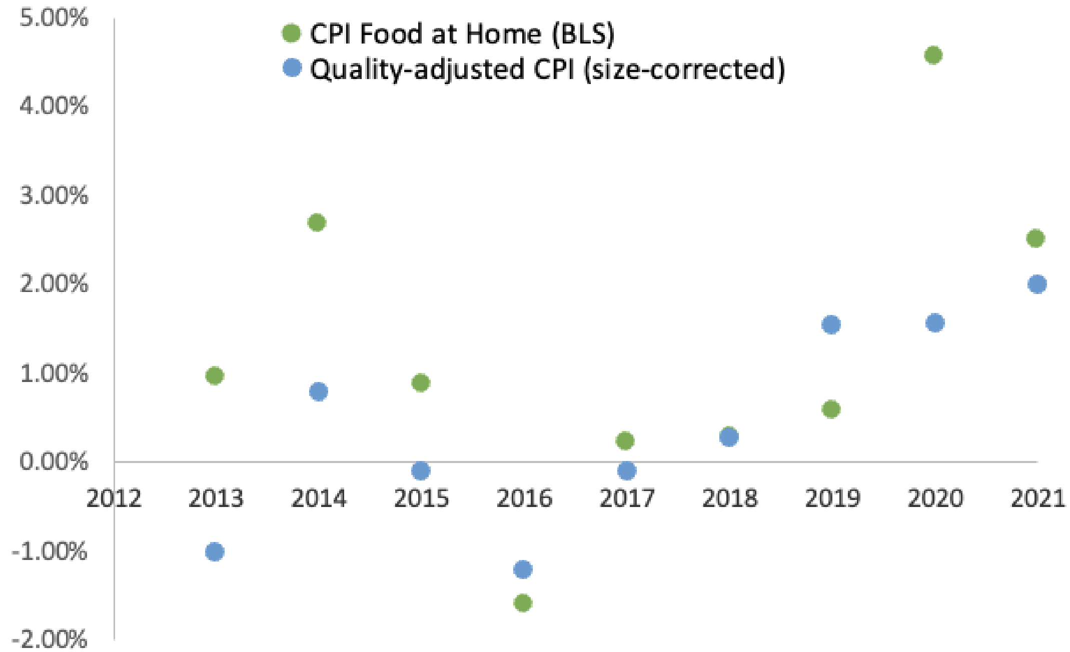


Figure A4: Chained (quality-adjusted) price index, packaged food - Household Panel

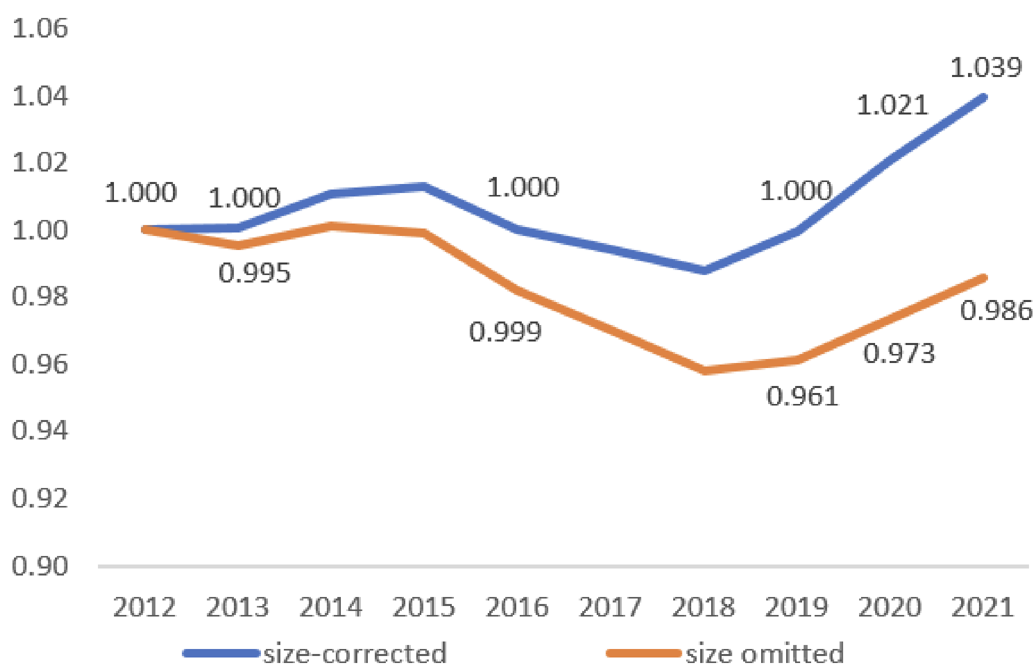


Figure A5: Chained (quality-adjusted) price index, packaged food - Quadratic Size Specification

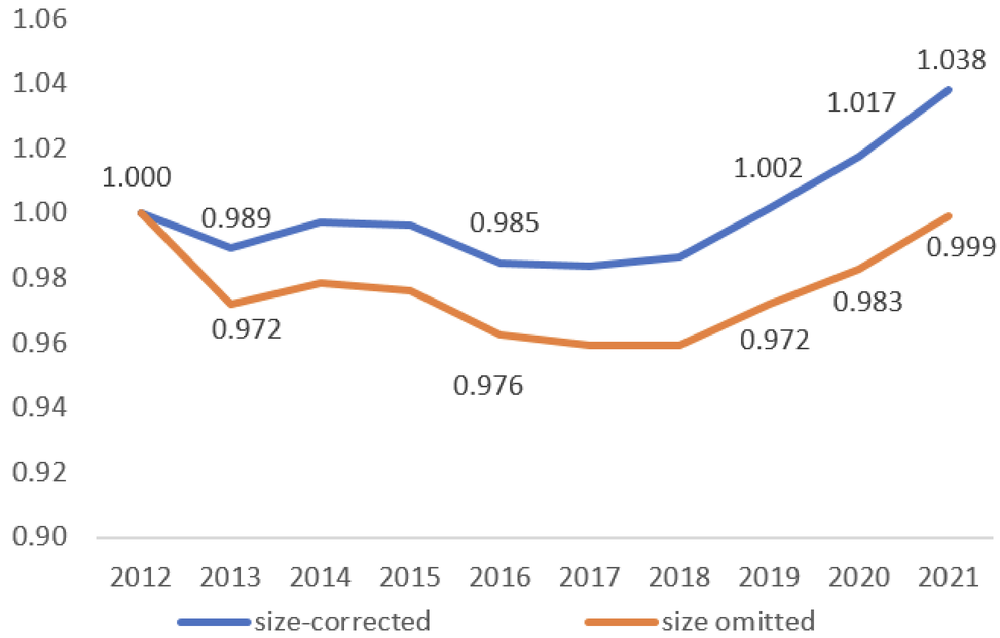


Figure A6: Chained (quality-adjusted) price index, packaged food - Food Category-Specific Hedonics

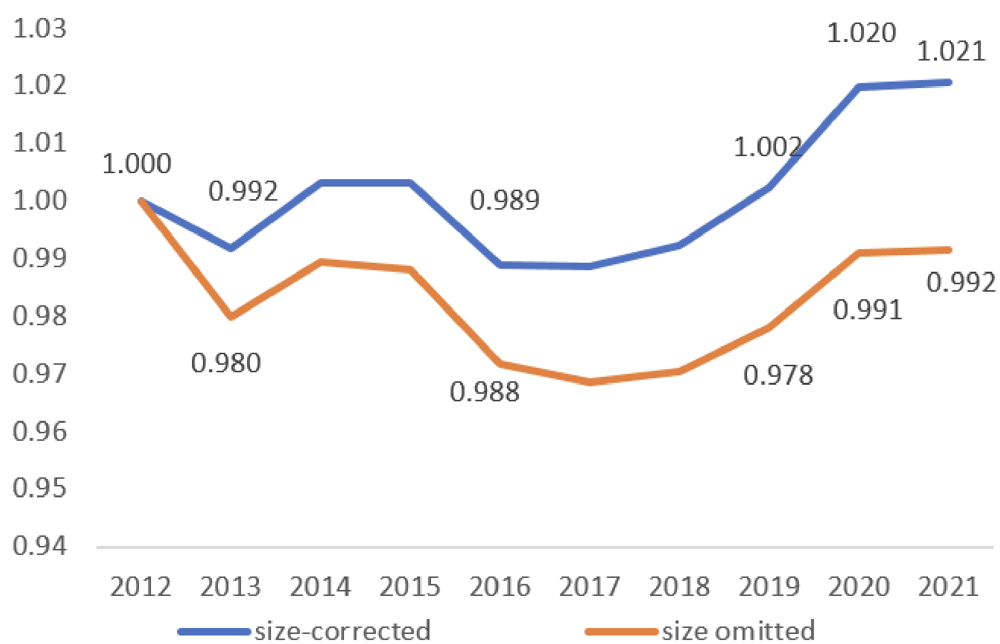
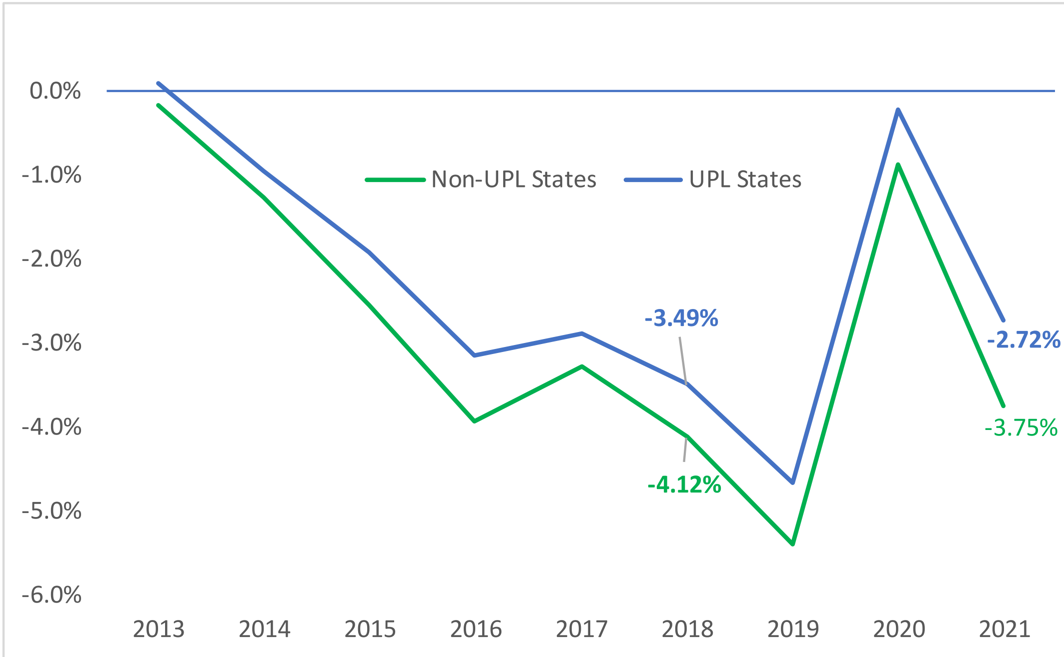
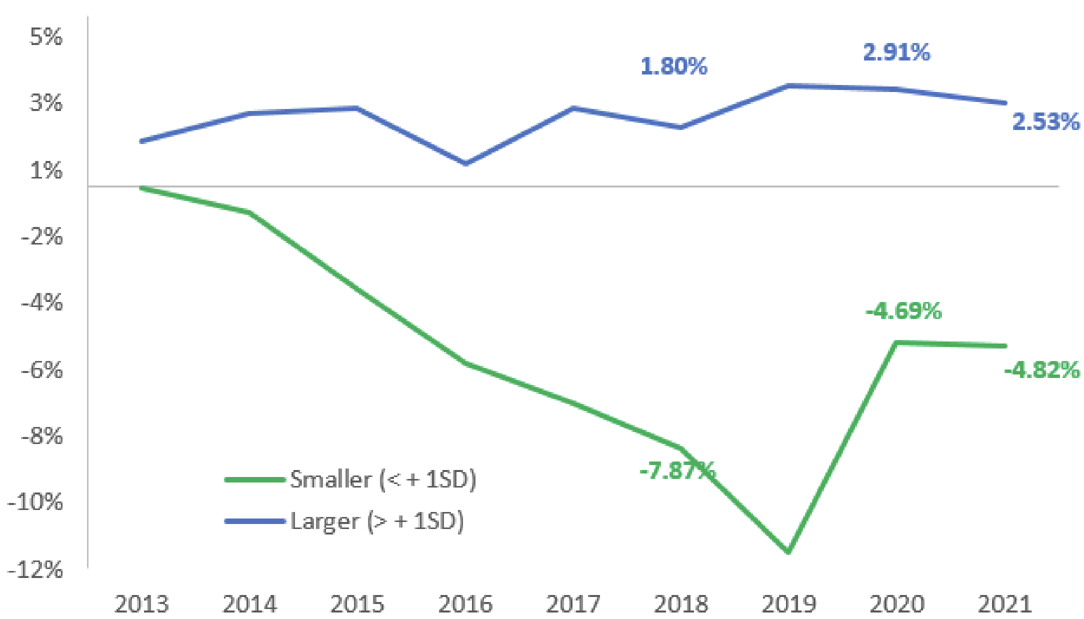


Figure A7: Accumulated average package size change, by UPL regulation - Household Panel



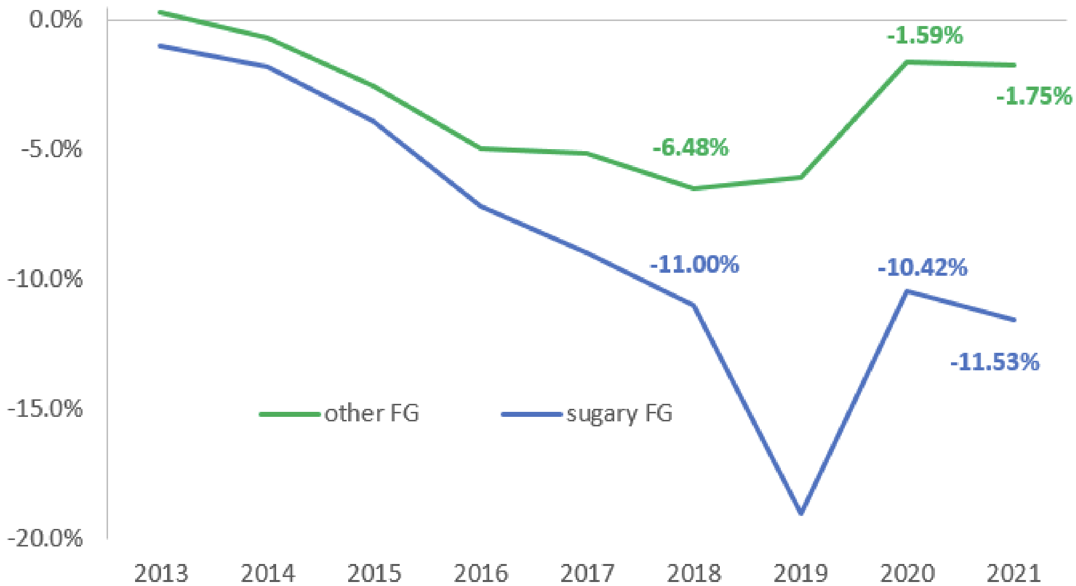
Note: UPL v. non-UPL difference is statistically significant at the 95% level for all years, except 2013.

Figure A8: Accumulated average package size change, by bulkiness of product - Household Panel



Note: the difference between the two lines is statistically significant at the 95% confidence level in all years.

Figure A9: Accumulated average package size change, by sugary v. non-sugary food category - Household Panel



Note: the difference between the two lines is statistically significant at the 95% in all years except 2014 and 2015.