# Does Peter Piper Pick Pepper Inattentively? Consumer Inattention to Package Content

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*Firms can increase unit prices by decreasing package content, a practice known as product downsizing. Because consumers tend to underuse size information, they may fail to notice size changes. Downsizing in the pepper industry provides an opportunity to test consumer inattention. We build a structural demand model that incorporates inattention to changes in package content and apply it to grocery scanner data. We find that almost all consumers fail to notice change in package content. With full information, consumers would switch to larger packages, but the overall improvement in welfare is small as consumers care more about price than size.*

## 1. Introduction

Food manufacturers sometimes replace packaged goods with smaller versions, a practice known as product downsizing.[1] Some manufacturers shrink their packaging to reflect the reduced content, but many do not. Examples of downsizing abound. In 2023, Folgers reduced the amount of coffee in a canister of Breakfast

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[1] The literature has used various terms to describe this practice, including **package downsizing** (Cakir and Balagtas, 2014; Yonezawa and Richards, 2016; Cakir and Balagtas, 2014), **downsizing price increase** (Gourville and Koehler, 2004), **content reduction** (Kachersky, 2011), and **shrinkflation** (Ochirova, 2017). Some papers (e.g. Gupta et al., 2007) add the additional requirement that the package price remains the same. As Imai and Watanabe (2014) show, large decreases in package content may lead to decreases in the package price even if the unit price increases.

Blend by 2.8 ounces; Pepperidge Farm reduced the amount of gold fish in a carton by 2.7 ounces; Frito-Lay reduced the amount of pita chips in a bag of Stacy's Pita Chips by 2.0 ounces; and Nutri Source reduced the amount of Large Breed dog food by 4.0 ounces (Dworsky, 2023). As these examples show, product downsizing occurs across a wide range of products. In some industries, downsized products constitute a large fraction of the available products.

Manufacturers often use downsizing as a way to increase unit prices (i.e. price per ounce), keeping package prices constant while reducing package content. Most firms do not advertise such size changes. To identify downsizing, consumers must correctly process the available sizes. Because many consumers use visual estimates in place of explicit size information, they may fail to notice the reduced content as firms downsize their products in a number of different, and often subtle, ways. If consumers are inattentive, downsizing represents a hidden price increase.

We test whether consumers are inattentive to reductions in package content in the pepper industry. To recover the degree of inattention, we develop a model of inattention and show how it can be recast as a standard random coefficient model. In the model, inattention results in consumers evaluating product utility according to the product's original net weight, causing the change in the net weight to enter utility as an additional product characteristic with a random coefficient. The distribution of this random coefficient characterizes the degree of inattention. Estimating the extent of inattention thus amounts to estimating the distribution of the random coefficient, allowing us to estimate the model using standard, demand estimation techniques.

We consider a downsizing event in the pepper industry where McCormick, the industry's largest firm, shrank the content of eleven black pepper products, representing 33% of the market. This downsizing event provides an ideal opportunity to study inattention due to the wide range of available sizes. Consumer substitution between products with different net weights allows us to estimate how much consumers value net weight. We then recover inattention by comparing how product shares change after downsizing to how product shares should have change given consumers' preferences for net weight before downsizing. When consumers are inattentive, product shares will remain constant as consumers do not notice the change, whereas when consumers are attentive, the product shares decline according to consumers' weight preferences. The difference between the observed trend and the expected trend after downsizing identifies inattention. Previous studies on downsizing (Cakir and Balagtas, 2014; Yonezawa and Richards, 2016) do not examine inattention and may not be able to as they consider industries with relatively little variation in package content. Existing variation is necessary to construct the expected trend.

Applying the model to retailer-level data from NielsenIQ, we find that almost all consumers fail to notice a change in the net weight. We also find that consumers are far more sensitive to changes in package prices compared to changes in net weight even when fully attentive. Due to this differential sensitivity, the removal of inattention does not have a large impact on consumer choices. The share of the downsized products falls by around 7.5 percentage points relative to other pepper products. Small changes in market shares translate to small changes in consumer welfare.

## 2. Literature

Previous studies of downsizing in the US ice cream (Cakir and Balagtas, 2014) and cereal (Yonezawa and Richards, 2016) industries find that consumers are less sensitive to size than price. Neither Cakir and Balagtas (2014) nor Yonezawa and Richards (2016) explore why consumers appear to undervalue package content. There are several possible explanations. One possibility is that consumers care about other product features more than the weight. For example, when buying ice cream, consumers may place more emphasis on quality and taste than on whether a container has 48 or 56 ounces. Another possibility is that consumers are attached to the downsizing brand. Brands with strong customer loyalty may be confident that downsizing will not affect consumer attachment.

In an article examining downsizing in the Korean milk industry, (Kim, 2024) also finds that consumers prefer downsizing to price increases and additionally, that this preference persists over time. He argues that the benefit-price ratio of a product is higher for downsizing relative to a price increase for fully rational consumers.

Given consumers' insensitivity to size, several articles consider firm's decisions to use downsizing. (Cakir, 2022) shows that firms that use downsizing are able to achieve higher pass-through rates, implying that downsizing can be an effective strategy to increase profits. In contrast, Yonezawa and Richards (2016) find that price and size are strategic complements and that downsizing intensifies price competition, reducing the profits of the downsizing firm.

In this article, we explore another explanation for consumers' apparent preference for downsizing. We argue that the lack of response to size reductions is due in part to inattention. Consumers frequently ignore explicit information on net weight and instead rely on visual cues (Lennard et al., 2001). Visual estimates can be inaccurate as they are subject to cognitive biases. For instance, consumers perceive tall, narrow objects to be larger than short, wide objects of the same volume (Krishna, 2006). Such perception biases grow when the packaging changes across multiple dimensions (Chandon and Ordabayeva, 2009). Particular packaging changes can result in consumers failing to notice even a 24% decrease in package size (Ordabayeva and Chandon, 2013).

Consumers' poor grasp of volumes translates to unit prices as well. Many consumers do not compare unit prices across different sizes of the same product and often pay a surcharge for larger quantities (Clerides and Courty, 2017). Consumers who do not compare unit prices within brands are unlikely to compare unit prices across brands. This suggests that downsizing can be an effective strategy to hide an increase in the unit price. Determining the level of inattention is important as it dictates the degree to which firms can engage in downsizing.

Inattention complements existing explanations for consumers' apparent insensitivity to downsizing. As we show later, fully attentive consumers will respond less to reductions in net weight than to price increases. This pattern is consistent with Kim (2024).

Even if consumers are inattentive to changes in package content, exploiting inattention comes with risks. Consumers may feel deceived and react negatively toward the downsizing brand upon discovery of the size decrease. In experiments, consumers presented with downsized products expressed a lower willingness to buy the presented brand (Kachersky, 2011; Wilkins et al., 2016; Evangelidis, 2023). Evangelidis (2023) finds that participants are more likely to view downsizing as unfair compared to a price increase due to their beliefs that downsizing is deceptive. The possibility of a backlash may explain why many firms do not advertise their downsizing decisions.

Consumers exhibit inattention and cognitive biases in a variety of settings. Many do not pay close attention to hidden attributes like shipping costs (Brown et al., 2010) or sales taxes (Chetty et al., 2009). Consumers can also misperceive product attributes. Allcott (2013), for example, finds that consumers misjudge the value of fuel economy when choosing cars. In some cases, consumers give particular attributes too much consideration. For instance, many consumers place overemphasize the left-most digit and pay higher prices for cars whose mileage falls below 10,000 miles (Lacetera et al., 2012). When consumers are behavioral, changing the available information affects consumers' decisions and therefore their welfare. If cognitive biases can influence major purchases, they should also impact minor ones.

A number of studies provide methods to identify and to recover inattention to product attributes. Abaluck and Compiani (2020) test for inattention using the cross derivatives of the choice probabilities. Their method is not applicable in our context because it assumes that consumers ignore the hidden attribute when searching. Brown and Jeon (2020) provide a method for recovering consumers' information processing strategies grounded in a rational inattention framework. For their method to be tractable, they place restrictions on the prior distribution of product utilities and hence the information processing strategy. In contrast, our model recovers the level of inattention without functional form assumptions, but unlike Brown and Jeon (2020), our model does not explain how consumers become inattentive.

## 3. Data

To analyze downsizing, we use the NielsenIQ Retail Scanner data and the NielsenIQ Consumer Panel data from the Kilts Center at the University of Chicago. The Retail Scanner data provides weekly point-of-sale data for around 35,000 stores in the United States and covers over 4 million consumer package goods. The Consumer Panel provides a micro-level panel of consumer purchases. It tracks between 40,000 and 60,000 households. We use the Scanner data from 2014 to 2016 in the structural estimation and we use the individual-level purchase data to inform the modelling.

Pepper products encompass a wide variety of spices that add heat and flavor to food. The products range from true pepper, *Piper nigrum*, to botanically unrelated chilies like cayenne and include seasoning blends whose primary ingredient is pepper like lemon pepper. In the scanner data, we observe 1,468 unique pepper products, which we categorize into 22 different varieties. The two most popular varieties are black and white pepper, which account for 63.9 percent of sales. Other pepper popular categories include red pepper, cayenne pepper, and black pepper blended with some type of citrus. Many of the pepper categories are quite niche and have only a few products. We group these pepper categories into a single other category.

Pepper is staple seasoning with the majority of households purchasing it at least once in the five-year span from 2012 to 2016.[2] While most consumers will purchase pepper at some point, they do so infrequently. In any given year, only around 40% of consumers buy pepper. Many go over a year before purchasing pepper again. Long interpurchase times are due to pepper's high storability. As pepper products come from dried berries or chilies, they do not easily spoil, but instead lose their pungency over time (Feucht, 2019).

[2]Author's calculation based on a balanced panel from the NielsenIQ Consumer Panel data.

The different types of pepper in flavor and heat levels. However, pepper products of the same type are very similar in most respects as they come from the same plants. Products within the same variety differ slightly in terms of quality and taste which stem from differences in soil, climate, and processing method. For a given type of pepper product, the largest differences are in branding and packaging. From 2014 to 2016, there are 247 different brands in the scanner data.

Given the similarity between products, many consumers opt for cheaper store brands. Store brands capture around 40% of the market during this period. In contrast, the typical name brand is a small and regional with a market share that is less than 0.1%. Among name brands, McCormick stands out with its 40% market share. The brand's owner McCormick & Co. dominates the industry, owning three of the top five selling name brands in McCormick, 5th Season, and Spice Classics. Through its various brands and private labels, the company controls around 50% of the market. The next largest firm B&G Foods, the producer of the brands Tone's and Durkee, accounts for approximately 2.5% of the market and almost no other brands exceed more than 2% of the market.

In addition to the large number of brands, the industry features a wide array of product weights. In the consumer panel data, products range from 0.4-ounce bags to 32-ounce containers with many weights in between (Figure 8)[3]. Examining the histogram of weights purchased from 2014 to 2016 among the panelists, the most-frequently purchased sizes were two and four ounces, which correspond to the standard weights of small and medium tins of black pepper, respectively.

Most stores in the scanner data offer these two sizes of black pepper along with many others. The typical store offers 23 different sizes of pepper products at any given month (Figure 9), 14 of which are black pepper products. Some stores offer as many as 53 distinct sizes and others as few as a single size. Although most stores offer more than twelve sizes, a noticeable percentage of stores offer a limited variety, having fewer than four distinct sizes at a given point in time. Differences in the available sizes across stores force consumers to substitute to similarly sized products and directly reveals consumer substitution patterns, which in turn allows us to separate size preferences from inattention.

□ **Estimation Sample.** The sheer size of the data poses problems for the structural estimation. The weekly store-level data has more than 40 million observations. To ease the computational burden, we aggregate the data from the store-level to the level of retailer and designated market area.[4] As DellaVigna and Gentzkow (2019); Hitsch et al. (2021) show, prices and product offers are very similar within the same retailer. Aggregating to the DMA level preserves some of the geographic variation in the original data. We also aggregate from weekly data to monthly data. Given the infrequency of pepper purchases, we do not need to worry about consumers buying multiple products in a given month.

After aggregating, we have 1,369 retailer-DMA combinations for a total 1,377,556 observations. For simplicity, we will refer to a retailer-DMA combination as a retailer in what follows.

In the estimation sample, the typical retailer offers 30 unique sizes of pepper products with most retailers offering between 22 and 52 different sizes. Figure 10 shows the number of unique sizes offered at a retailer in a given month. As with the store-level data, there are some retailers that offer a limited selection of sizes.

[3]There are a few outliers of 80-ounce sales

[4]Following DellaVigna and Gentzkow (2019) and others, we define a retailer as a combination of the *parent_code* and *retailer_code*.

While the aggregation process inflates the number of distinct sizes, the overall variation is similar to that of the store level.

In estimation sample, the mean price of a pepper product during this period was \$3.93. Most prices are between \$0.99 and \$7.99. This translates to an average unit price of \$0.84 per ounce. Most unit prices are between \$0.01 and \$4.00.

## 4. Downsizing in the Pepper Industry

□ **Background.** Downsizing in the pepper market came in response to rising commodity costs. From 2009 to 2014, wholesale black pepper prices were increasing due to growing demand in emerging markets (Figure 11). With prices trending upward, a poor harvest in 2014 caused the wholesale prices to spike (Figure 11). Over the course of 2014, the wholesale price of black pepper increased by over 30%. Manufacturers responded to this sudden cost increase in different ways. Most chose to increase their product prices, while others like McCormick and Spice Classics reduced the content of select black pepper products. Except for one blend pepper product, these firms only adjusted their black pepper products.

Faced with higher wholesale prices, retailers responded by adjusting their product offerings, with some phasing out larger products for smaller ones. In addition, some retailers chose to downsize their store-brand black pepper products. A federal court noted that McCormick asked the private-labeled brands that it manufactures to reduce their fill levels and most agreed to the new smaller sizes for black pepper (*In Re: McCormick & Co.*, 2019).

McCormick downsized its black pepper products and store brands in February 2015. Figure 1 provides an example of McCormick's downsizing. As the figure shows, McCormick initially downsized its products by reducing the fill levels while keeping the packaging the same size. The company eventually adjusted its package sizes to reflect the reduced content in the middle of 2016 (*In Re: McCormick & Co.*, 2019). This change is not observable in the data as it does not affect the product codes or descriptions. We do see some private-label brands that switch their packaging from glass to plastic after downsizing.

Figure 1: Comparison of Medium Tins


From left to right: Watkins's 4 oz tin, McCormick's old 4 oz tin, McCormick's new downsized 3 oz tin
Source: *Watkins v. McCormick* (2015, p. 7)

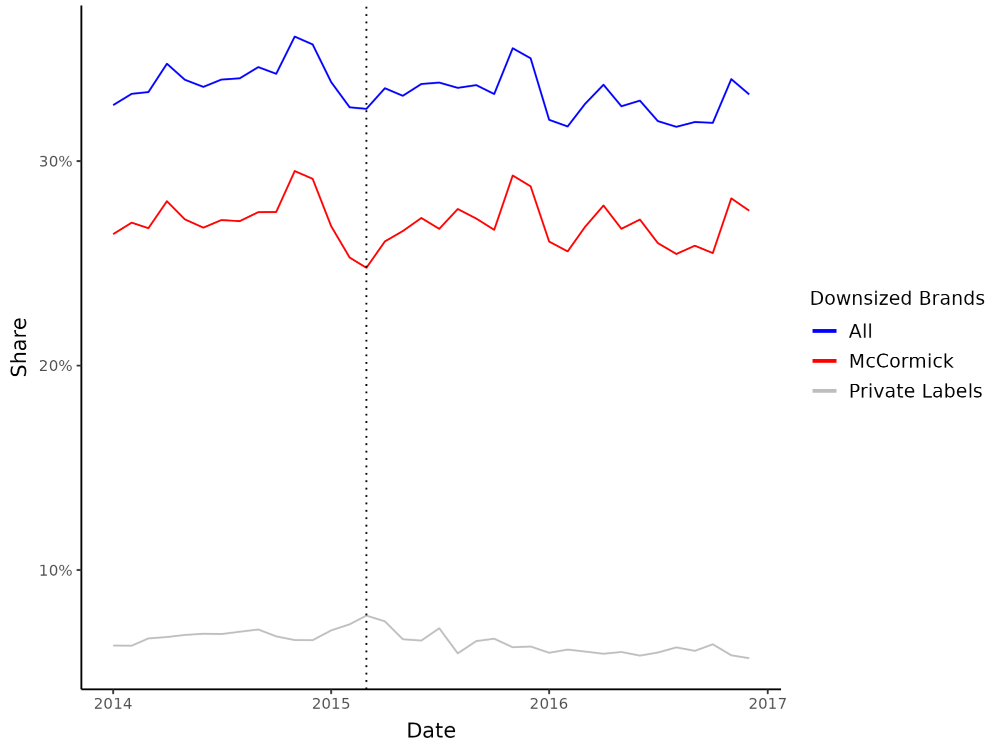
☐ **Identification of Downsized Products.** Downsized products can have different Universal Product Codes than their original versions. To determine the downsized products present in the data, we examined the unit sales of every pepper product over time. As retailers sell out their existing product inventories and stock up on the new smaller version, sales of the original product should decrease and sales of the downsized version should increase. We therefore look for a pattern of declining sales for one product and increasing sales for another slightly smaller product with an identical description. For private-label products, we consider the total units sold across stores within the same retailer.

From comparing time series plots, we identified 30 downsized products, including 15 McCormick and 15 private-label products Table 4 provides a complete list of the name brand products in the estimation sample. Spice Classics and Spice Supreme are the only other name brands to engage in downsizing with each shrinking only a single product. The sales of these two products are negligible and as such, we ignore them and instead focus on downsizing by McCormick and private labels.

☐ **Market Shares and Prices.** While the number of downsized products is small, these products account around 33.5 percent of all pepper sales in the data. McCormick's downsized products account for around 27 percent of sales and the downsized private-label products for around 7.5 percent.

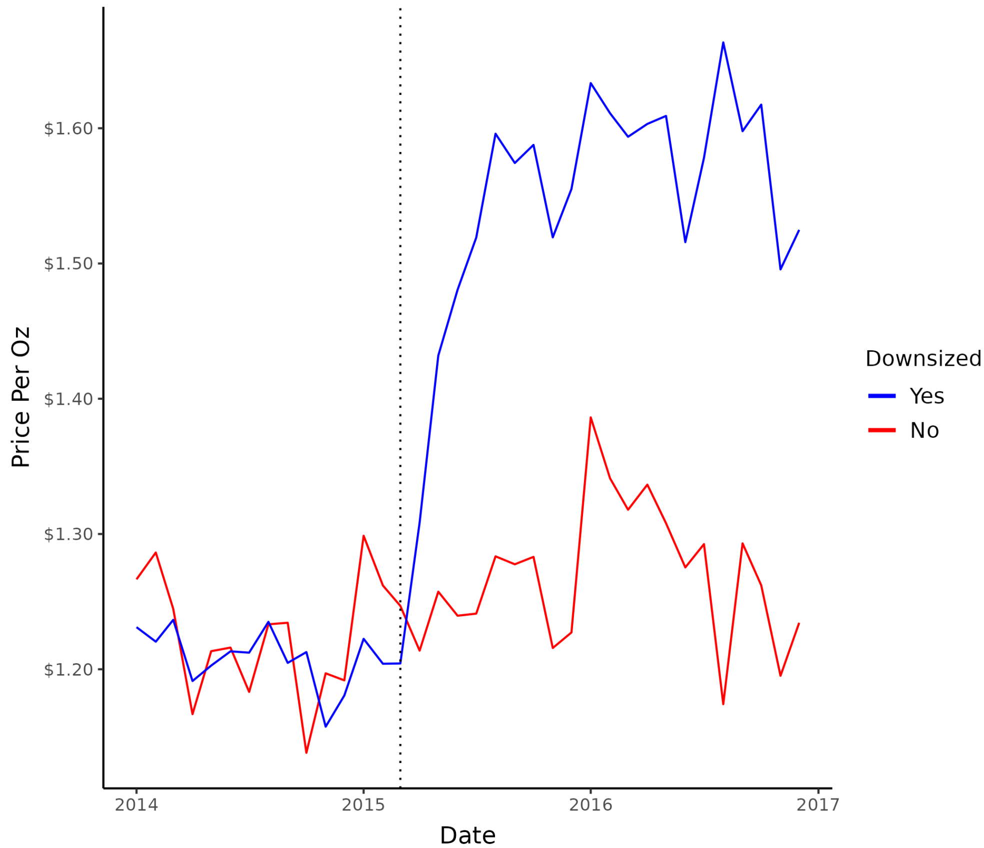
Figure 2 shows the share of the downsized products, separately by McCormick and private labels. The dashed line represents the date when McCormick started to ship its downsized products. The shares include the sales of both the original and downsized versions. Before downsizing, the share represents the original product. Just after downsizing, the shares represent a combination of downsized and original versions as retailers sell out their existing inventory of the original version and replace it with the new version. By the middle of 2016, the share mainly reflects shares of the downsized version.

Figure 2: Market shares of the downsized products




As the figure shows, the share of the downsized products is stable over time both for McCormick and the private-labels products. The stability of the shares is surprising given the unit price changes. 3 shows the average price per ounce of the downsized products relative to the nondownsized products. From 2014 to 2017, the average unit price of the nondownsized products increased by \$0.10. In contrast, the average unit price of the downsized product increases by around \$0.35, more than three times the amount of the downsized products. Despite this large increase in relative unit prices, there was not a corresponding decline in the share of the downsized products.

Figure 3: Unit prices




There are several possible explanations for the observed trends in shares and unit prices. The first is brand loyalty. Consumers may have a strong attachment to the downsized products and as a result, do not substitute away from these products despite high unit prices. However, given that black pepper products are fairly homogeneous, strong brand attachment is irrational in some sense.

Another possibility is that fully rational consumers are more sensitive to package prices than package content. In his article on downsizing in the milk industry, Kim (2024) argues that consumers do not respond to content reductions because consumers receive more surplus from downsizing than an equivalent price change. Our structural model will address this possibility.

We consider third possibility that consumers are inattentive. Consumers do not respond to downsizing because they do not notice it. None of these explanations for downsizing are mutually exclusive. For instance, consumers can be less sensitive to size changes and inattentive. In that case, consumers will substitute away from the downsized product by very much even if they were fully attentive.

# 5. Evidence of Inattention

The strongest evidence for inattention comes from stores that sell both the original and downsized versions at the same time. During the transition period from the old product to the new one, some stores start to stock the downsized version before selling out of the original, resulting in both versions appearing side by side (e.g. Figure 4).

Figure 4: Original and Downsized Versions Side by Side


The downsized tin is on the right.
Source: *Watkins v. McCormick* (2015, p. 10)

In the data, we observe 2,558,006 store-weeks where both the original and downsized versions of a product appear in the same week. This does not mean that the products appear together. Because stores report their units sold weekly, they could sell out of the original product on Wednesday and start selling the new product on Thursday. Subsequently, both products appear in the scanner data in the same week without actually being together on store shelves. To minimize this possibility, we consider a smaller sample with downsized pairs that appear before the last week where the original product has positive units sold. This smaller sample consists of 374,848 store-weeks.

We further focus our attention on McCormick's downsized products because McCormick did not initially change its packaging. McCormick's original and downsized products are identical except for the fill levels and the statement of net weight. This leaves 107,752 store-weeks.

We consider a reduced-form regression where the response variable is the difference in the number of units sold of downsized product compared to the original product. We regress this on an indicator for whether the downsized product is more expensive. If consumers are fully attentive, they should purchase the original product as the downsized product has a higher package price. After all, consumer pays a lower price for a greater amount of pepper. As the packaging is the same, there is no difference to the consumer in terms of storage cost.

Table 1 shows the regression results. The positive coefficient on the indicator implies that consumers prefer the downsized product despite it being smaller and more expensive. On average, consumers are paying more for less.

Table 1: Difference in sold units between downsized products and their original counterparts

| | (1) | (2) |
|---|---|---|
| Intercept | 1.587 | |
| | (0.096) | |
| Downsized Product is Pricier | 0.878 | 0.965 |
| | (0.099) | (0.103) |
| Num. Obs. | 107,752 | 107,752 |
| Product & Time FE | NO | YES |

We also consider whether this pattern changes as the difference between the price of the downsized and original products grow. We regress the difference in units of the downsized and original products on the difference in package prices. In many cases, the original and downsized products do not sell in the same week but are available. For example, the downsized product sells in the first week and the original product sells in the second week. It is likely that both products were available in both weeks. However, we do not observe there price at the same time. We impute the missing prices in these cases.

Table 2: Difference in sold units between downsized products and their original counterparts

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Intercept | 2.141 | | 2.428 | |
| | (0.033) | | (0.014) | |
| Price Difference | -0.523 | -0.608 | -0.520 | -0.511 |
| | (0.048) | (0.049) | (0.024) | (0.025) |
| Num. Obs. | 85,695 | 85,695 | 349,000 | 349,000 |
| Product & Time FE | NO | YES | NO | YES |
| Imputed Prices | NO | NO | YES | YES |

Table 2 shows the results of regression on the difference in units sold on the difference in package price. The negative coefficient on the price difference implies that consumers will switch to the original product as the downsized product is more expensive. However, if we consider the magnitude, we find that consumers are not responsive enough. The coefficient of $-0.523$ in column (1) implies that the downsized product needs to be at least two dollars more for a single consumer to switch from the downsized to the original. For context, two dollars is around the price of an average pepper product. This result is consistent if we include various fixed effects and if we use imputed prices.

Overall, these descriptive results suggest that consumers fail to notice downsizing. They do not respond nearly enough to differences in the package price, preferring instead to buy the more expensive downsized product.

# 6. Product Choice under Inattention

□ **Model.** In period $t$, $M_{kt}$ consumers visit retailer $k$ looking to buy pepper. Each consumer selects one product from the available pepper products $J_{kt}$ or selects the no-purchase option 0. Consumer $i$'s *actual* utility from purchasing product $j$ is:

$$U^a_{ijkt} = x_{jkt}\beta + \gamma_i z_{jkt} - \alpha_i p_{jkt} + \xi_{jkt} + \epsilon_{ijkt} \tag{1}$$

where $x_{jkt}$ is a set of observable characteristics; $p_{jkt}$ is the price; $z_{jkt}$ is the current net weight; $\xi_{jkt}$ is the unobserved product attributes; and $\epsilon_{jkt}$ is a random shock. The utility of the outside option is:

$$U^a_{i0kt} = 0 + \epsilon_{i0kt} \tag{2}$$

Some consumers may be inattentive and fail to notice changes in net weight. They may remember the old weight and simply assume that weight has not changed since their last purchase. Other consumers may evaluate product weights based on package sizes and mistakenly conclude that the downsized products have the same weight as rival products because they have the same package size.[5] Regardless why inattention occurs, inattentive consumers evaluate the product using its original product weight, whereas attentive consumer evaluate the product using its current product weight.

Consumers are either attentive or inattentive to downsizing. Let $\tau_i$ be an indicator for whether consumer $i$ is attentive. An *inattentive* consumer evaluates the downsized product $j$ using its original weight and *perceives* his utility from $j$ as:

$$\begin{aligned} U^p_{ijkt} &= x_{jkt}\beta + \gamma_i z_{jk0} - \alpha_i p_{jkt} + \xi_{jkt} + \epsilon_{ijkt} \\ &= x_{jkt}\beta + \gamma_i z_{jkt} + \gamma_i\big(z_{jk0} - z_{jkt}\big) - \alpha_i p_{jkt} + \xi_{jkt} + \epsilon_{ijkt} \\ &= U^a_{ijtk} + \gamma_i \Delta_0 z_{jkt} \end{aligned} \tag{3}$$

where $z_{jk0}$ is the original weight before downsizing and $\Delta_0 z_{jkt} = z_{jk0} - z_{jkt}$ is the change in the product weight. In our context, product weights change once or not at all. If the size changes in period $t'$, $z_{jkt} = z_{jk0}$ for all periods $t < t'$. In contrast to actual utility, perceived utility depends both on the current and original weight. Inattention drives a wedge between the perceived and actual utility for downsized product $j$ equal to $\gamma_i \Delta_0 z_{jkt}$.

For attentive consumers, actual and perceived utility are the same. We can write the perceived utility of any consumers as:

$$U^p_{ijkt} = U^a_{ijtk} + (1 - \tau_i)\gamma_i \Delta_0 z_{jkt} \tag{4}$$

where $\tau_i$ is an indicator for if the consumer is attentive. Because types are idiosyncratic and not observable, we can view $\tau_i$ as a random coefficient that follows a Bernoulli distribution where the probability of success $\eta$ represents the probability of being attentive. In essence, inattention causes the change in the weight to enter perceived utility as an additional product characteristic with a random coefficient. We denote the cumulative distribution function of the random coefficients as $G(\tau_i, \gamma_i, \alpha_i)$ where $\tau|_{\gamma,\alpha} \sim \text{Bernoulli}(\eta)$.

Assuming that the random taste shock $\epsilon$ is drawn i.i.d. from a Type I extreme value distribution, the retailer

[5] In this case, consumers misevaluate product size only when rival products occupy a large enough shelf space. As the shelf space devoted to a product is not observable in the NielsenIQ data, we cannot model inattention stemming from a reference size.

share for product $j$ at retailer $k$ in period $t$ conditional on the random coefficients is:

$$s_{jkt}(\boldsymbol{\beta}, \alpha, \tau_i, \gamma_i) = \frac{\exp\left\{x_{jkt}\beta - \alpha_i p_{jkt} + \xi_{jkt} + \gamma_i z_{jkt} + (1-\tau_i)\gamma_i \Delta_0 z_{jkt}\right\}}{1 + \sum_{l \in J_{kt}} \exp\left\{x_{lkt}\beta - \alpha_i p_{lkt} + \xi_{lkt} + \gamma_i z_{lkt} + (1-\tau_i)\gamma_i \Delta_0 z_{jkt}\right\}} \tag{5}$$

Integrating over the joint distribution of the random coefficients, the unconditional retailer share for $j$ in period $t$ is:

$$s_{jkt} = \int s_{jkt}(\boldsymbol{\beta}, \alpha, \boldsymbol{\tau}, \gamma) dG(\boldsymbol{\tau}, \alpha, \gamma) \tag{6}$$

and the expected demand for product $j$ in period $t$ at retailer $k$ is then:

$$Q_{jkt} = s_{jkt} M_{kt} \tag{7}$$

The model ignores retailer choice. This abstraction is reasonable as consumers select a retailer based on a basket of products rather just than pepper (Thomassen et al., 2017). In the consumer panel data, every household purchases pepper with another product. As a result, pepper prices are likely not an important determinant of retailer choice.

□ **Generalization.** We can extend the model with two types to accommodate more varied forms of inattention if we instead assume that consumers are attentive or inattentive to specific products. With $L$ downsized products, there are $2^L$ combinations of downsized products to which a consumer can be inattentive. In this more general framework, we need an indicator $\tau_{ij}$ for whether consumer $i$ is inattentive to downsized product $j$. In all of the equations, we would have $\tau_{ij}$ rather than $\tau_i$.

Because a consumer's type is not observable, perceived utility has a latent structure. A latent class consists of a combination of downsized products for which a consumer is inattentive. With $L$ products, there are $2^L$ latent classes. The joint distribution $G(\boldsymbol{\tau}, \gamma, \alpha)$ dictates the probability of observing any one type and hence the latent structure. This more general model accommodates many types of inattention. For illustrative purposes, consider a set of 4 downsized products ordered from smallest to largest in terms of the absolute change in weight. Consumers that belong to the latent class $\{1, 2, 4\}$ do not notice the change in size of products 1, 2 and 4. Complete attention corresponds to the case where all consumers belong to the class, $\emptyset$. In contrast, complete inattention corresponds to the case where all consumers belong to the class $\{1, 2, 3, 4\}$. Another possibility is that consumers notice changes above a certain threshold (e.g. Han et al., 2001). In this case, consumers who notice small changes in size must notice larger ones. Under threshold perception, consumers must fall into one of 5 classes $\big\{\emptyset, \{1\}, \{1, 2\}, \{1, 2, 3\}, \{1, 2, 3, 4\}\big\}$. As these examples show, different assumptions about the type of inattention place different restrictions on the possible classes. While the modeling structure is flexible enough to find any of these outcomes as well as others, it scales poorly with the number of products. With just 20 products, the number of latent classes is well over a million. For computational tractability, we focus on the model with two types, but do consider alternative specifications that provide some flexibility.

□ **Identification.** There are two sources of variation that help pin down the inattention parameter. The first is retailers that offer the original and downsized versions of the product at the same time. The second is deviations in market shares from consumers' preferences for net weight.

As discussed previously, there are many retailers that offer both versions of the product at the same time. Differences in the market shares after accounting for other factors points to inattention.

We need to be cautious about using these period of overlap to identify inattention. Because we are aggregating the data to the monthly level, we may incorrectly conclude that the downsized and original products appear side-by-side. The original product may sell out in the first week of the month and then the downsized product is sold in the remaining three weeks. The market shares would imply that consumers favor the downsized product when side-by-side when in actuality the retailer never offered these products together.

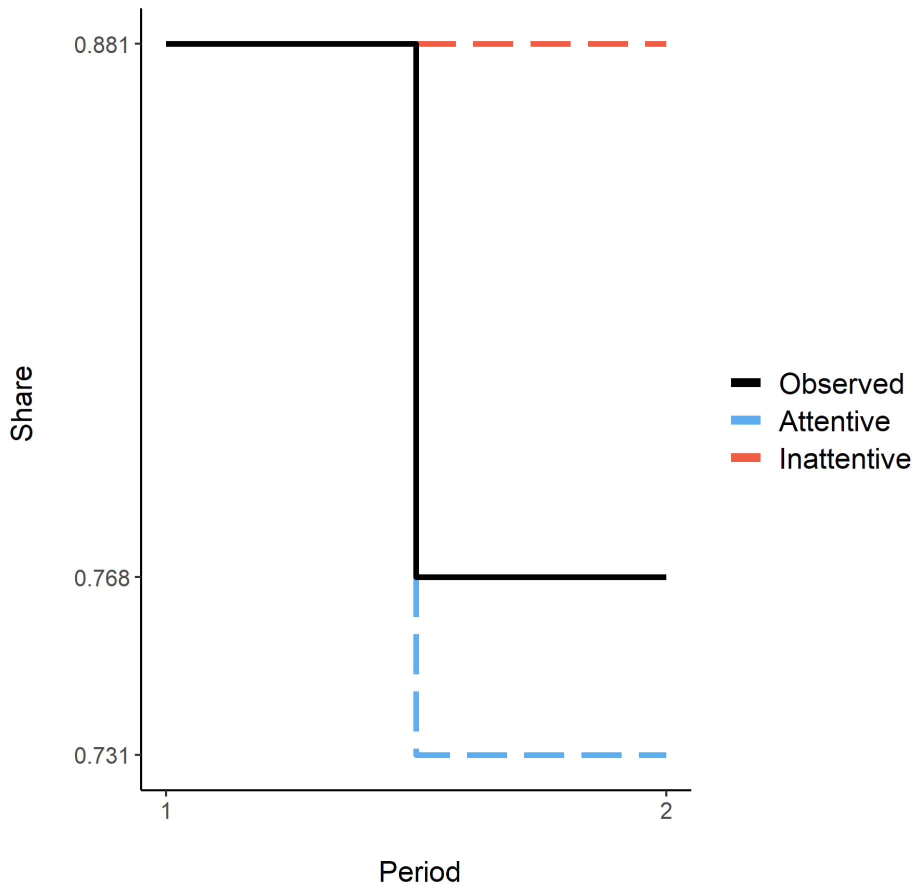
The second source of identifying is deviations in relative market shares from consumers' preferences for net weight. When a product's net weight decreases, its share should change in line with consumers' weight preferences when consumers are fully attentive. Inattention will dampen this response. Thus, a smaller than expected change in retailer shares or no change at all would indicate inattention.

If consumers are attentive, the difference in the shares of the original and downsized versions will reflect the difference in the weight all else equal. In contrast, if consumers are inattentive, there will be no difference in the shares. The degree of inattention therefore governs how closely the observed difference is to the expected difference.

The above logic applies not just to the original product, but to any product, including the outside option. As an illustrative example, consider a retailer that offers a single product over two periods $t = 1, 2$. In both periods, consumers can select the product or an outside option. The utility of the product is $u_{1t} = \gamma z_t + \epsilon_{1t}$ where $z_t$ is the product's weight in period $t$ and $\epsilon_{1t}$ is a random shock drawn from a Type I extreme value distribution and the utility of the outside option is $u_{0t} = 0 + \epsilon_{0t}$. Initially, the product's weight is 2 and its market share is $s_1 = \frac{e}{1+e} \approx 0.731$. The product's weight and market share imply a value of $\gamma$ equal to $\frac{1}{2}$. Before period 2, the weight of product declines from 2 to 1.

Suppose that 20 percent of consumers are inattentive and fail to notice the change in downsizing. Figure 5 shows the observed change in market shares after downsizing (the black line), the change in market shares that would occur under complete attention (blue line), and the change in market shares that would occur on complete inattention (red line).

Figure 5: Market Shares




If consumers are fully attentive, the product's market share in period 2 will decrease in line with consumers' weight preferences to $s_2 = \frac{e^{0.5}}{1+e^{0.5}} \approx 0.622$ (the red line). However, if consumers are fully inattentive, they will evaluate the product's utility using the original weight $z_1 = 2$ and the product share would remain constant (the blue line). In reality, the observed product share (the black line) reflects a combination of attentive and inattentive consumers. The observed market share is $s_2 = \eta\frac{e^{0.5}}{1+e^{0.5}} + (1-\eta)\frac{e}{1+e}$ where $\eta$ is 0.8, the fraction of attentive consumers.

The greater the fraction of attentive consumers the closer the observed trend is to the expected trend (a smaller vertical distance between the black and blue lines). Because of this, the difference between the observed change in the product's share and the expected change if consumers were attentive identifies the percentage of attentive consumers. The distance between the blue and black lines relative to the blue and red lines is 0.8, which is the faction of attentive consumers.

This comparison is possible only because the weight preferences $\gamma$ are observable from the initial period and do not change over time. If $\gamma$ is unknown or changes over time, we could not determine the product's share under complete attention.

This argument assumes that weight preferences are time-invariant. If weight preferences change over time, a shift in weight preferences in favor of smaller amounts would also explain a smaller than expected decline after downsizing. The time-invariance of weight preferences is therefore a key identifying assumption.

□ **Limitations.** Our model has two main limitations. The first is that the model does not describe the frictions that lead to inattention. Consumers are either attentive or inattentive. This prevents us from considering how changes in information, like labels with unit prices, affect the degree of inattention. Other frameworks, like the rational inattention, would allow us to model the information acquisition process. This flexibility comes at the cost of clarity. A rational inattention model in the vein of Brown and Jeon (2020) requires specifying the functional form of the prior beliefs over product utility.

The model also abstracts away dynamics. Given pepper's long shelf life, consumers may make dynamic inventory decisions. For example, they may stockpile pepper products that are on sale. The consumer panel data suggests that stockpiling behavior is not of huge concern. Figure 12 shows the number of units purchased on any given shopping trip broken down by whether the product was on promotion. As the figure shows, the vast majority of consumers, over 84 percent, do not buy pepper on promotion. Moreover, when consumers buy pepper, they buy only a single unit. Very few consumers buy more than one unit even when the product is on promotion. In general, pepper products are rarely on promotion. All of this suggests that consumers buy pepper when they run out of it and modelling it as a static decision is reasonable.

# 7. Estimation Details

□ **Market Size.** Because the number of potential pepper customers $M_{kt}$ is unobservable, we proxy for it using total sales in the seasoning product category. In addition to pepper, this product category includes various seasoning blends like Old Bay and spices like cinnamon. We assume that the number of potential pepper customers at a retailer is equal to the total sales of all such products at that retailer. We do not use the number of visitors to a retailer as some consumers never buy pepper. Given this market size, the share of the outside option is between 60.5 and 97.1 percent and is 89.7 percent on average.

□ **BLP Estimation.** With the shares defined, we estimate our model of inattention following Berry et al. (1995). In the inner loop, we choose the unobservable demand shocks $\xi_{jt}$ to equate the observed market shares with those predicted from the model. In the outer loop, we choose the model parameters to minimize sample versions of the unconditional moment restrictions $\mathbb{E}\left[\xi_{jt} z_{jt}\right]$ given instruments $z_{jt}$. For the instruments, we use a combination of exogenous product characteristics and the local differentiation instruments from Gandhi and Houde (2019).

We allow random coefficients on price and net weight drawn from independent normals with means $\bar{\alpha}$ and $\bar{\gamma}$ and standard deviations $\sigma^p$ and $\sigma^w$, respectively. The inattention parameter follows a Bernoulli distribution with a success indicator that a consumer is attentive. The probability of a success is $\eta$. Direct estimation of this probability can result in numerical problems due to the probability bounds. To avoid boundary issues, we recast the Bernoulli probability in terms of the logit so that we are estimating a continuous parameter. We define the probability of being attentive as:

$$\eta = \frac{e^{\zeta}}{1 + e^{\zeta}} \tag{8}$$

The random coefficient $\tau_i$ is a draw from this Bernoulli.

The inattention coefficient $\tau_i$ modifies the standard BLP estimation procedure slightly. Normally, one recovers mean utility with the BLP contraction and then recovers the fixed coefficients and the means of the random coefficients using an IV regression. However, with inattention, the random coefficient on net weight $\gamma_i$ is multiplied by the inattention parameter $\tau_i$. As a result, we need to search over the mean of the net weight distribution $\bar{\gamma}$ in the outer loop.

Following BLP, we rewrite the conditional shares in (5) in the following form:

$$s_{jkt}(\boldsymbol{\beta}, \alpha, \tau_i, \gamma_i) = \tau_i \, \frac{\exp\left\{\delta_{jt} + \mu_{ijt}\right\}}{1 + \sum_{l \in J_{kt}} \exp\left\{\delta_{kt} + \mu_{ikt}\right\}} + (1 - \tau_i) \, \frac{\exp\left\{\delta_{jt} + \mu_{ijt}^{inattention}\right\}}{1 + \sum_{l \in J_{kt}} \exp\left\{\delta_{kt} + \mu_{ikt}^{inattention}\right\}} \tag{9}$$

where

$$\delta_{jkt} = x_{jkt}\beta - \bar{\alpha} p_{jkt} + \xi_{jkt} \tag{10}$$

and

$$\mu_{ijt} = (\bar{\gamma} + \sigma^w \nu_i^w) \, z_{jkt} + \sigma^p \cdot \nu_i^p \; p_{jkt} \tag{11}$$

$$\mu_{ijt}^{inattention} = (\bar{\gamma} + \sigma^w \nu_i^w) \, z_{jkt} + \sigma^p \cdot \nu_i^p \; p_{jkt} + (\bar{\gamma} + \sigma^w \nu_i^w) \, \Delta_0 z_{jkt} \tag{12}$$

with $\nu_i^w$ and $\nu_i^p$ being draws from standard normals.

We account for the Bernoulli parameter in closed form and do not have to integrate over its distribution. Following BLP, we can integrate over the normally distributed parameters to retrieve the estimated shares.

With this formulation, we can apply the standard BLP algorithm. We draw 100 randomized Halton draws from the distribution of the random coefficients. We simulate the shares and then use the BLP contraction mapping to recover $\boldsymbol{\delta}$. We then recover the parameters $(\beta, \bar{\alpha})$ using IV estimation. Finally, we find unobserved quality $\boldsymbol{\xi}$ as the residual and construct the sample moments to be minimized with two-step GMM.

Finally, to quantity the uncertainty around our estimates, we construct bootstrapped confidence intervals using 250 bootstrap replicates. When constructing the bootstrapped sample, we sample retailer-DMA combinations to preserve the structure of the data.

# 8. Empirical Results

Table 3 contains the point estimates and 95% confidence intervals from the BLP estimation. The different columns represent different specifications of the random coefficients. All of the columns include the inattention term. Column (1) does not include random coefficients of price and net weight; column (2) includes for a random coefficient on price, but not net weight; column (3) includes for a random coefficient on net weight, but not price; and column (4) includes random coefficients on price and net weight.

Table 3: BLP Results

| | | (1) | (2) | (3) | (4) |
|---|---|---|---|---|---|
| Means | Price | -1.062<br>[-1.106; -1.016] | -1.062<br>[-1.104; -1.022] | -1.037<br>[-1.122; -1.006] | -1.058<br>[-1.181; -1.015] |
| | Net Weight | 0.395<br>[0.376; 0.412] | 0.395<br>[0.378; 0.414] | 0.380<br>[0.363; 0.420] | 0.392<br>[0.379; 0.453] |
| | Whole | 0.016<br>[-0.006; 0.038] | 0.0145<br>[-0.009; 0.040] | 0.003<br>[-0.011; 0.051] | 0.012<br>[-0.004; 0.081] |
| | Black Pepper | 0.140<br>[0.083; 0.194] | 0.140<br>[0.080; 0.198] | 0.177<br>[0.035; 0.219] | 0.146<br>[-0.052; 0.185] |
| | Blend Pepper | 0.043<br>[0.008; 0.080] | 0.042<br>[-0.001; 0.082] | 0.077<br>[0.021; 0.122] | 0.0450<br>[-0.054; 0.076] |
| | Cayenne Pepper | -0.504<br>[-0.563; -0.442] | -0.504<br>[-0.565; -0.451] | -0.462<br>[-0.583; -0.407] | -0.496<br>[-0.675; -0.459] |
| | Citrus Pepper | -1.105<br>[-1.193; -1.009] | -1.106<br>[-1.203; -1.012] | -1.036<br>[-1.238; -0.945] | -1.093<br>[-1.388; -1.026] |
| | Garlic Pepper | -1.144<br>[-1.215; -1.080] | -1.145<br>[-1.215; -1.081] | -1.097<br>[-1.238; -1.043] | -1.136<br>[-1.350; -0.089] |
| | Red Pepper | -0.436<br>[-0.507; -0.367] | -0.437<br>[-0.504; -0.373] | -0.388<br>[-0.514; -0.324] | -0.428<br>[-0.626; -0.383] |
| | Other Pepper | -0.832<br>[-0.866; -0.801] | -0.832<br>[-0.865; -0.807] | -0.808<br>[-0.858; -0.779] | -0.827<br>[-0.907; -0.808] |
| Random Coefficients | Bernoulli: Attention | 0.0001<br>[0.0001;0.00015] | 0.001<br>[-0.004; 0.001] | 0.006<br>[-0.713; 0.010] | 0.001<br>[-0.717; 0.002] |
| | $\sigma$: Price | | 0.000<br>[-0.007; 0.000] | | 0.001<br>[-0.118; 0.002] |
| | $\sigma$: Net Weight | | | 0.000<br>[-0.003; 0.000] | 0.000<br>[-0.010; 0.000] |

95% Confidence Intervals are bootstrapped.

The parameter estimates are stable across specifications. Most notably, the probability of being attentive is close zero across all specifications, indicating that consumers are fully inattentive. In specifications (2), (3), and (4), the probability of being attentive is statistically indistinguishable from zero. The probability is statistically significant in specification (1), but in practical terms it is very close to zero. Our results suggest that every consumer fails to notice downsizing.

The price and net weight coefficients have the correct expected signs. Consumers prefer to pay less and to have larger packages, all else equal. The coefficient on price is much larger than the coefficient on size. The coefficients yield own-price elasticities that are larger in magnitude than the net weight elasticities. Removing inattention, the average own-price elasticity is $-4.17$, whereas the own-net weight elasticity is 1.22. So, even if consumers were fully attentive, they would be more than three times more sensitive to a price increase than to a size decrease. As a result, downsizing can be an effective strategy even when consumers are attentive. This result is consistent with Kim (2024) who argues that attentive consumers respond less to downsizing than price increases.

The previous result highlights that differential sensitivity to price and net weight does not imply consumers are inattention. Here, consumers respond less to net weight, but are also inattentive. Inattention simply makes consumers even less sensitive to changes in net weight.

The standard deviations of the price and net weight distributions are close to zero and statistically insignificant across all of the specifications. This suggests that consumers do not have heterogeneous preferences for price and net weight. Because of this, we use the estimates from specification (1) where price and net weight preferences are homogeneous in the counterfactual exercises that follow.

# 9. The Impact of Inattention

□ **Prices.** By distorting product utilities, inattention affects demand and hence prices. If consumers are fully attentive ( $\boldsymbol{\tau_i} = 1$), prices would adjust to some new level $p^a_{kt}$. We recover these counterfactual prices from the demand-side estimates by making assumptions on the supply-side model.

Because consumers choose retailers based on basket of goods, pepper prices are unlikely to impact consumers' choice of retailer. Consequently, retailer will act as local monopolists when pricing pepper. Under this assumption, retailer $k$'s profits in period $t$ is:

$$\pi_{kt} = \sum_{j \in J_{kt}} \left[ p_{jkt} - w_{jkt} - mc^s_{jkt} \right] s_{jkt}(p_{kt}) \tag{13}$$

where $w_{jkt}$ is the wholesale price of product $j$ and $mc^s_{jkt}$ is the retailer's marginal cost of product $j$. Differentiating with respect to prices, the first-order conditions are:

$$s_{jkt} + \sum_{j \in J_{kt}} \left[ p_{jkt} - w_{jkt} - mc^s_{jkt} \right] \frac{\partial s_{jkt}}{\partial p_{jkt}} = 0 \tag{14}$$

We do not consider changes in wholesale prices. Such pricing behavior is consistent with a number of models in which manufacturers set the wholesale margin to zero. A zero wholesale margin can arise from the use of a nonlinear pricing or substantial retailer bargaining power Villas-Boas (2007). The first-order conditions now becomes:

$$s_{jkt} + \sum_{j \in J_{kt}} \left[ p_{jkt} - mc^m_{jkt} - mc^s_{jkt} \right] \frac{\partial s_{jkt}}{\partial p_{jkt}} = 0 \tag{15}$$

where $mc^m_{jkt}$ is the manufacturer's marginal cost of product $j$. Stacking the first-order conditions and rearranging terms, the optimal prices satisfy:

$$p_{kt} + \Delta^{-1}_{kt} s_{kt}(p_{kt}) = mc^m_{kt} + mc^s_{kt} \tag{16}$$

where $\Delta_{kt}$ is a matrix with entry $(m, n)$ equal to $\frac{\partial s_{mkt}}{\partial p_{nkt}}$ if retailer $k$ sells products $m$ and $n$ during period $t$ and zero otherwise. Because changes in attention affect prices through demand and not through marginal costs, store and manufacturer marginal costs remain the same after the removal of inattention.

When consumers are fully attentive, product demands $s^a_{kt}(p^a_{kt})$ do not depend on the size change. In addition, the response matrix $\Delta^a_{kt}$ now depends on the new demand with entry $(m, n)$ equal to $\frac{\partial s^a_{mkt}}{\partial p_{nkt}}$. Given that marginal costs remain the same, the counterfactual prices $p^a_{kt}$ satisfy:

$$p^a_{kt} + \Delta^{-1}_{a,kt} s^a_{kt}(p^a_{kt}) = p_{kt} + \Delta^{-1}_{kt} s_{kt}(p_{kt}) = mc^m_{kt} + mc^s_{kt} \tag{17}$$

This equation defines the counterfactual prices as an implicit function of the demand-side parameters.

We first find the marginal costs from the observed prices using the second equality in equation (17). To solve for the counterfactual prices, we follow Conlon and Gortmaker (2020) and Morrow and Skerlos (2011) and rewrite the markup equation as a contraction mapping. We then simply iterate on the modified markup equation.

In theory, the removal of inattention represents a quality decrease for the downsized products because newly attentive consumers now find these products less attractive than before. The decrease in demand for the downsized products should result in lower prices for the downsized products and higher prices for the nondownsized ones.

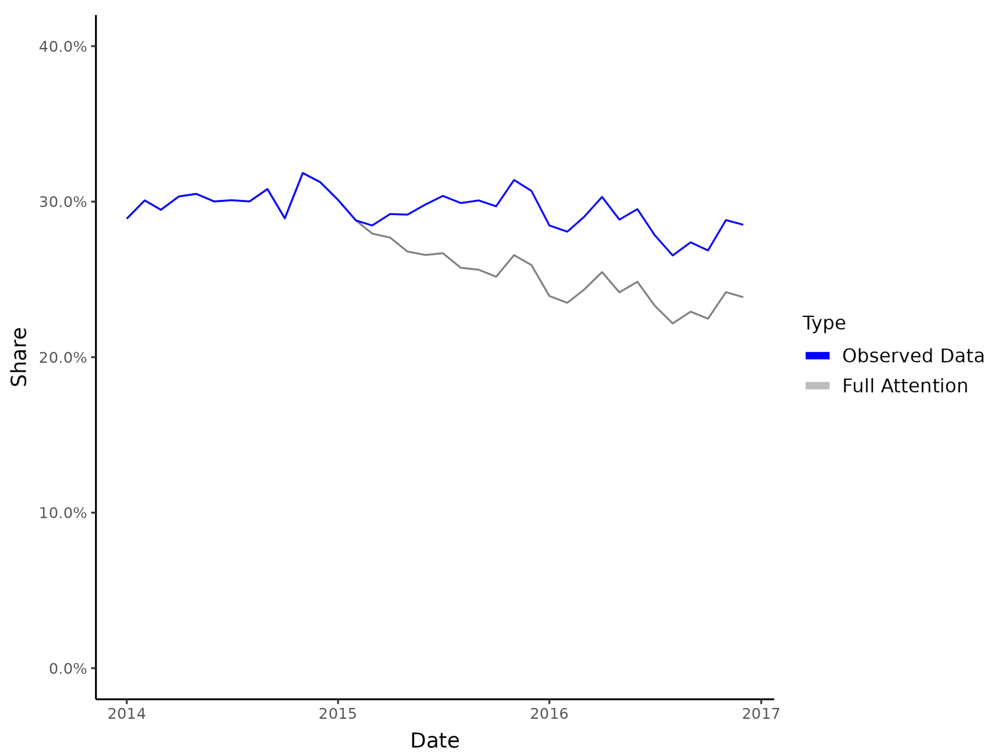
Figure 13 shows the difference between the observed prices and the counterfactual prices for all products, and figure 14 shows the difference for the downsized products. In many cases, prices do not change because many retailers do not offer the downsized products. However, most of the price decreases are small and close to zero. Almost all of the price changes are less than \$0.04. As figure 14 shows, prices decrease for the downsized products. Even for the downsized products, the price changes are small.

The fact that prices do not changes by much is not surprising given the restrictions of the supply-side model. Because we assume marginal cost pricing for the wholesale prices and marginal costs do not change, wholesale prices do not change. In essence, McCormick is not responding to the decline in the demand for its downsized products.

□ **Market Shares.** Another reason that prices do not change by very much is consumers' preferences. Consumers are far more sensitive to changes in package prices than to changes in net weight. As a result, shares will decrease but not by much.

Figure 6 shows the equilibrium market shares when inattention is removed. We rescale the market shares so they are in terms of the inside goods. The blue line represents the observed share of the downsized products while the grey line represents the share of the downsized products under complete attention.

Figure 6: Market Shares



If consumers were attentive, the share of the downsized products would fall from approximately 30 percent to 22.5 percent. This is a fairly small decline given that the downsized products are around \$0.30 more expensive per ounce in the counterfactual equilibrium. The small change in shares stems from consumers' differential preferences between price and net weight.

☐ **Consumer Welfare.** Inattentive consumers purchase a downsized product under the belief that it contains more pepper than it actually does. After purchasing, some of these consumers may experience discontent when they discover the smaller package content. Post-purchase discontent, however, does not necessarily imply welfare losses.

For inattention to reduce consumer welfare, inattention must alter the final choice that the consumers make or must allow firms to charge higher prices. By distorting product utilities, some inattentive consumers choose a product that is not utility maximizing. Only inattentive consumers can experience this loss. Inattention also affects the welfare of all indirectly through prices. Under inattention, consumers pay more for the downsized products. So even attentive consumers who would choose the downsized products are hurt due to the higher prices.

Consumers can choose the wrong product because they base their purchase decision on perceived utility rather than on actual utility. For instance, an inattentive consumer at retailer $k$ in period $t$ chooses the product that maximizes perceived utility $j^* = \underset{1,\dots,J_{kt}}{\arg\max}\, U^p_{ijkt}$ instead of the one that maximizes actual utility is $m^* = \underset{1,\dots,J_{kt}}{\arg\max}\, U^a_{ijkt}$. This assumes that prices remain the same. If we remove inattention, the prices change which affects the choice. To assess the welfare loss from inattention, we need to examine the choice that maximizes actual utility under the new prices, $c^* = \underset{1,\dots,J_{kt}}{\arg\max}\, U^a_{ijkt}(p^a_{kt})$ The consumer experiences a loss in utility of:

$$\mathcal{W} = U^a_{ic^*kt}(p^a_{kt}) - U^a_{ij^*kt} \tag{18}$$

Note that $j^*$ and $c^*$ depend on the random parameters and the taste shock $\epsilon_{ijkt}$. Taking the expectation over these gives the average welfare loss from imperfect knowledge:

$$\Delta CS = \frac{\mathbb{E}\big[\mathcal{W}\big]}{\alpha} = \frac{\mathbb{E}\big[U^a_{ic^*kt}(p^a_{kt})\big]}{\alpha} - \frac{\mathbb{E}\big[U^a_{ij^*kt}\big]}{\alpha} \tag{19}$$

Given the logit-form, the welfare loss has the form:

$$\begin{aligned}\Delta CS = \frac{1}{\alpha}\mathbb{E}_\tau\Bigg[ &\log\left(1 + \sum_{J_{kt}} \exp\left\{x_{jkt}\beta - \alpha p^a_{jkt} + \xi_{jkt} + \gamma z_{jkt}\right\}\right) \\ &- \log\left(1 + \sum_{J_{kt}} \exp\left\{x_{jkt}\beta - \alpha p_{jkt} + \xi_{jkt} + \gamma z_{jkt} + (1-\tau_i)\gamma\big(z_{jk0} - z_{jkt}\big)\right\}\right) \\ &+ \sum_{J_{kt}} s_{jkt}\ (1-\tau_i)\gamma\big(z_{jk0} - z_{jkt}\big)\Bigg]\end{aligned} \tag{20}$$

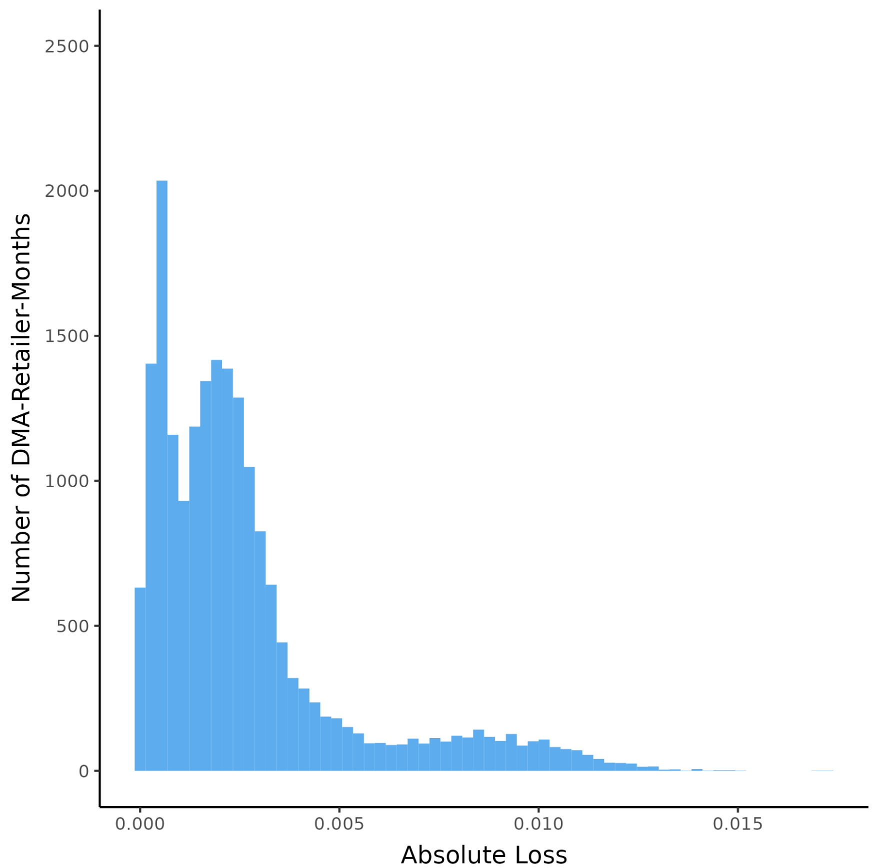
where the market shares correspond to consumers' observed choices under imperfect attention. Our formula for the welfare loss is close to that of Train (2015). The only difference is that we incorporate price changes due to the removal of imperfect knowledge, similar to Stivers (2019).

The first term is the standard log-sum formula based on actual utility evaluated at the counterfactual prices. The log-sum formula is the closed form for the expectation from making the choice. The second term is the log-sum formula based on perceived utility and the final term is the average difference between actual and perceived utility. The final term is really a summation over the downsized products as size does not change for the nondownsized products.

Consumers can only experience a loss in welfare at retailers who offer downsized products. If a retailer does not does not stock downsized products, consumers cannot mistakenly choose those products. In the estimation sample, there are 36,682 DMA-retailer-months. Of these, 53.2 percent feature downsized products. Thus, most consumers do not experience any welfare loss since they are not interacting with any downsized products.

Figure 7 shows the the histogram of the absolute welfare losses for retailers with downsized products. We find that inattention reduces consumer welfare by a tiny amount in absolute terms. The welfare loss ranges from around \$0.00 to \$0.017, and the average loss is \$0.001.

Figure 7: Absolute Welfare Loss from Inattention




The welfare loss is also small in relative terms. In figure 15, we compared the welfare loss to the share-weighted average price at a given retailer in a given month. On average, the loss from inattention represents approximately 0.1 percent of the product price on average. Moreover, the loss never exceeds one percent. In practical terms, inattention has a negligible effect on inattention both in absolute and relative terms. This result is not that surprising given the small changes in shares and prices.

# 10. Conclusion

The practice of product downsizing occurs across a wide range of products and represents one strategy that firms use to increase unit prices. When consumers underuse size information or ignore unit prices, downsizing represents a hidden price increase. We utilize a downsizing event in the black pepper industry to determine whether consumers are inattentive to decreases in product size. The large amount of existing size variation in this industry allows us to recover the degree to which consumers are inattentive.

To study how consumers respond to downsizing, we build a demand model that incorporates inattention to size changes and apply it to scanner data. In the model, inattentive consumers misperceive the net weights of the downsized products and as a result, they evaluate them based on their original net weights. Because of this, the change in net weight enters utility as an additional product characteristic with a random coefficient, whose distribution we recover using standard demand estimation techniques.

We find that almost all consumers fail to notice the reduction in fill levels. Moreover, the estimated preferences' suggest that even if consumers were fully aware, they would be more responsive to price than to product size. Inattention simply makes downsizing more effective than it already is.

Although inattention distorts product choices, its removal has only a small impact on shares, prices, and consumer welfare. If consumers were fully attentive, share of the downsized products would fall by 5 percentage points relative to the inside goods or one percentage point relative to the total market. These relatively small changes in shares translate into small price changes. Given the small changes in price and size, inattention has a very small effect on consumer welfare.

Our results suggest that statements of net weight do not prevent consumers from misperceiving product sizes. In fact, the vast majority of consumers appear to ignore such statements. Although inattention distorts choices, it has only a small impact on consumer welfare, at least for pepper. Our results suggest that policies aimed at decreasing inattention to downsizing, like a proposed French law requiring food retailers to notify consumers of downsizing (Rajbhandari and Adghirni, 2023), will have limited benefits.

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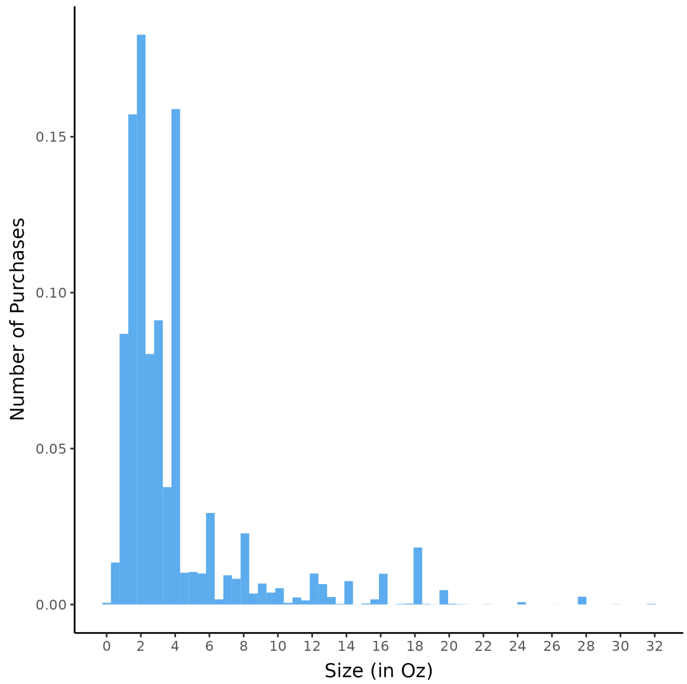
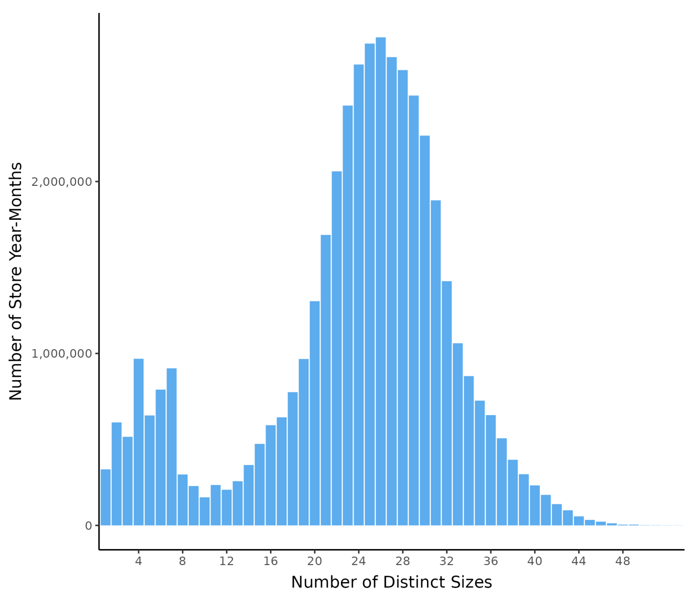
# Appendix A Figures and Tables

Figure 8: The Distribution of Sizes Purchased



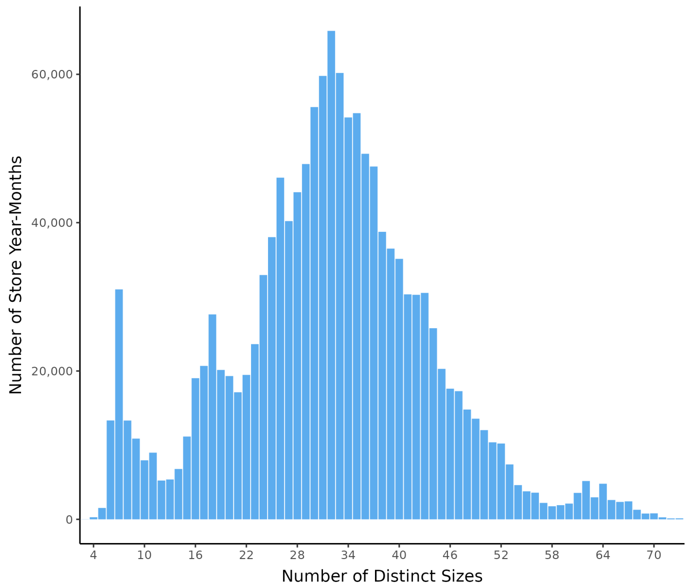

Based on household purchases from 2014 to 2016.

Figure 9: The Distribution of Distinct Sizes Offered
Store-Level Scanner Data



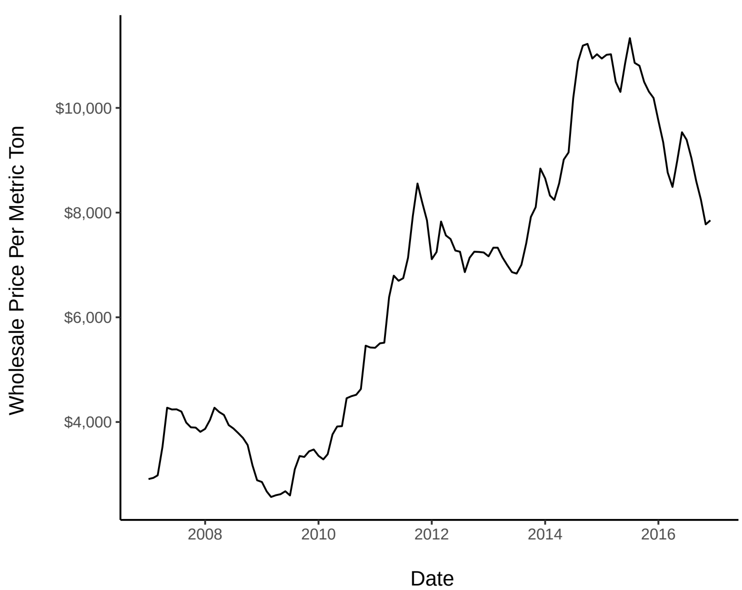

Based on the scanner data from 2014 to 2016.

Figure 10: The Distribution of Distinct Sizes Offered
Retailer-Dma Code Scanner Data



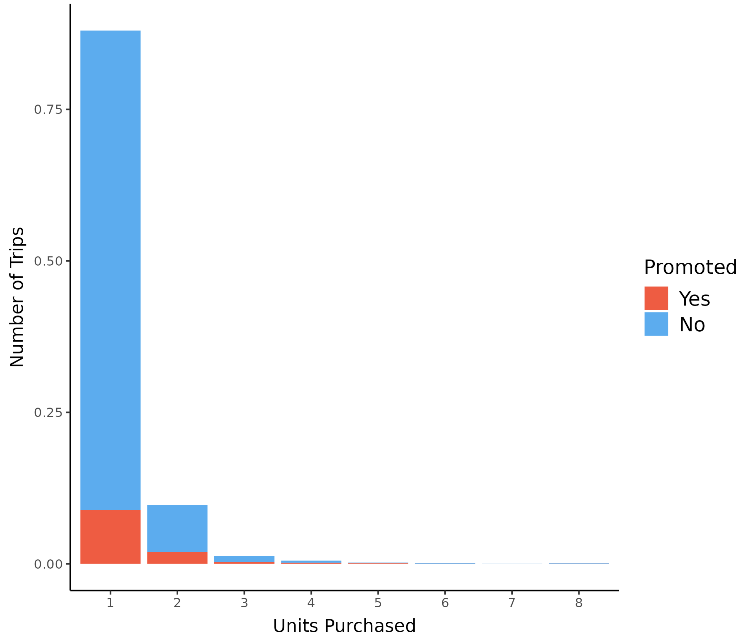

Based on the scanner data from 2014 to 2016.

Figure 11: Spot Price of Black Pepper in New York




Source: Pepper Statistical Yearbook 2018, International Pepper Community

Figure 12: The Distribution of Units Purchased per Shopping Trip




Only shopping trips with a pepper purchase are included. Based on household purchases from 2012 to 2016.

Table 4: Downsized Products

| | Product | Pepper Type | Original Size (Oz) | New Size (Oz) | Size Decrease (Oz) | |
|---|---|---|---|---|---|---|
| 1. | McCormick Large Jar | Black | 18 | 16 | 2 | 11% |
| 2. | McCormick Large Jar | Black | 8.75 | 7.75 | 1 | 11% |
| 3. | McCormick Large Tin | Black | 8 | 6 | 2 | 25% |
| 4. | McCormick Medium Jar | Black | 4.25 | 3.5 | 0.75 | 17% |
| 5. | McCormick Medium Tin | Black | 4 | 3 | 1 | 25% |
| 6. | McCormick Medium Jar | Black | 4 | 3.12 | 0.88 | 22% |
| 7. | McCormick Medium Grinder | Black | 3.1 | 2.5 | 0.6 | 19% |
| 8. | Spice Supreme Medium Tin | Black | 2.5 | 1.62 | 0.88 | 35% |
| 9. | McCormick Medium Jar | Black | 2.37 | 1.87 | 0.5 | 21% |
| 10. | McCormick Small Tin | Black | 2 | 1.5 | 0.5 | 25% |
| 11. | Spice Classics Small Jar | Black | 2 | 1.62 | 0.38 | 19% |
| 12. | McCormick Small Jar | Red | 1.75 | 1.37 | 0.38 | 22% |
| 13. | McCormick Small Jar | Blend | 1.62 | 1.25 | 0.37 | 23% |
| 14. | McCormick Blend Small Jar | Black | 1.62 | 1.25 | 0.37 | 23% |
| 15. | McCormick Small Grinder | Black | 1.24 | 1 | 0.24 | 19% |

The list includes only name brand products. The products are ordered from largest to smallest size change.

Figure 13: Distribution of Changes in Prices (All Products)

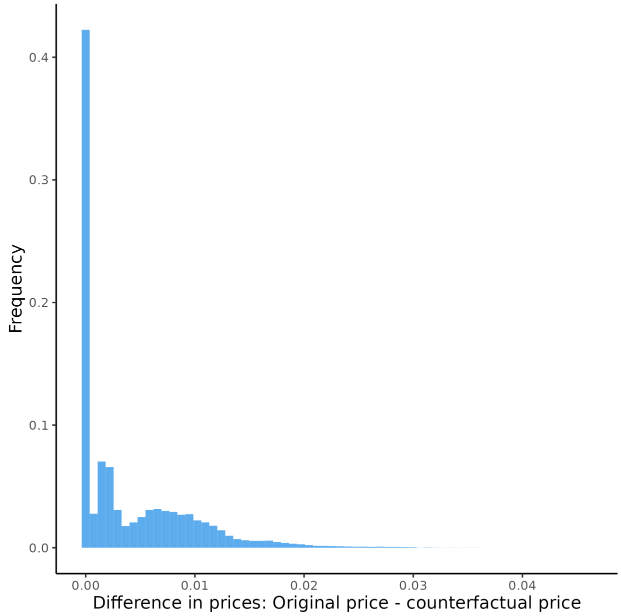



Figure 14: Distribution of Changes in Prices (Downsized Products)

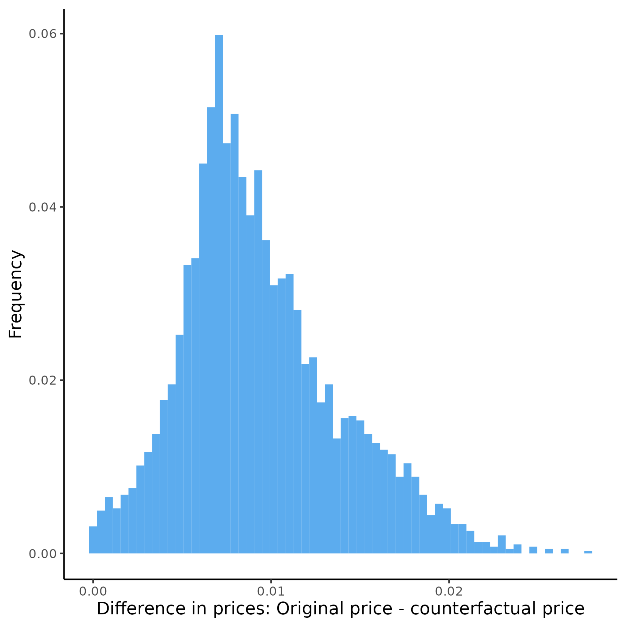
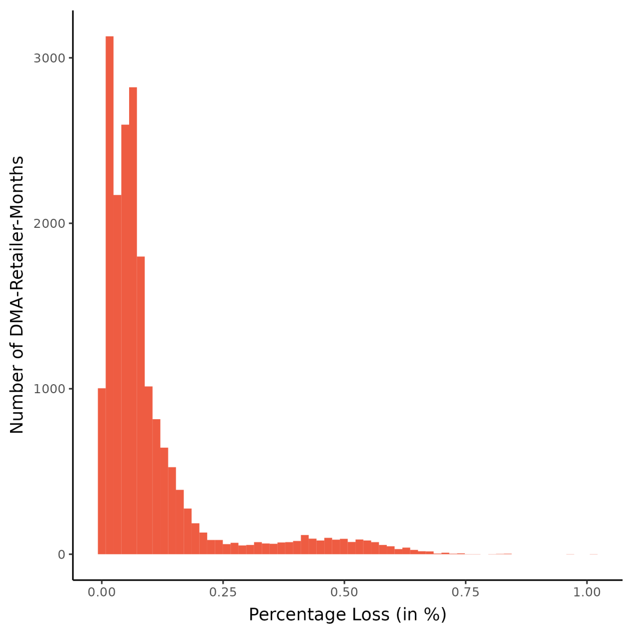


Figure 15: Relative Welfare Loss from Inattention




The figures shows the change in consumer surplus at a given retailer in a particular month relative to the share-weighted average price at that retailer.