Shrinkflation*

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Abstract

This paper studies the macroeconomic relevance of product size adjustment–changes in products' weight or volume–using U.K. CPI microdata from 2012-2023: (i) Product size is relevant for 35% of the CPI. (ii) Each month, 0.26% of goods experience size changes (1% for food, 12% for chocolate). (iii) 80% of adjustments are reductions, 90% of these are "downgrades," i.e., higher unit price. (iv) Size reductions and downgrades are strongly procyclical; size increases and upgrades are acyclical. (v) Price and size adjustments are unrelated. (vi) The contribution to CPI inflation is small: 0.03 percentage points per month (0.15 for Food, 1.2 for chocolate).

Keywords: Inflation, aggregate price dynamics, product size adjustment, shrinkflation
JEL-Codes: E31, E32, E52, E71, L11, M37

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1 Introduction

Understanding how firms adjust to changes in economic conditions is a central question in macroeconomics. This paper examines the macroeconomic relevance of product size adjustment, whereby firms alter the weight or volume of their goods and services. Size changes–particularly reductions–have consistently attracted media attention, supported by ample anecdotal evidence. For instance, during the 2012–2023 inflation surge, numerous reports suggested that firms reduced the size of products like chocolate bars or frozen pizzas while keeping prices unchanged.[1] This practice, known as "shrinkflation," is potentially used to raise a product's unit price in a way that often goes unnoticed by consumers.

Using monthly price microdata underlying the consumer price index for the United Kingdom from the Office for National Statistics (ONS), I document several key features of product size adjustment between January 2012 and December 2023. Since around 2010, the ONS microdata have included consistent information on product size changes of individual items in the CPI. This enables the identification of both size decreases and increases.

To begin, I estimate the proportion of products in the CPI for which product size changes are relevant. Naturally, they matter only for consumption items that can be quantified by weight or volume (e.g., a box of cookies or a bag of chips), but not for indivisible products like plane tickets or insurance.[2] Around 35% of products–weighted by CPI weights–underwent size changes over the sample. This share varies substantially across sectors: around 80% in Food and non-alcoholic beverages, 60% in Alcoholic Beverages and Tobacco, 30% in Personal Care, and 15% in Furnishing. The lowest shares are found in service sectors such as Transport and Information.

The second feature is the frequency of product size changes. I find that the average monthly frequency of size changes in the aggregate CPI is 0.26%, with a peak of 0.73%. However, once again, frequencies vary considerably across sectors and products. Most product size changes occur in the Food sector, where the average and maximum monthly frequencies are around 1% and 3%, respectively. Within this sector, some products change their size very frequently– for instance, chocolate bars average 12% per month with a peak of 67%.

How does this compare to the frequency of adjustments in the posted prices of products? At the aggregate level, prices clearly change more frequently. From 2012–2023, the average monthly frequencies of regular price increases and decreases are 6.5% and 3.6%, respectively. Yet, in some categories, size adjustments are more frequent than price changes. For chocolate bars, price increases and decreases occur at only 4.6% and 2.8% per month.

The third feature is the nature of product size adjustments. Here, I distinguish along two dimensions: (i) decreases or increases in product size and (ii) increases or decreases in the product's

[1] See, for example, BBC (2023), The Economist (2019, 2022), Bloomberg (2022, 2023). Earlier examples of shrinkflation have also been documented. For instance, after the Brexit referendum in 2017, the Toblerone chocolate bars sold in the U.K. had fewer peaks. This was reportedly a reaction to the devaluation of the pound sterling, which reduced real profits of international firms selling to the U.K. market, see e.g. Forbes (2017).

[2] For such goods, product quality changes may be relevant. Note that the ONS treats size and quality changes separately.

unit price. In this context, I define product size changes that lead to a higher unit price as ”downgrades” and those that lead to a lower unit price as ”upgrades”.

Between 2012 and 2023, around 80% of all product size changes are reductions. Of these, 90% are downgrades, primarily because posted prices remain constant. Conversely, around 80% of all product size increases are upgrades, as prices either stay constant or rise by less than the size increase.

The fourth feature is the business cycle behavior. I find that reductions in product size are strongly procyclical. Their frequency closely tracks the CPI inflation rate–for example, between 2015 and 2018 during the recovery from the Great Recession, and again from 2021 onward amid the post-Covid inflation surge. A regression analysis confirms this visual pattern: product size reductions are positively correlated with lagged CPI and PPI inflation and negatively with the unemployment rate, all significant at the 1% level. Specifically, a one-percentage-point increase in the one-month-lagged CPI (PPI) inflation rate is associated with a 0.024-percentage-point (0.005-percentage-point) increase in the frequency of size reductions. Moreover, a one-percentage-point rise in the unemployment rate corresponds to a 0.062-percentage-point decline in size reductions. Interestingly, these results are mainly driven by downgrades. Size reductions that are upgrades show no significant relationship with aggregate variables.

In contrast, size increases–whether downgrades or upgrades–show no consistent business cycle behavior. They are weakly correlated with lagged PPI inflation and the unemployment rate, but the model fit is low.

The fifth feature is the relationship between posted prices and product size changes. I estimate the correlation between the frequencies of price and size changes for individual products. However, there is no systematic relationship; the correlation is essentially flat.

Finally, I quantify the impact of size adjustments on inflation. I construct a counterfactual CPI series excluding all ONS adjustments for size changes in the data. Comparing this with official CPI inflation reveals that the aggregate impact of product size adjustments is small: on average, size changes–both decreases and increases–increased the CPI inflation rate by 0.03 percentage points per month between 2012 and 2023.[3]

At a more disaggregated level, the effects on inflation can be larger. For example, for Food and non-alcoholic beverages, size changes add around 0.15 percentage points per month on average to sectoral inflation. For specific goods, the effects can be even more pronounced: 1.7 percentage points for cola-flavored drinks, 1.2 for chocolate sweets, or 0.54 for toilet rolls.

Despite being more relevant in certain categories, studying product size alterations remains important from a macroeconomic perspective. First, they can cause market inefficiencies. Shrinkflation is often seen as a strategy that exploits consumers' inattention to changes in product size (e.g., Jami and Mishra (2014); Çakir and Balagtas (2014); Evangelidis (2024)). Whether consumers fail to notice these changes or choose to overlook them due to high cognitive costs, unit prices may no longer serve as accurate price signals, leading to distorted demand responses. Snir and Levy

[3]If official inflation is 2% in a given month, the rate excluding size adjustments would be 1.97%.

(2011) shows that greater consumer attention to price than to size changes can alter market equilibria.[4] Given the strong procyclicality of product size reductions, such inefficiencies are likely to be particularly pronounced during economic booms.

Second, these inefficiencies may have distributional consequences. Lower-income households tend to allocate a larger share of their expenditures to food and household essentials (see, e.g., Attanasio and Pistaferri (2016), Blundell et al. (2008))–precisely the categories most affected by product size changes. This implies that shrinkflation may disproportionately burden poorer households, effectively raising their experienced inflation relative to wealthier ones. Firms, too, may be affected unevenly. Even if they produce similar products, some may find it technically easier or more cost-effective to alter product sizes (e.g., reducing the number of chocolate sweets in a bag vs. shrinking a chocolate bar), which could affect the distribution of markups and profits.

Finally, the findings of this paper help put recent public concern over shrinkflation into perspective. The practice has featured prominently on the political agenda in numerous countries in recent years.[5] Shrinkflation is often cited as a reason why consumers dislike inflation (Stantcheva (2024)). On the one hand, this paper provides empirical support for those concerns, showing that firms systematically use product size reductions as a margin of adjustment over the cycle. On the other hand, the quantitative importance of this channel is relatively small compared to the adjustment of prices.

This paper contributes to the literature on non-price adjustments, including product size alterations (e.g., Snir and Levy (2011), Danziger (2001), Andersen and Toulemonde (2004), Çakir and Balagtas (2014)) and quality or service changes (e.g., Carlton (1977, 1986, 1991); Epstein (2007)). Empirical work is relatively scarce, primarily due to data limitations. An exception is Imai and Watanabe (2014), who examine the extent of product size adjustments during Japan's deflationary period using supermarket scanner data from 2000 to 2012. They find robust evidence that (i) unit prices tend to increase following product size reductions and (ii) product replacements often involve size drops. These findings broadly align with the results in this paper. In both cases, product size adjustments appear to reflect firms' non-price responses to higher cost pressures.

More broadly, this paper also relates to the literature that examines the sources of price rigidity.[6] In this context, psychological factors, such as pricing thresholds, may also play a role. According to this theory, certain prices–such as those ending in .99–carry psychological significance for consumers and act as barriers to price adjustments (e.g., Hahn and Marenčák (2020)). For instance, posted prices often remain at values like 4.99 rather than adjusting to, say, 5.12. Levy et al. (2011) provide

[4]In this model, consumers face cognitive costs when processing both price and size information. However, consumers prioritize prices because they change more frequently and directly affect budget constraints. Alternatively, Rebelo et al. (2024) propose a model in which households make errors in purchase decisions due to cognitive frictions. Firms can benefit from these errors by keeping prices constant and deterring consumers from incurring the cognitive cost of making more informed choices.

[5]In Brazil, Italy, France, Hungary, and Romania, firms must disclose size reductions. The U.K. will introduce a similar regulation in October 2025. In Norway, "krympflasjon" was the word of the year in 2022. In 2024, U.S. President Joe Biden criticized the practice.

[6]See, for example, Bils (1987), Rotemberg (1987, 2005), Bils and Klenow (2004), Klenow and Kryvtsov (2008), Nakamura and Steinsson (2008), and Eichenbaum et al. (2011).

empirical evidence for this behavior. Product size adjustments may thus serve as an alternative channel for firms to adjust unit prices while avoiding price changes.

The rest of the paper is structured as follows. Section 2 describes the U.K. micro price data and explains the methodology for the identification of product size changes in the data. Section 3 presents the main findings of the paper. Finally, Section 4 concludes.

2 Data and definitions: ONS price microdata

This paper presents evidence from the public monthly price micro dataset underlying the CPI for the United Kingdom, published by the Office for National Statistics (ONS).[7]

The public dataset covers approximately two-thirds of the total CPI by weight. Goods and services are categorized into COICOP (Classification of Individual Consumption by Consumption Purpose) categories (e.g., ”Food and non-alcoholic beverages”, ”Clothing”) and further subdivided into groups (e.g., ”Bread”) and items (e.g., ”large loaf, white, sliced (800g) bread”).[8] For each item and stratum (defined by the region and shop type pairing), the ONS provides sampling weights reflecting its relative household expenditure shares. These weights are updated annually. Unless stated otherwise, all statistics are calculated using these CPI weights. Appendix A provides further details.

The dataset includes a variable ”indicator_box”, which is marked with ”W” when the ONS detects a change in an item's weight or volume. The ”W-flag” has been used consistently since around 2012.[9]

When a size change is detected, the ONS makes two adjustments (Office for National Statistics, 2019a). First, it replaces the product with the closest equivalent in the new size. Second, it adjusts the base price of the product to reflect the size change. From February to December, the base price is the price from January of the same year; for January observations, it is the price from the previous January.

The adjustment uses the formula:

$$\textit{new base price} = \textit{current base price} \times \frac{\textit{new weight}}{\textit{old weight}} \tag{1}$$

For example, if a chocolate bar with a current base price of £1 shrinks by 10% from 100 grams to 90 grams, the new base price becomes £0.90. This adjusted base price is then applied until the next January.

Adjustments to the base price affect the CPI. The ONS computes the CPI as a chained index based on weighted price-to-base price ratios (Office for National Statistics, 2017). A lower base price raises the ratio; a higher base price lowers it.

[7] `https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/consumerpriceindicescpiandretailpricesindexrpiitemindicesandpricequotes`. Historical data are available via the ONS online archives.

[8] An ”item” refers to a product category, not to a brand.

[9] The ONS has tracked size changes since the 1990s. However, earlier coding practices varied, e.g., ”C” for ”Comparable good”.

I utilize the panel structure of the data to identify product size decreases and increases:

- **Product size decreases**: A decrease in product size is identified if (i) the W-flag is active and (ii) the base price in the current month is *lower* than in the previous month (for March to January observations), i.e., $base\ price_t < base\ price_{t-1}$, or lower than the January price of the same year (for February observations), i.e., $base\ price_t < price_{t-1}$.[10]

- **Product size increases**: An increase in product size is identified if (i) the W-flag is active and (ii) the base price in the current month is *higher* than in the previous month (for March to January observations), i.e., $base\ price_t > base\ price_{t-1}$, or higher than the January price of the same year (for February observations), i.e. $base\ price_t > price_{t-1}$.

In some cases, the W-flag is active but the base price is unchanged. This may reflect packaging changes that do not alter net weight, or coding errors. In this paper, I take a conservative approach and focus only on size changes that correspond to reductions or increases.

Next, I examine how size changes affect the product's unit price. Whether the unit price increases or decreases depends on how the product's posted price evolves in conjunction with the size change. For instance, if a chocolate bar shrinks by 10% but the posted price remains unchanged, the unit price increases. I define this case as a "downgrade." If the posted price decreases, but by less than 10%, it is still a downgrade. Conversely, if the price falls by more than 10%, the unit price decreases. I define this case as an "upgrade." The reverse logic applies for size increases.

I apply the following classification:

- **Downgrades:** (i) The W-flag is active and (ii) $\frac{price_t}{baseprice_t} > \frac{price_{t-1}}{base\ price_{t-1}}$ for March to January observations, or $\frac{price_t}{price_{t-1}} > \frac{price_{t-1}}{base\ price_{t-1}}$ for February observations.

- **Upgrades:** (i) The W-flag is active and (ii) $\frac{price_t}{base\ price_t} < \frac{price_{t-1}}{base\ price_{t-1}}$ for March to January observations, or $\frac{price_t}{price_{t-1}} < \frac{price_{t-1}}{base\ price_{t-1}}$ for February observations.

- **No change:** (i) The W-flag is active, but (ii) $\frac{price_t}{base\ price_t} = \frac{price_{t-1}}{base\ price_{t-1}}$ for March to January observations, or $\frac{price_t}{price_{t-1}} = \frac{price_{t-1}}{base\ price_{t-1}}$ for February observations.

It is important to note that this classification is based on comparing the posted price and base price in the current and the previous month. However, a one-month window might be too short. In practice, retailers may use temporary sales to soften the transition to a new size.[11] As a result, a price promotion could mask a downgrade, leading to misclassification. Prior research (e.g., (Budianto, 2024; Anderson et al., 2017)) documents that firms often pair discounts with permanent price changes. In Appendix A, I explore longer reference windows but find very similar results.

Following ONS practice, I apply the product size change label to all observations from the month of the size change until the following January. This creates a seasonal pattern, with more changes recorded late in the year or in January.

[10]Recall that the base price is the January price of the same year for observations from February to December, and the base price for all observations in January is the January price of the previous year.

[11]The "indicator_box" variable only records one event per observation and month and does not capture overlapping changes like sales and size changes.

The sample period spans 144 months from January 2012 to December 2023. I exclude invalid or implausible entries (e.g., £1.10 changing to £110). The cleaned dataset contains 16.8 million observations.

3 Empirical results

3.1 The frequency of product size adjustments

To start, Table 1 presents key statistics on product size changes in the CPI microdata.[12] The first column reports the share of goods and services–weighted by CPI weights–that experienced at least one size adjustment during the sample period. Overall, approximately 35% of products by CPI weight underwent a size change at some point between 2012 and 2023. This share varies considerably across sectors (top 5 are shown in Table 1). For example, it is 78.5% in ”Food and non-alcoholic beverages,” 59.2% in ”Alcoholic beverages and tobacco,” and 30.5% in ”Personal care” products.

The next columns display the mean and maximum monthly frequencies of product size changes. On average, the monthly frequency of size changes is 0.26%, with a maximum of 0.73% over the sample period. In the Food sector, the frequencies are higher, averaging 1.01% with a peak of 3.11%.

On average, approximately 80% of all size adjustments are reductions (0.21%), while only a small share are increases (0.06%). These patterns also hold across sectors.

These frequencies may appear low, but it is important to note that they are calculated relative to *all* CPI items in a given month (weighted by CPI weights), including those that cannot be quantified by weight or volume. When focusing only on quantifiable items, the frequency of size adjustments can be considerably higher for certain products. For example, monthly frequencies average 11.8% (peaking at 67.1%) for chocolate bars, 6% (50%) for dishwasher tablets, and 2.8% (24.4%) for toilet rolls.

How does the frequency of product size adjustments compare to that of posted price changes? At the aggregate level, prices clearly change more frequently. Between 2012 and 2023, the average monthly frequencies of regular price increases and decreases are 6.5% and 3.6%, respectively.[13] However, for some goods, size adjustments are more frequent than price changes. For example, the frequency of price increases (decreases) for chocolate bars is 4.6% (2.7%), for dishwasher tablets 5.6% (5.6%), and toilet rolls 6.7% (5.4%).

[12] For more detailed statistics, see Appendix B.1.

[13] These figures refer to changes in the regular posted prices of products, i.e., excluding temporary sales. For comparison, Kryvtsov and Vincent (2021) estimate monthly frequencies of 7.6% for regular price increases and 3.3% for decreases in the U.K. from 1996 to 2013. Nakamura and Steinsson (2008) report an average frequency of regular price changes of approximately $9'$% for the U.S. (1998–2005).

Table 1: Key statistics for product size adjustments from 2012-2023

	Overall share affected by size adj.	Monthly frequencies: All mean	All max	Decreases in size mean	Decreases in size max	Increases in size mean	Increases in size max
Aggregate	35.41	0.26	0.73	0.21	0.61	0.06	0.30
COICOP2							
Food and non-alc. beverages	78.48	1.01	3.11	0.88	2.87	0.13	0.48
Alc. beverages and tobacco	59.15	0.30	3.48	0.03	0.22	0.27	3.38
Personal care, misc	30.45	0.21	0.98	0.20	0.96	0.02	0.08
Recreation	14.81	0.07	0.38	0.06	0.33	0.01	0.08
Furnishing and household equipment	9.73	0.06	0.30	0.05	0.30	0.01	0.04
Items							
Chocolate bar		11.80	67.06	11.80	67.06	0.00	0.00
Cola flavored drink		11.30	50.13	11.17	50.13	0.12	1.32
Fresh orange juice		6.71	50.01	6.53	47.99	0.18	2.26
Dishwasher tablets		5.96	15.11	4.27	10.43	1.69	4.80
Chocolate sweets		5.58	26.99	5.34	26.99	0.25	1.39
Cooked ham prepacked		5.41	5.41	5.41	5.41	0.00	0.00
Hand rolled tobacco		5.01	58.86	0.13	1.87	4.88	57.17
Dry dog food		2.93	9.63	2.57	7.95	0.36	3.76
Toilet rolls		2.83	24.43	2.75	24.00	0.09	0.99
Washing liquid		2.82	17.92	2.60	17.92	0.21	2.09
Disposable nappies		2.35	14.17	1.88	13.89	0.47	4.12
Fabric conditioner		1.62	13.79	1.58	13.26	0.04	1.14
Sanitary towels		1.41	2.43	1.41	2.43	0.00	0.00
Baby wipes		1.31	5.72	1.19	5.09	0.12	4.20
Tissues		1.05	8.51	1.05	8.51	0.00	0.60
Potting compost		0.99	6.12	0.80	6.12	0.19	1.75
Bird seeds		0.67	10.44	0.30	3.80	0.38	6.64
Cans of bitter		0.63	5.81	0.41	4.49	0.22	1.31
Apple cider		0.55	6.77	0.55	6.77	0.00	0.00
Dog treats		0.44	1.17	0.43	1.17	0.01	0.43
Cat food		0.43	5.57	0.43	5.57	0.00	0.00
Cans of lager		0.26	7.99	0.26	7.99	0.00	0.00
Fortified wine		0.18	2.36	0.00	0.00	0.18	2.36

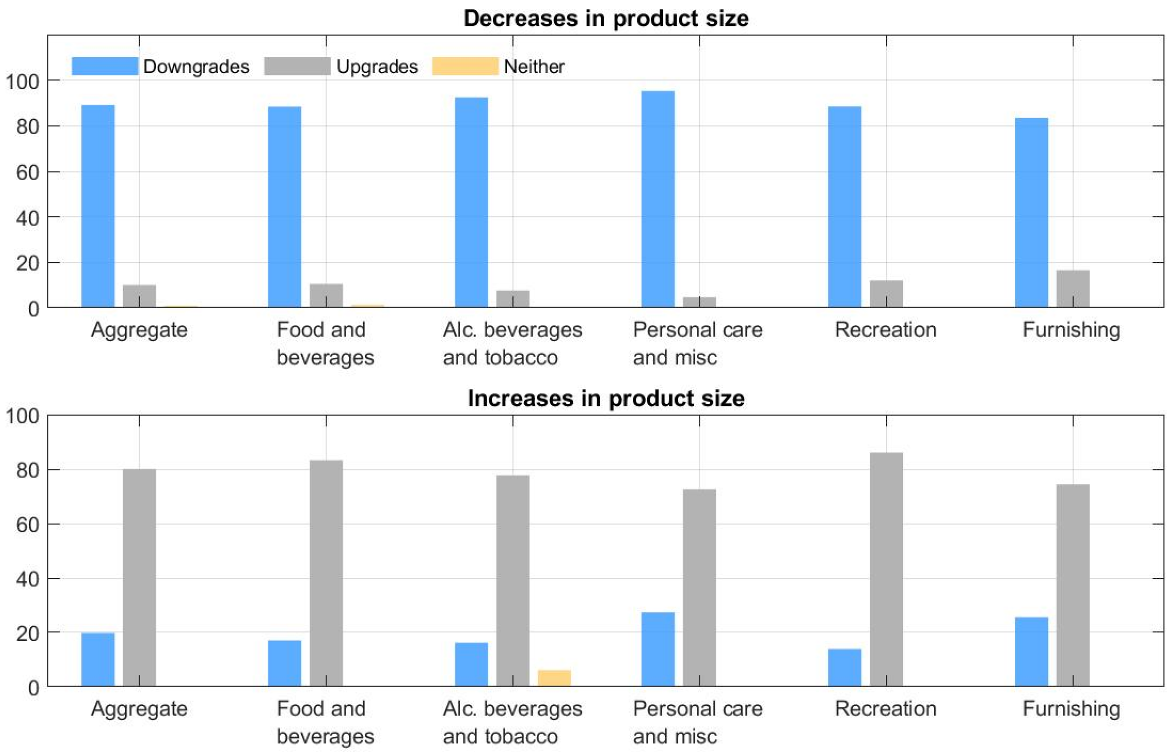
Notes: in per cent. Monthly averages from 2012-2023. "Overall share affected by size adjustment" is calculated as the share of goods and services that have experienced a product size change at least once between 2012 and 2023.

3.2 The nature of product size adjustments

Next, I analyze the implications of product size adjustments for unit prices. Recall that "downgrades" refer to cases where the unit price increases, and "upgrades" to those where it decreases. The extent of the change in the unit price depends on both the change in product size and posted price.

Figure 1 illustrates the distribution of downgrades and upgrades. Between 2012 and 2023, around 90% of all size reductions result in downgrades, while only 10% are upgrades (top panel). Most size reductions are downgrades because the posted price of the product typically remains unchanged (in 65% of cases), increases (20%), or decreases by less than the reduction in size (5%).[14] These patterns are consistent across sectors. The highest share of downgrades is observed in the Personal Care category (about 95%), where the posted price remains constant in most cases when package sizes shrink.

Figure 1: Distribution of downgrades and upgrades



Notes: in per cent. Monthly averages from 2012-2023. ”Downgrades:” unit price increases, ”Upgrade:” unit price decreases.

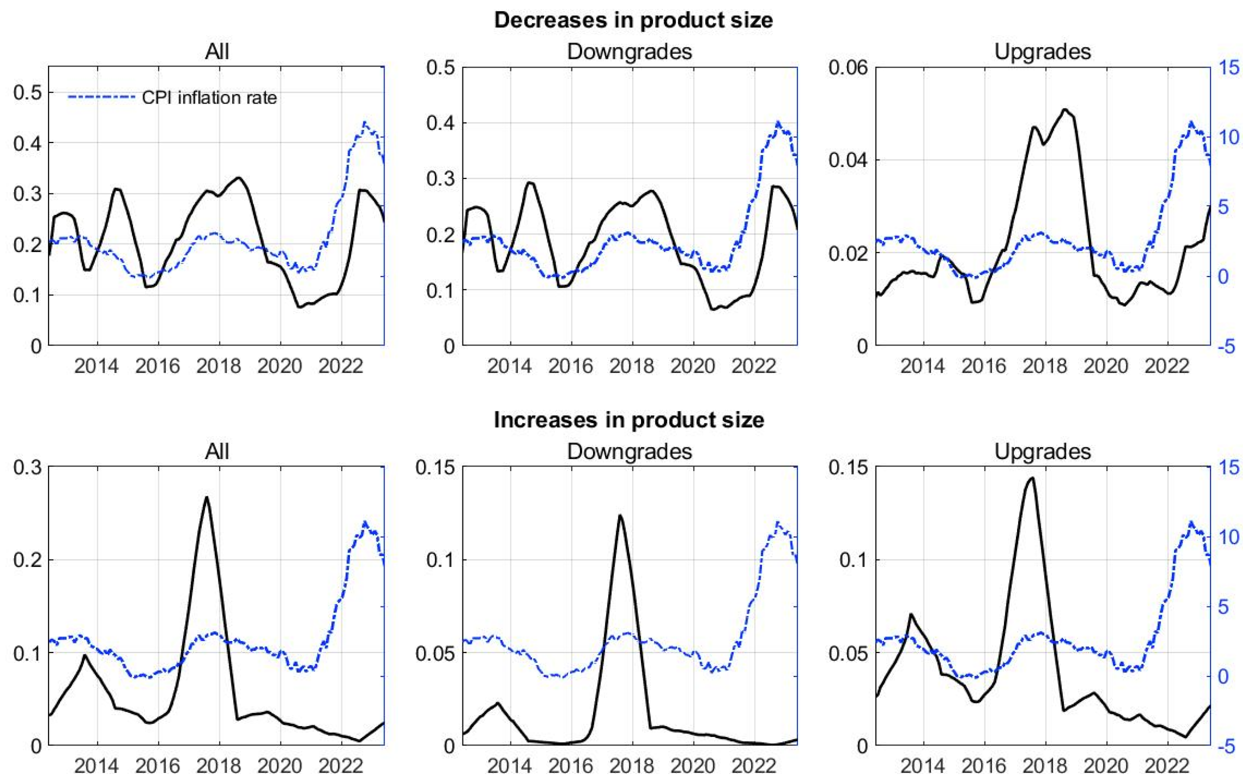
The pattern is reversed for product size increases (bottom panel): about 80% of size increases result in upgrades. Moreover, I find that product size increases are more frequently accompanied by increases in the posted price: in 30% of cases, the price rises when the product size increases, in 55% it remains unchanged, and in 15% it falls. These figures are also relatively similar across sectors. Note that for ”Alcoholic beverages and tobacco,” some cases cannot be classified as either upgrades or downgrades–here, an increase in product size is exactly offset by a corresponding increase in the product’s price, leaving the unit price unchanged.

[14] Figure B.2.1 in Appendix B.2 provides further details on the distribution of posted price changes that occur alongside product size adjustments.

3.3 The business cycle behavior

This section investigates the business cycle behavior of product size adjustments. I begin with a visual examination of their relationship with aggregate fluctuations. Figure 2 plots the aggregate frequency of product size adjustments and CPI inflation as 12-month centered moving averages.

Figure 2: Frequency of product size changes (left axis) vs. CPI inflation (right axis)



Notes: in per cent. Black lines show 12-month moving average of fractions of decreases and increases in product size (left: all, middle: size decreases (increases) that are downgrades, right: size decreases (increases) that are upgrades). Blue dashed lines show 12-month moving average of CPI inflation rate.

The top-left panel shows the frequency of size reductions. Starting in the mid-2010s, there is a clear positive correlation between these reductions and CPI inflation. At times, the co-movement is remarkably close. For example, the frequency of size reductions rose in 2016 along with inflation, then declined again in 2020 during the Covid-19 pandemic. It spiked from 2021 to 2022 during the post-Covid inflation surge and fell back as inflation subsided in 2023.

The other top panels further distinguish between product size reductions that are downgrades and upgrades. Downgrades are strongly procyclical, closely tracking fluctuations in CPI inflation. In contrast, upgrades show some correlation with the inflation rate, but the relationship appears weaker than for downgrades (e.g., a spike in 2018 with only a modest increase in inflation).

The bottom panels focus on the frequency of product size increases. There appears to be no clear correlation between the frequency of size increases and the CPI inflation rate. Apart from the periods in 2013 and 2017, the time series for product size increases remains relatively flat.

The large spike in 2017 was caused by a change in U.K. tobacco regulation: since May 2017, cigarettes must be sold in standardized packaging that is large enough to display graphic health warnings (The Guardian (2017)). This requirement led to a size increase for many products. Although driven by a one-time regulation, I retain this period in the sample for the remainder of the analysis. The reason is that, while cigarette manufacturers had limited discretion over package size, they could still adjust posted prices in ways that resulted in downgrades, upgrades, or no change in the unit price. Overall, however, these adjustments appear largely acyclical. Appendix C.1 provides a robustness analysis without this period.

To investigate the business cycle behavior of product size changes in more detail, I estimate OLS time-series regressions based on the following specification: $y_t = \alpha + \beta x_t + X_t'\gamma + error_t$, where y_t is either the frequency of product size decreases, increases, downgrades or upgrades in month t. The variable x_t is either the one-month-lagged CPI inflation rate, the one-month-lagged PPI inflation rate, or the contemporaneous unemployment rate.[15] Additionally, X_t is a set of control variables, including a linear year time trend, calendar month dummies, and the frequencies of increases and decreases in the products' posted price. The time trend captures general trends in product size changes, while the calendar month dummies account for seasonality. Including the frequencies of price changes controls for potential co-movement between price and size adjustments.

Table 2 presents the results of the regression analysis. Given the relatively small sample size, standard errors are computed using a non-parametric bootstrap procedure.[16] The regression analysis confirms the graphical evidence: product size reductions exhibit strong and statistically significant procyclical behavior (first half of Table 2). Specifically, the frequency of size reductions is positively correlated with lagged CPI and PPI inflation rates, and negatively correlated with the unemployment rate, all significant at the 1% level. A one-percentage-point increase in lagged CPI (PPI) inflation is associated with a 0.024-percentage-point (0.005-percentage-point) increase in the frequency of product size reductions. Moreover, a one-percentage-point increase in the unemployment rate is associated with a 0.062-percentage-point decrease in the frequency of size reductions.

[15] Lagged inflation rates are used to avoid potential simultaneity bias, given that the ONS accounts for product size changes in the construction of the CPI. However, since product size changes affect only a small share of goods, they are unlikely to be a major determinant of the CPI.

[16] Appendices C.3 and C.4 provide results based on alternative methods for computing standard errors.

Table 2: Regression results for aggregate data

	Frequency of decreases in product size											
	All				Downgrades				Upgrades			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
cpi_{t-1}	0.024***			0.033***	0.022***			0.030***	0.002**			0.003***
	(0.006)			(0.005)	(0.006)			(0.005)	(0.001)			(0.001)
ppi_{t-1}		0.006***				0.005**				0.001***		
		(0.002)				(0.002)				(0.000)		
$unempl_t$			-0.062***	-0.079***			-0.053***	-0.069***			-0.009***	-0.010***
			(0.013)	(0.014)			(0.012)	(0.013)			(0.002)	(0.002)
$freq\_up_t$	-0.012	-0.003	0.021***	-0.010	-0.009	0.000	0.021***	-0.007	-0.003**	-0.003***	0.001	-0.002**
	(0.008)	(0.007)	(0.005)	(0.006)	(0.007)	(0.006)	(0.005)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
$freq\_do_t$	-0.003	-0.006	-0.005	0.015	-0.002	-0.005	-0.005	0.013*	-0.001	-0.000	-0.001	0.001
	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)	(0.008)	(0.001)	(0.001)	(0.001)	(0.001)
trend	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***	0.000	0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.195***	0.166**	0.571***	0.806***	0.213***	0.183**	0.531***	0.744***	-0.009	-0.007	0.048***	0.071***
	(0.074)	(0.074)	(0.114)	(0.120)	(0.070)	(0.072)	(0.100)	(0.108)	(0.007)	(0.009)	(0.018)	(0.019)
Adj. R^2	0.53	0.51	0.55	0.64	0.52	0.50	0.54	0.63	0.33	0.37	0.40	0.45

	Frequency of increases in product size											
	All				Downgrades				Upgrades			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
cpi_{t-1}	-0.002			0.002	-0.001			0.001	-0.001			0.001
	(0.004)			(0.004)	(0.002)			(0.002)	(0.002)			(0.002)
ppi_{t-1}		0.003*				0.002**				0.001		
		(0.002)				(0.001)				(0.001)		
$unempl_t$			-0.035***	-0.037***			-0.017***	-0.018***			-0.019***	-0.019***
			(0.010)	(0.011)			(0.005)	(0.005)			(0.005)	(0.005)
$freq\_up_t$	0.003	-0.007	0.006*	0.004	0.001	-0.004*	0.003**	0.002	0.002	-0.003	0.003*	0.003
	(0.006)	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
$freq\_do_t$	-0.009**	-0.003	-0.002	-0.001	-0.004*	-0.000	-0.000	0.000	-0.005*	-0.002	-0.001	-0.001
	(0.004)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
trend	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.100***	0.135***	0.368***	0.383***	0.024**	0.043***	0.153***	0.163***	0.074***	0.090***	0.218***	0.223***
	(0.025)	(0.035)	(0.082)	(0.087)	(0.010)	(0.015)	(0.043)	(0.044)	(0.015)	(0.020)	(0.042)	(0.045)
Adj. R^2	-0.01	0.04	0.11	0.11	-0.08	-0.00	0.04	0.03	0.08	0.10	0.19	0.18

Notes: Sample from January 2012 to December 2023, i.e. 144 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Bootstrapped standard errors in brackets. All regressions include a constant, a linear time trend, calendar month dummies and the frequencies of nominal price increases and decreases (freq_up and freq_do).

These patterns are primarily driven by downgrades, which are positively correlated with both

CPI and PPI inflation rates, and negatively with the unemployment rate, all at the 1% significance level. Upgrades are also mildly procyclical: they are positively correlated with CPI and PPI inflation at the 5% significance level, and negatively correlated with the unemployment rate at the 1% level. However, the estimated coefficients are substantially smaller than those for downgrades, and the adjusted R-squared values are relatively low.

A potential challenge in using CPI and PPI inflation as business cycle indicators is that, unlike the unemployment rate, they are not standard measures of economic slack.[17] In this sample, CPI and PPI inflation are negatively correlated with the unemployment rate, indicating that inflation typically increased during expansions. To better control for the relationship with inflation versus economic slack, I estimate regressions with both CPI inflation and the unemployment rate as independent variables. The coefficients are slightly larger in absolute terms in the joint specification than in the separate regressions, but overall they are fairly similar.

How can we interpret the procyclicality of product size reductions and downgrades? The results suggest that the likelihood of observing "shrinkflation" increases during economic expansions. A natural explanation is that these are typically periods in which firms face higher cost pressures but also enjoy stronger demand and lower consumer price elasticity, potentially making consumers either less attentive to product size changes or more willing to accept them.

There is some empirical evidence that consumer attention to product attributes varies across different times and contexts. For example, Levy and Snir (2013) find in survey data that consumers are more sensitive to quantity attributes when purchasing large volumes, such as during holiday periods. Evangelidis (2024) shows that consumers exhibit "shrinkflation aversion," judging product downsizing as more unfair than an equivalent price increase because it is perceived as deceptive. However, Evangelidis (2024) also finds that this aversion diminishes when consumers are informed about the size reduction itself or the reasons behind it (e.g., rising production costs).

The second half of Table 2 focuses on product size increases. The frequency of size increases is positively correlated with the lagged PPI inflation rate at the 5% significance level and negatively correlated with the unemployment rate at the 1% level. However, the explanatory power of the model is low, with R-squared values of only 0.03 and 0.11, respectively. Downgrades and upgrades following size increases also exhibit some correlation with PPI inflation and unemployment, but the model fit remains weak. Consequently, it is difficult to draw firm conclusions about the business cycle behavior of product size increases.

Finally, the frequencies of price changes are largely unrelated to product size adjustments. The regression coefficients for the frequency of price increases and decreases are either statistically insignificant or very small. In Appendix C.5, I explore this relationship in greater detail by estimating the correlation between the frequencies of price and size adjustments at the disaggregated level. I find that these correlations are either flat or have a poor model fit.

Moreover, I find no discernible time trend for product size changes. The coefficients on the

[17] Consumer and producer price inflation may rise or fall during recessions or expansions, depending on the nature of the underlying shock (e.g., a demand or supply shock).

linear time trend are statistically insignificant or effectively zero in all regressions. As a result, a common perception that shrinkflation has become more prevalent over time is not supported by the data.

Appendix C.2 provides a detailed robustness analysis. The main results remain robust across alternative specifications. For instance, I include additional independent variables, such as moving averages of CPI inflation, PPI inflation, and the unemployment rate, to account for the possibility that product size changes are related to economic developments over a longer horizon, as firms may take time to implement them. Moreover, I consider two additional indicators of economic slack: a business confidence index and a consumer confidence index. Finally, I also examine an alternative proxy for product size changes, based on product replacements recorded in the ONS microdata.

3.4 Implications for CPI inflation

This section examines the contribution of product size adjustments to CPI inflation. To do so, I construct a counterfactual measure that excludes their effects by reversing all adjustments made by the ONS. Recall that the ONS recalculates the base price to reflect the product size change. I reconstruct the time series using each product's original base price. [18] Appendix B.3 provides methodological details and an alternative approach to constructing counterfactual inflation.

Figure 3 plots the *difference* between inflation rates using the official CPI microdata and the counterfactual excluding product size adjustments, for both aggregate CPI (left) and sector-specific inflation for "Food and non-alcoholic beverages" (right). Units are expressed in percentage points. For instance, in December 2022, aggregate CPI inflation was 0.07 points higher due to size adjustments.

On average, product size adjustments add approximately 0.03 percentage points per month to aggregate inflation between 2012 and 2023, with peaks around 0.07 percentage points in 2018 and 2022. The difference is generally positive over the sample, indicating that product size adjustments tend to increase measured inflation. This reflects the prevalence of product size reductions and downgrades. The only notable exception is in 2017, when a regulation-driven increase in tobacco package sizes caused a temporary decline.

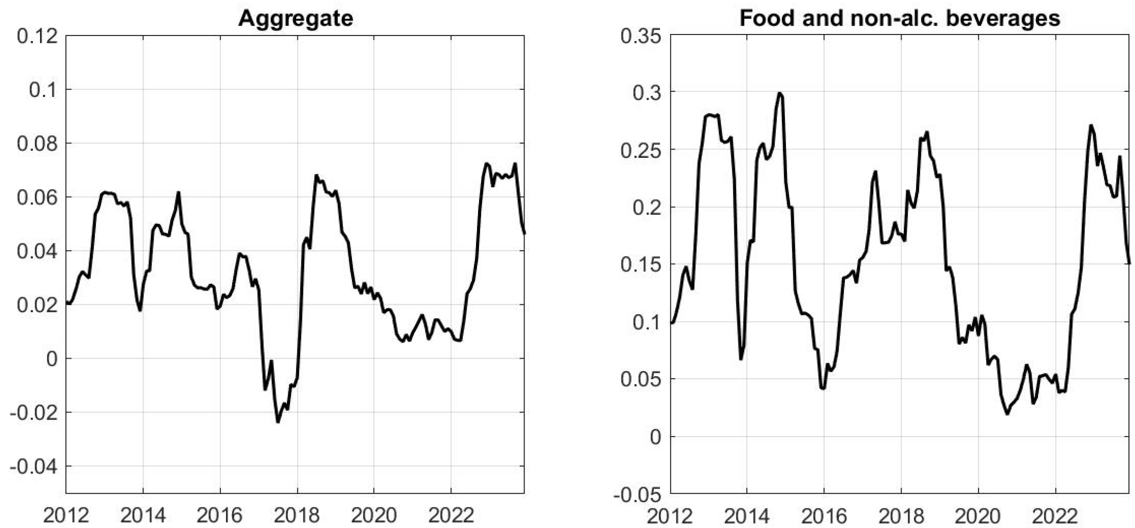
Overall, the figures suggest that aggregate CPI inflation is mainly driven by changes in the posted prices of goods and services, and only to a limited extent by adjustments in product size. The main reason is that the latter are less frequent and more concentrated in certain sectors (see Section 3.1). Interestingly, this concentration does not offset the fact that individual size changes tend to be relatively large: the median (mean) unit price increase due to product size adjustments over the sample period is 8.3% (6.3%).[19] In contrast, the median (mean) size of changes in regular posted prices is 3% (3.3%).

The contribution to inflation is slightly larger for Food and non-alcoholic beverages, the category

[18] Specifically, I replace the ONS-adjusted base price with the base price observed in the month preceding the size adjustment, for all months affected by the ONS procedure.

[19] Refer to Appendix B.1 for more details.

Figure 3: Difference in CPI inflation with and without size adjustment



Notes: in percentage points. Year-on-year inflation rates.

in which most product size changes occur. Here, product size adjustments increased inflation by an average of 0.15 percentage points per month, with peaks of 0.3 percentage points in November 2014 and 0.27 during the 2021-2023 inflation surge.

Finally, there are products for which the contribution to the product-specific inflation rate can be large. For example, product size changes add around 1.7 percentage points to the inflation rate for cola-flavored drinks, 1.2 percentage points for chocolate sweets, 0.54 percentage points for toilet rolls, and 0.51 percentage points for washing liquid.[20]

An additional question is whether the contribution of product size changes to CPI inflation exhibits systematic patterns over the business cycle. I find a statistically significant positive relationship between the difference in the official rate and its counterfactual and lagged inflation: the inflationary impact of product size adjustments tends to be larger when overall inflation is high. This relationship is strongest for Food and non-alcoholic beverages but is also evident in other sectors such as Furnishings, Recreation, and Personal Care. Most of this relationship is driven by size reductions and downgrades. In contrast, the contribution to CPI inflation from size increases and upgrades shows no systematic link to aggregate inflation. Appendix B.3 summarizes these results.

4 Conclusion

This paper presents novel evidence on the macroeconomic relevance of product size adjustment. Using monthly price microdata underlying the CPI for the U.K. from 2012 to 2023, I find that product size changes, particularly reductions, are an important margin of adjustment over the business

[20]See Appendix B.3 for more sector-level and item-level statistics.

cycle. However, their impact on aggregate CPI inflation is small. These findings help assess the economic relevance of shrinkflation and place recent public attention on the issue into perspective. Future research should examine the economic implications of cyclical non-price adjustments such as product size changes on allocative efficiency, the distribution of inflation costs across firms and households, or the design of monetary policy when effective price changes are difficult to observe.

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Appendix

A ONS price quote data

This section provides a detailed overview of the public CPI micro dataset published by the U.K.'s Office for National Statistics (ONS).[21] Additional information is available in the ONS 2019 Technical Manual.

To construct the CPI, the ONS surveys the prices of goods and services included in the household final consumption expenditure component of the U.K. National Accounts. Each month, prices for over 1,000 goods or services are collected locally from more than 14,000 retail stores. Each item is classified by month, year, shop type, and region. Shop types distinguish between "multiples," i.e., chain stores with 10 or more outlets, and "independents," with fewer than 10 outlets. Regional classification is based on the 12 geographic regions defined by the ONS (London, South East, South West, East Anglia, East Midlands, West Midlands, Yorkshire and the Humber, North West, Wales, Scotland, Northern Ireland, and "none"). Additionally, the ONS uses a classification system known as "stratum," which further stratifies the data based on shop type, region, or both. Within these stratum types, "stratum cells" track subgroups for more detailed analysis and representation. To ensure comprehensive national coverage, the ONS uses complex sampling across regions, shop types, product categories, and varieties.

Typically, items have broad specifications (e.g., 1kg of potatoes or women's jeans). The ONS staff selects products that match these specifications and are representative of consumer purchases. For products with multiple pack sizes, a range is provided. Most prices are collected monthly, except for some services and seasonal items.

I made several adjustments to ensure the data's suitability for analysis. First, I removed observations not marked valid by the ONS ($validity = 3$ or 4). Next, I eliminated entries with zero or negative prices. I also removed instances where price deviated by over 200% or fell by more than 99% from the base price (January of the same year), unless marked as sale items. These outliers likely reflect misreporting (e.g., £1.60 instead of £160). Lastly, I constructed price time series using the identifiers $item_id$, $region$, $stratum_cell$, $shop_type$, $shop_code$, $start_date$, and end_date. Between 2012 and 2023, the original files contained 18,557,213 observations. After cleaning, 16,858,765 remained.

A.1 Identification of product size changes in the data

Over the sample period from 2012 to 2023, a product remains in the dataset for an average of 23.7 months. During this time, products undergoing a size adjustment change their size approximately 1.12 times. Of these, 84.6% are decreases and 15.4% are increases.

[21] `https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/consumerpriceindicescpiandretailpricesindexrpiitemindicesandpricequotes`. This link provides data for the most recent years, while historical data can be accessed via the ONS online archives.

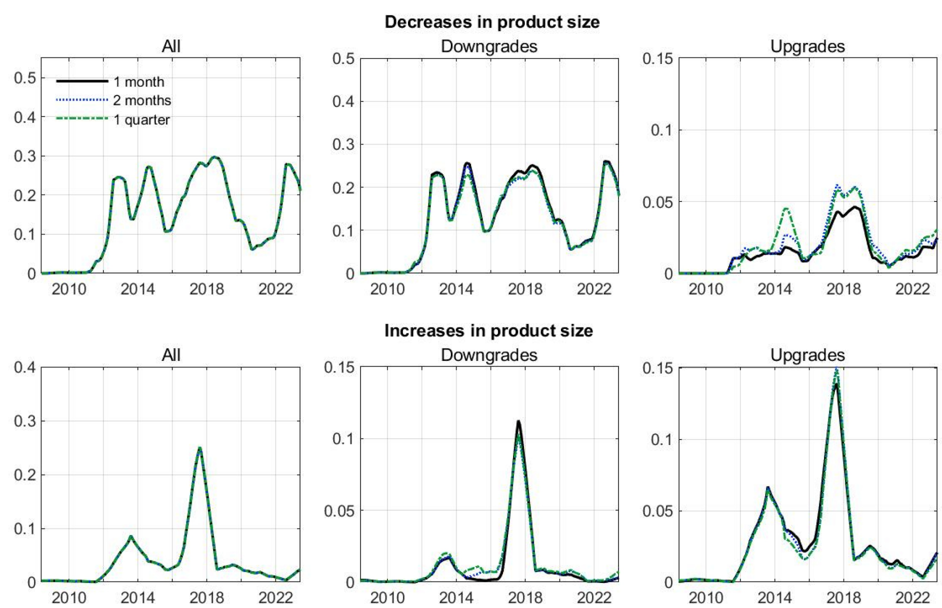
In some instances, the time series for a product is too short to identify product size increases or decreases. Specifically, this occurs when observations one month before the product size change are missing. Products are often sampled across multiple strata (region and shop type combinations). In such cases, I impute the price and base price using the average across all strata for the given month.

In the paper, downgrades and upgrades are identified by comparing the ratio of price to base price in the current and previous months. However, as discussed, a one-month reference period may be too short, as firms might use pricing strategies–such as temporary sales–that complicate the classification of product size changes. Figure A.1.1 compares the frequency of downgrades and upgrades using one-month, two-month, and one-quarter reference periods. For the latter two, I compute average prices and base prices over the respective window before and after the size change.

Overall, the differences between specifications are minor. Importantly, the overall variation in the time series remains largely unchanged, implying that the choice of reference period has little impact on the general business cycle behavior. Downgrades–whether from size reductions or increases–are nearly identical across specifications, indicating that the choice of period is mostly irrelevant.

There is some variation in the time series for upgrades. Specifically, upgrades from size reductions show discrepancies from 2014 to 2016 and 2017 to 2019. During these periods, upgrades are more frequent when identified using two-month or quarterly windows. Generally, such upgrades require that the posted price declines by more than the reduction in size. One explanation is that firms may delay price cuts following size reductions by several months.

Figure A.1.1: Comparison of reference periods



Notes: in per cent. 12-month moving averages.

B More detailed empirical results

B.1 Basis statistics: all sectors

Table B.1.1 reports detailed statistics on changes in product size and regular posted prices (i.e., excluding price changes due to temporary sales) for all sectors and selected items within each sector.

The aggregate figures show that regular price changes are far more frequent than size adjustments (price rises: 6.52 %, cuts: 3.62 %). The same holds at the COICOP2 level: in every category, prices adjust more often than package sizes. For instance, within Food and non-alcoholic beverages, 0.88 % (0.13 %) of goods, CPI-weighted, exhibit a monthly size increase (decrease), whereas 7.18 % (4.62 %) record price rises (cuts).

However, for certain items, product size adjustments are substantial. Examples include chocolate bars (size adjustments: 11.8% vs. regular price adjustments: 7.32%), cola drinks (11.3% vs. 11.62%), and dishwasher tablets (5.96% vs. 11.28%).

Figure B.1.1 shows the distribution of the magnitudes of unit price changes due to product size adjustments (top) and regular posted price changes (bottom). Over the sample period from 2012 to 2023, the median (mean) change in unit prices resulting from product size adjustments is 8.3% (6.3%), whereas the median (mean) magnitude of regular price changes is 3% (3.3%). Moreover, unit price changes caused by product size adjustments are more tightly concentrated around the mean than the distribution of changes in regular posted prices.

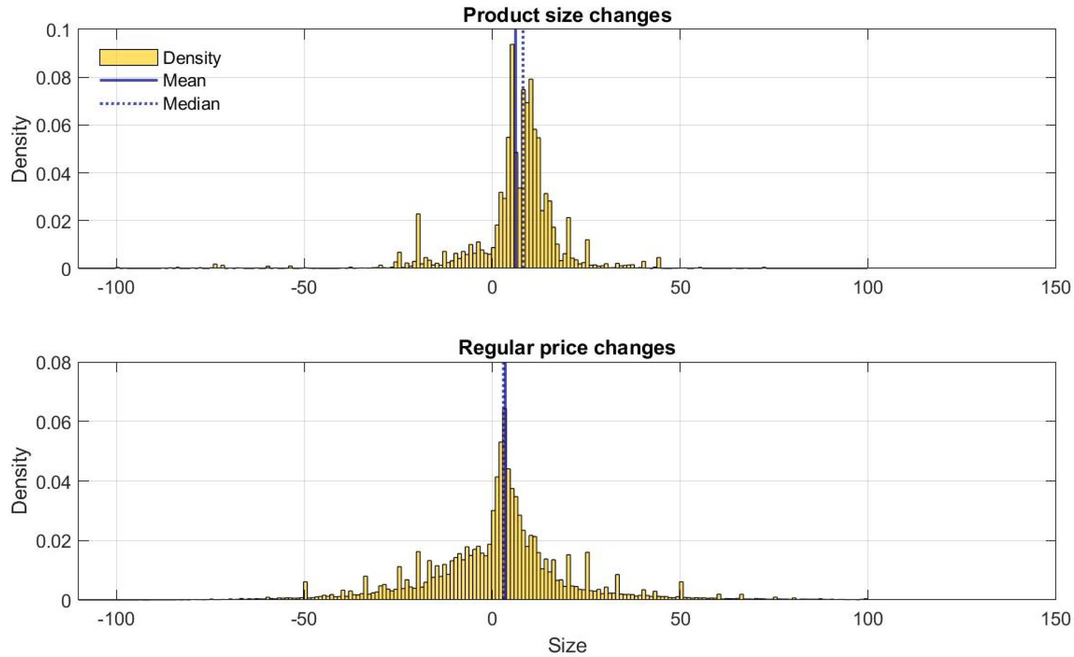
Table B.1.1: Average monthly frequencies from 2012-2023, in %

	Product size changes						Price changes					
	All		Decreases		Increases		All		Increases		Decreases	
	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
All	0.26	0.19	0.21	0.15	0.06	0.07	10.14	2.52	6.52	2.24	3.62	0.85
						COICOP2						
Food & non-alc. beverages	1.01	0.72	0.88	0.68	0.13	0.09	11.81	4.37	7.18	4.13	4.62	1.67
Alc. beverages & tobacco	0.30	0.88	0.03	0.05	0.27	0.85	18.96	11.94	14.46	11.68	4.50	2.28
Personal care	0.21	0.23	0.20	0.22	0.02	0.02	5.89	1.42	3.76	1.15	2.13	0.64
Recreation	0.07	0.08	0.06	0.08	0.01	0.02	6.55	1.56	3.64	1.23	2.91	0.65
Furnishing & household equipm.	0.06	0.06	0.05	0.05	0.01	0.01	9.64	2.51	5.74	2.09	3.90	0.94
Restaurants & hotels	0.04	0.08	0.02	0.02	0.03	0.07	12.56	5.41	8.90	4.65	3.66	1.74
Health	0.01	0.02	0.01	0.02	0.00	0.01	5.48	2.35	3.88	2.02	1.60	0.77
Housing	0.00	0.01	0.00	0.01	0.00	0.00	25.57	6.63	13.44	7.10	12.13	8.24
Clothing & footwear	0.00	0.00	0.00	0.00	0.00	0.00	6.95	1.72	3.39	1.02	3.56	1.05
Transport	0.00	0.00	0.00	0.00	0.00	0.00	7.33	3.27	5.00	2.56	2.33	1.03
Information & communication	0.00	0.00	0.00	0.00	0.00	0.00	11.63	6.66	6.00	4.92	5.63	4.54

	Items											
Chocolate bar	11.80	21.78	11.80	21.78	0.00	0.00	7.32	4.44	4.58	3.48	2.74	2.59
Cola flavored drink	11.30	18.79	11.17	18.65	0.12	0.31	11.62	11.00	5.84	7.96	5.77	7.67
Fresh orange juice	6.71	14.32	6.53	13.90	0.18	0.58	11.81	9.62	7.07	8.53	4.74	5.81
Dish washer tablets	5.96	5.87	4.27	4.06	1.69	2.13	11.28	7.26	5.64	5.07	5.64	4.97
Chocolate sweets	5.58	6.71	5.34	6.61	0.25	0.39	10.39	6.58	5.66	5.37	4.72	4.68
Cooked ham	5.41	0.00	5.41	0.00	0.00	0.00	10.73	4.93	5.70	4.98	5.03	3.47
Frozen garden peas	5.05	8.72	2.92	6.98	2.14	5.03	12.81	11.61	8.06	10.21	4.75	5.53
Hand rolling tobacco	5.01	15.45	0.13	0.42	4.88	15.05	25.59	20.96	20.88	21.09	4.72	5.66
Biscuits	4.54	11.80	4.54	11.80	0.00	0.00	13.01	11.33	8.84	10.24	4.17	4.57
Frozen berries	4.39	3.35	4.39	3.35	0.00	0.00	10.51	8.93	5.26	7.71	5.25	6.96
Breakfast cereal	4.09	7.46	3.48	6.88	0.61	1.60	11.26	7.05	6.89	5.62	4.37	3.78
Meat-free sausages	3.91	5.33	3.85	5.24	0.06	0.13	12.31	6.69	8.19	5.95	4.12	4.87
Frozen pizza	3.62	2.34	2.26	2.16	1.35	0.72	9.43	5.06	4.64	4.00	4.78	3.39
Baby formula	3.50	4.98	3.47	4.99	0.03	0.10	9.94	11.59	7.27	10.98	2.67	4.22
Canned tuna	3.47	3.65	3.24	3.55	0.22	0.43	10.43	7.05	6.03	6.14	4.40	4.06
Dessert	3.46	8.09	3.13	8.09	0.33	0.68	8.78	10.44	6.15	9.20	2.63	5.18
Fruit pastilles	3.45	7.95	3.11	7.49	0.35	1.13	6.39	5.28	4.08	3.95	2.31	2.65
Dry dog food	2.93	3.15	2.57	2.71	0.36	0.85	11.41	4.91	6.58	4.60	4.82	3.49
Toilet rolls	2.83	4.94	2.75	4.83	0.09	0.25	12.05	9.19	6.66	7.32	5.39	5.72
Washing liquids	2.82	3.77	2.60	3.77	0.21	0.41	8.93	6.71	5.04	5.47	3.89	4.28
Nappies	2.35	2.90	1.88	2.67	0.47	0.92	8.69	6.28	4.75	5.39	3.93	3.83
Fabric conditioner	1.62	2.63	1.58	2.54	0.04	0.18	10.74	8.54	6.30	6.83	4.44	4.30
Sanitary towels	1.41	0.98	1.41	0.98	0.00	0.00	8.81	5.92	5.78	5.21	3.03	2.67
Baby wipes	1.31	1.50	1.19	1.40	0.12	0.62	7.25	5.19	3.62	3.80	3.62	3.41
Tissues	1.05	1.66	1.05	1.65	0.00	0.05	8.68	6.83	5.26	5.61	3.41	3.53
Kitchen rolls	1.05	2.28	0.32	1.02	0.72	2.00	12.13	8.93	7.23	8.06	4.90	4.41
Potting compost	0.99	1.50	0.80	1.40	0.19	0.48	5.75	5.50	3.76	4.71	1.99	2.85
Potato chips	0.80	1.92	0.34	0.52	0.46	1.83	4.66	6.38	3.76	6.04	0.90	2.34
Tampons	0.78	1.81	0.78	1.81	0.00	0.00	6.60	4.94	3.51	3.44	3.09	3.76
Shower gel	0.67	2.63	0.67	2.63	0.00	0.00	6.69	4.58	3.56	3.46	3.13	2.84
Bird seed	0.67	2.19	0.30	0.79	0.38	1.42	5.91	7.19	4.05	6.12	1.86	3.42
Hair conditioner	0.63	1.06	0.56	1.04	0.07	0.18	6.62	4.28	3.69	3.36	2.93	2.63
Bitter	0.63	1.58	0.41	1.24	0.22	0.41	14.50	12.80	8.81	9.86	5.70	7.90
Apple cider	0.55	1.68	0.55	1.68	0.00	0.00	14.32	8.80	7.79	7.77	6.53	5.36
Wallpaper paste	0.48	0.51	0.48	0.51	0.00	0.00	6.29	6.57	3.61	3.48	2.69	5.31
Dog treats	0.44	0.32	0.43	0.31	0.01	0.08	12.75	7.65	7.58	7.25	5.17	4.08
Cat food	0.43	1.04	0.43	1.04	0.00	0.00	10.24	7.16	6.45	6.83	3.79	2.32
Staff rest. drink	0.39	0.78	0.32	0.79	0.08	0.18	6.45	4.42	4.47	4.04	1.98	1.30
Shampoo	0.35	0.63	0.30	0.60	0.06	0.16	6.68	4.95	3.85	3.84	2.83	2.96
Takeaway coffee	0.30	0.01	0.00	0.00	0.30	0.01	4.76	2.28	3.80	2.14	0.96	0.58
Lager	0.26	1.34	0.26	1.34	0.00	0.00	18.14	12.29	9.34	10.97	8.80	7.68
Takeaway soft drink	0.25	0.60	0.25	0.60	0.00	0.02	8.04	6.98	6.04	6.33	2.00	2.79
Refuse sack	0.25	0.49	0.06	0.19	0.18	0.48	6.57	6.66	4.65	6.04	1.91	2.64
Condoms	0.23	0.68	0.07	0.23	0.16	0.53	6.29	5.97	4.16	5.22	2.13	2.88
Aluminium foil	0.22	1.33	0.21	1.32	0.01	0.10	11.51	10.28	7.22	8.21	4.29	5.98
Sunscreen	0.19	0.75	0.17	0.69	0.02	0.08	10.29	7.68	5.60	6.92	4.69	5.17
Mascara	0.16	0.36	0.11	0.29	0.05	0.24	4.39	4.74	3.29	4.64	1.10	1.00
Self-tanning product	0.16	0.33	0.16	0.33	0.00	0.00	9.36	5.40	5.97	5.06	3.39	2.41

Notes: in per cent. Monthly averages from 2012-2023.

Figure B.1.1: Distribution of the size of unit price changes due to product size changes (top) and the size of regular posted price changes (bottom)



Notes: Size in per cent.

B.2 Simultaneous product size and posted price changes

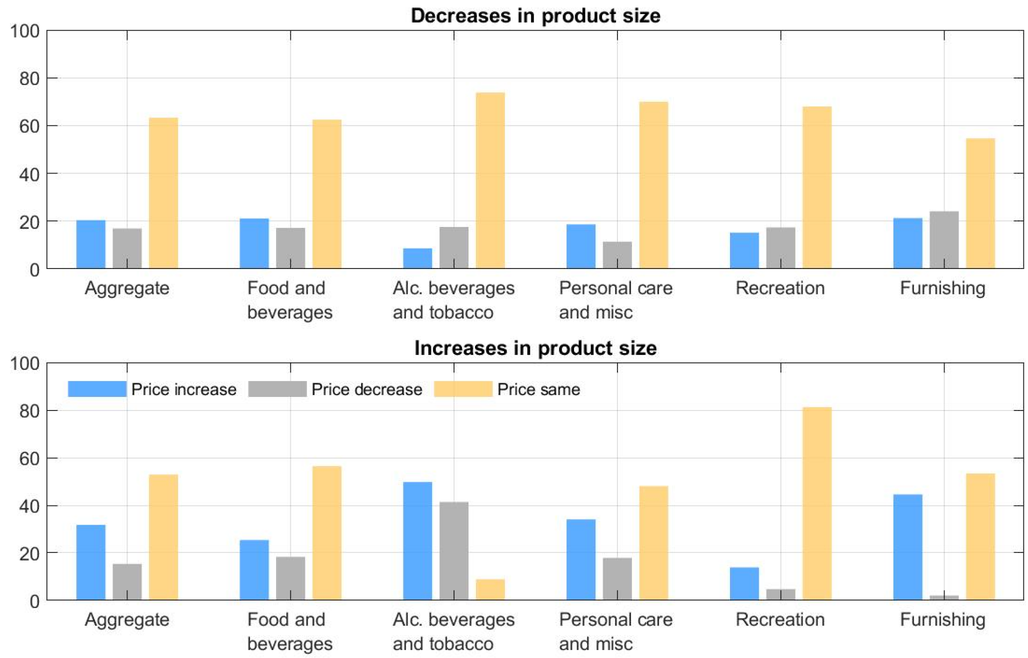
Figure B.2.1 illustrates the distribution of the posted prices for products that experience a size change in the same month. The top panel focuses on reductions in product size. Overall, the price remains constant in 65% of cases, increases in 20%, and decreases in 15%. These patterns are broadly similar across sectors, albeit with some variation. For Alcoholic beverages and tobacco, the share of constant prices is particularly high (75%), while the share of price increases is relatively low (10%). These figures are generally consistent with ONS calculations for the period 2015–2017 (Office for National Statistics (2019b)).

The bottom panel displays the distribution of posted price changes after product size hikes. Price changes are a slightly more balanced: prices remain constant in about 55% of cases, increase in 30%, and decrease in 15%. These shares, however, vary across sectors. In Alcoholic beverages and tobacco, posted prices increase in the majority of cases (53%) and remain constant in 40%.

B.3 Product size adjustment and CPI inflation

To analyze the implications of product size adjustments on aggregate inflation, I proceed as follows. First, I reverse all adjustments made by the ONS related to product size changes. Specifically, the ONS modifies a product's base price to reflect a size change, applying the new base price from the month in which the change is observed until January of the following year. Instead, I assume the product retains its original base price from the month before the size change.

Figure B.2.1: Distribution of changes in the posted price



Notes: in per cent. Monthly averages from 2012-2023. Nominal price changes are measured in the same month as the product size change occurs.

For example, suppose a product has a base price of £1 in May 2022. In June 2022, the ONS observes a 10% size reduction and reports a base price of £0.90 from June through January 2023. In my counterfactual analysis, I retain the £1 base price during that period.

Second, I calculate aggregate CPI inflation following the official ONS methodology (e.g., Office for National Statistics (2019a)), using both the public dataset and my adjusted version.

Table B.3.1 presents statistics on the impact of product size adjustments on CPI inflation. All figures report the difference between official CPI inflation with and without size changes. At the aggregate level, size adjustments raised inflation by an average of 0.03 percentage points per month during 2012-2023, with a maximum monthly effect of 0.07 and a minimum of -0.02. Most of this effect stems from size reductions, which alone contributed 0.04 points monthly on average.

The largest impact is observed in the food category, where size changes increased inflation by 0.15 points per month on average (max 0.30, min 0.02). In other COICOP2 sectors, the effects are smaller. Except for Alcoholic beverages and tobacco, the upward effect on inflation is primarily driven by product size reductions.

At a more disaggregated level, size adjustments can strongly affect item-level inflation. For example, average monthly inflation increased by 1.66 percentage points for cola-flavored drinks, 1.20 percentage points for chocolate sweets, and 1.08 percentage points for chocolate biscuits. At the peak, size reductions raised inflation by 7.77 points for cheese spread, 7.21 for cola drinks, and 7.09 for potato chips.

Conversely, size increases can lower official inflation figures. Notable examples include reductions of -1.81 points for cheese spread, -1.42 for frozen pizza, and -1.09 for a box of chocolates.

Table B.3.1: Key statistics for Δ CPI inflation with and without size adjustments from 2012-2023

	All			Decreases in size			Increases in size		
	mean	max	min	mean	max	min	mean	max	min
Aggregate	0.03	0.07	-0.02	0.04	0.08	0.01	-0.01	0.00	-0.08
					COICOP2				
Food and non-alc. beverages	0.15	0.30	0.02	0.17	0.35	0.03	-0.02	0.01	-0.05
Alc. beverages and tobacco	-0.06	0.05	-0.83	0.00	0.03	-0.01	-0.07	0.05	-0.85
Personal care, misc	0.04	0.12	-0.01	0.05	0.12	0.00	0.00	0.00	-0.01
Recreation	0.02	0.07	0.00	0.02	0.07	0.00	0.00	0.00	-0.01
Furnishing	0.01	0.04	-0.03	0.01	0.05	0.00	0.00	0.00	-0.03
					Items				
Cola flavored drink	1.66	7.21	-0.09	1.68	7.25	-0.09	-0.01	0.39	-0.36
Bag of chocolate sweets	1.20	4.99	-0.32	1.21	4.91	-0.32	-0.02	0.14	-0.17
Chocolate biscuits	1.08	6.24	-0.05	1.08	6.24	-0.05	0.00	0.00	0.00
Chocolate	0.92	6.16	0.00	0.92	6.16	0.00	0.00	0.00	0.00
Cheese spread	0.91	7.77	-1.81	1.05	7.77	-1.59	-0.15	0.09	-1.81
Canned tuna	0.64	2.53	-0.40	0.65	2.53	-0.43	0.00	0.35	-0.39
Potato chips	0.54	7.09	-0.69	0.63	7.60	0.00	-0.08	0.00	-0.69
Powdered baby formula	0.54	3.26	-0.26	0.54	3.26	-0.26	0.00	0.06	-0.09
Toilet rools	0.54	2.11	-0.01	0.54	2.11	-0.01	0.00	0.00	-0.03
Washing up liquid	0.47	2.37	-0.52	0.51	2.48	-0.04	-0.05	0.12	-0.60
Dry dog food	0.45	1.56	-0.15	0.49	1.56	-0.12	-0.04	0.08	-0.28

Notes: in percentage points. Monthly averages from 2012-2023.

To assess whether product size adjustments systematically contribute to CPI inflation over the cycle, I estimate OLS time-series regressions using the specification $y_t = \alpha + \beta x_t + X_t'\gamma + error_t$, where y_t is the difference between official CPI inflation and its counterfactual excluding size changes.

Table B.3.2 reports the results. At the aggregate level, product size changes are positively correlated with lagged CPI inflation at the 1% significance level: a one-percentage-point increase in lagged CPI inflation is associated with a 0.007 percentage-point increase in inflation due to product size changes. They are also negatively correlated with lagged PPI inflation and unemployment, although the model's explanatory power is low.

The strongest relationship is observed in the Food and non-alcoholic beverages category, where a one-percentage-point increase in lagged sectoral inflation is associated with a 0.03 percentage-point increase in inflation due to product size changes.

Unsurprisingly, the main effect stems from product size reductions and downgrades–both at the aggregate and sectoral levels. These components exhibit strong and statistically significant correlations with lagged inflation, indicating that their contribution to CPI inflation systematically rises with the inflation rate. In contrast, increases in product size and quality upgrades show no clear or significant relationship with macroeconomic variables.

There are, of course, different ways to construct a counterfactual measure of inflation that excludes product size changes. Besides the method proposed in this paper, one option is to simply drop all observations affected by size changes from the dataset. Figure B.3.1 compares the official aggregate CPI inflation with both counterfactual measures. For most of the sample, the inflation gap is smaller when affected observations are dropped (blue dashed line). The exception is around 2017, when this gap turns positive, while the difference from the adjusted base price method (black solid line) remains negative.

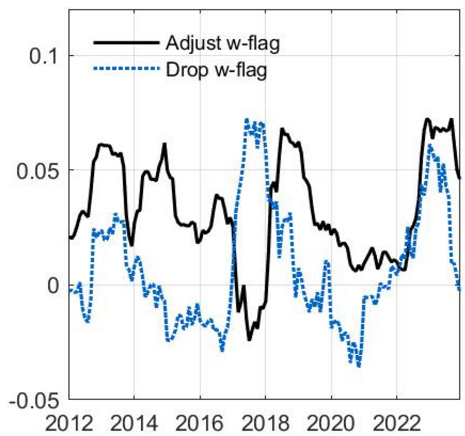
Table B.3.2: Regression results: Difference in CPI inflation with and without size adjustment

	Aggregate			Food			Alc. beverages			Restaurants			Personal care			Recreation			Furnishing			Health		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
	Dependent variable: Δ(CPI inflation - CPI infl. without product size adjustments)																							
cpi_{t-1}	0.007***			0.030***			0.000			-0.000			0.004**			0.003***			0.003***			-0.000		
	(0.001)			(0.003)			(0.004)			(0.000)			(0.002)			(0.001)			(0.001)			(0.000)		
ppi_{t-1}		-0.001***			-0.002			-0.007***			0.001***			-0.002***			-0.000			-0.001**			0.000	
		(0.000)			(0.002)			(0.003)			(0.000)			(0.001)			(0.000)			(0.000)			(0.000)	
$unempl_t$			0.006*			-0.011			0.109***			-0.001			-0.023***			-0.002			0.001			-0.002***
			(0.003)			(0.009)			(0.026)			(0.001)			(0.004)			(0.002)			(0.001)			(0.001)
Adj. R^2	0.12	0.01	-0.05	0.33	0.04	0.04	-0.11	-0.06	0.05	-0.02	0.02	-0.01	0.06	0.08	0.23	0.11	-0.01	-0.00	0.30	0.16	0.13	0.04	0.03	0.12
	Dependent variable: Δ(CPI inflation - CPI infl. without downgrades)																							
cpi_{t-1}	0.006***			0.032***			-0.000*			0.000			0.004***			0.003***			0.003***			-0.001***		
	(0.001)			(0.004)			(0.000)			(0.000)			(0.002)			(0.001)			(0.000)			(0.000)		
ppi_{t-1}		-0.001***			-0.003			0.000**			0.000***			-0.002**			-0.000			-0.000			-0.000	
		(0.000)			(0.002)			(0.000)			(0.000)			(0.001)			(0.000)			(0.000)			(0.000)	
$unempl_t$			0.000			-0.018*			-0.005***			-0.001*			-0.022***			-0.003			0.001			-0.003***
			(0.003)			(0.010)			(0.001)			(0.001)			(0.004)			(0.002)			(0.001)			(0.001)
Adj. R^2	0.18	0.04	-0.03	0.30	0.04	0.04	-0.10	-0.07	0.11	0.10	0.15	0.11	0.04	0.04	0.19	0.09	-0.03	-0.01	0.39	0.07	0.06	0.05	0.00	0.16
	Dependent variable: Δ(CPI inflation - CPI infl. without upgrades)																							
cpi_{t-1}	0.001*			-0.001*			0.000			-0.000			-0.000***			-0.000			-0.000			0.000***		
	(0.001)			(0.001)			(0.004)			(0.000)			(0.000)			(0.000)			(0.000)			(0.000)		
ppi_{t-1}		-0.000*			0.000			-0.007***			0.000**			-0.000			-0.000*			-0.000**			0.000***	
		(0.000)			(0.000)			(0.002)			(0.000)			(0.000)			(0.000)			(0.000)			(0.000)	
$unempl_t$			0.005***			0.006***			0.112***			-0.000			-0.001			0.001**			0.000			0.001***
			(0.001)			(0.002)			(0.026)			(0.001)			(0.000)			(0.000)			(0.000)			(0.000)
Adj. R^2	-0.04	-0.04	0.08	-0.01	-0.01	0.07	-0.11	-0.06	0.06	0.08	0.09	0.07	0.38	0.34	0.35	-0.03	-0.02	0.01	0.36	0.38	0.36	0.05	0.07	0.04

Notes: Sample from January 2012 to December 2023, i.e. 144 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Bootstrapped standard errors in brackets. All regressions include a constant, a linear time trend, calendar month dummies and the frequencies of nominal price increases and decreases (freq_up and freq_do).

The divergence between the two approaches arises from shifts in CPI weights. When affected observations are dropped, the relative weight of remaining items increases. Since dropped items often carry non-negligible weight, removing them can lead to notable differences compared to a method that retains weights and adjusts base prices

Figure B.3.1: Difference in CPI inflation with and without size adjustment



Notes: in per cent. Year-on-year inflation rates.

C Robustness analysis

C.1 Excluding the 2017 cigarette regulation

The large spike in product size increases in 2017 in Figure 2 is due to a one-time regulation on cigarette packaging in the U.K. (The Guardian (2017)). This section presents the frequencies of product size changes and benchmark regressions, excluding size changes from this regulation. To that end, I exclude cigarette products[22] from the 2017 sample of products that experience a change in product size.[23]

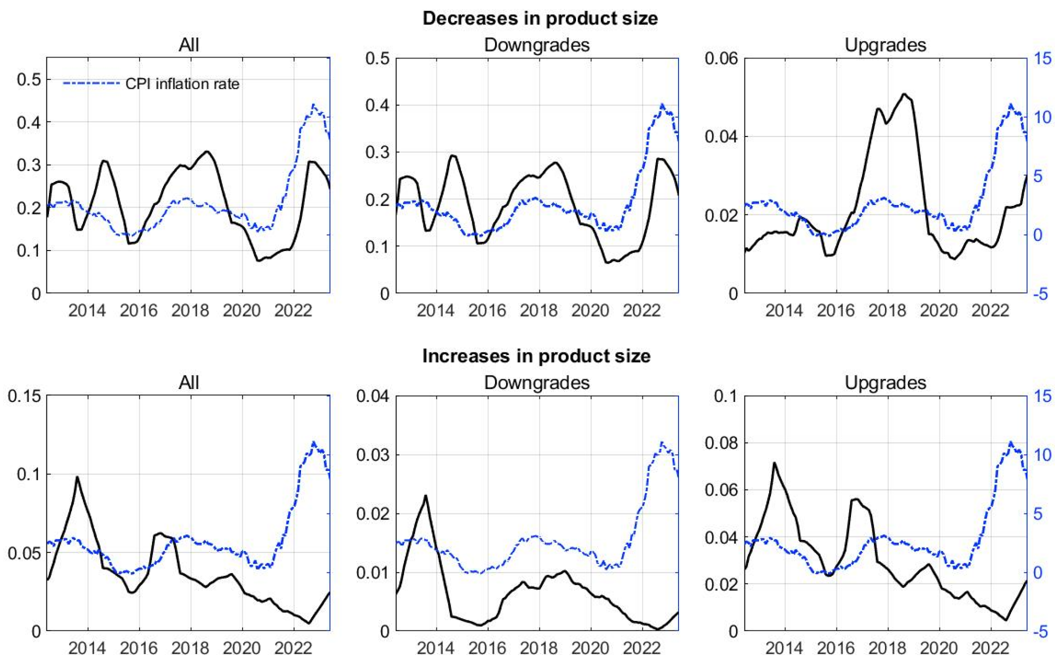
Figure C.1.1 shows the frequencies of product size increases and decreases, excluding the 2017 cigarette packaging adjustments. The time series for reductions in product size–and resulting downgrades and upgrades–remains virtually unchanged. In contrast, the spike in the frequency of product size increases in 2017 disappears. Nevertheless, the correlation between size increases–and the resulting downgrades and upgrades–and the CPI inflation rate remains less evident than the correlation observed for product size reductions.

Table C.1.1 reports regression results for the adjusted sample. The results for product size reductions–and the resulting downgrades and upgrades–remain unchanged. For size increases, the model fit improves slightly relative to the benchmark, though the regression coefficients for lagged CPI, lagged PPI, and unemployment are near zero and statistically insignificant.

[22] In the data, these products are identified by item_id = 320206.

[23] The share of product size changes for these products already increases before May 2017, likely due to anticipation effects.

Figure C.1.1: Frequency of product size changes without 2017 cigarette regulation (left axis) vs. CPI inflation (right axis)



Notes: in per cent. Black lines show 12-month moving average of fractions of decreases and increases in product size (left: all, middle: size decreases (increases) that are downgrades, right: size decreases (increases) that are upgrades). Blue dashed lines show 12-month moving average of CPI inflation rate.

Table C.1.1: Regression results excluding 2017 cigarette regulation

	Frequency of decreases in product size									Frequency of increases in product size								
	All			Downgrades			Upgrades			All			Downgrades			Upgrades		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
cpi_{t-1}	0.024***			0.022***			0.002**			0.001			0.000			0.000		
	(0.006)			(0.006)			(0.001)			(0.001)			(0.000)			(0.001)		
ppi_{t-1}		0.006***			0.005**			0.001***			-0.000			0.000			-0.000	
		(0.002)			(0.002)			(0.000)			(0.000)			(0.000)			(0.000)	
$unempl_t$			-0.061***			-0.052***			-0.009***			0.003			0.002**			0.000
			(0.013)			(0.012)			(0.002)			(0.003)			(0.001)			(0.002)
$freq\_up_t$	-0.012	-0.003	0.021***	-0.009	0.001	0.021***	-0.003**	-0.003***	0.001	-0.001	0.001	-0.001	-0.000	0.000	-0.000	-0.001	0.000	-0.000
	(0.008)	(0.007)	(0.005)	(0.007)	(0.006)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
$freq\_do_t$	-0.003	-0.006	-0.005	-0.002	-0.005	-0.005	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	0.000	0.000	-0.000	-0.001	-0.002	-0.001
	(0.010)	(0.011)	(0.010)	(0.009)	(0.010)	(0.009)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)
trend	-0.000***	-0.000**	-0.000***	-0.000***	-0.000**	-0.000***	0.000	0.000	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.194***	0.164**	0.563***	0.212***	0.181***	0.522***	-0.009	-0.008	0.048***	0.086***	0.081***	0.063***	0.016***	0.015***	0.002	0.068***	0.064***	0.064***
	(0.072)	(0.074)	(0.111)	(0.069)	(0.070)	(0.098)	(0.007)	(0.009)	(0.018)	(0.017)	(0.016)	(0.018)	(0.004)	(0.004)	(0.005)	(0.012)	(0.012)	(0.016)
Adj. R^2	0.53	0.51	0.55	0.52	0.50	0.54	0.33	0.37	0.40	0.32	0.32	0.32	0.09	0.09	0.13	0.35	0.35	0.35

Notes: Sample from January 2012 to December 2023, i.e. 144 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Bootstrapped standard errors in brackets. All regressions include a constant, a linear time trend, calendar month dummies and the frequencies of nominal price increases and decreases (freq_up and freq_do).

C.2 Alternative model specifications and independent variables

Tables C.2.1 and C.2.2 present regression results from alternative model specifications at the aggregate level. For instance, columns (1) and (2) show regressions using the contemporaneous CPI and PPI inflation rates, respectively. Columns (3) to (6) omit the frequencies of price increases and decreases as control variables. Overall, the sign and statistical significance of the coefficients remain largely consistent with the benchmark results. For product size reductions, the estimated coefficients are slightly larger in absolute value when the CPI rate and unemployment rate are included simultaneously.

Tables C.2.3 and C.2.4 present regression results using alternative independent variables. These include the one-month-lagged 12-month moving averages of the CPI and PPI inflation rates, as well as the unemployment rate. The motivation for including these variables is that implementing product size changes may take time and therefore be associated with economic developments over a longer horizon, rather than with contemporaneous or one-month-lagged observations.

In addition, I include alternative variables that capture economic slack: the business confidence index and the consumer confidence index for the UK. Both indices are published by the OECD.[24] The business confidence index is based on opinion surveys regarding developments in production, orders, and inventories of finished goods in the manufacturing sector. The consumer confidence index is derived from household surveys covering expectations about their financial situation, the general economic outlook, unemployment, and ability to save.

Using the lagged moving averages of CPI inflation, PPI inflation, and the unemployment rate leaves the benchmark results essentially unchanged. Regarding the alternative slack variables, I find a negative but relatively weak correlation between the frequency of product size reductions and changes in the business and consumer confidence indices, both significant at the 10% level. One possible explanation is that these confidence indices may not reliably reflect underlying economic slack. Indeed, I find no significant correlation between the year-on-year changes in either index and the unemployment rate.

[24] `https://www.oecd.org/en/data/indicators/consumer-confidence-index-cci.html` and `https://www.oecd.org/en/data/indicators/business-confidence-index-bci.html`

Table C.2.1: Regression results for alternative model specifications: Frequency of decreases in product size

	All						Downgrades						Upgrades					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
cpi_t	0.025***						0.024***						0.002					
	(0.007)						(0.006)						(0.001)					
ppi_t		0.003**						0.003**						0.000				
		(0.002)						(0.001)						(0.000)				
cpi_{t-1}			0.017***			0.033***			0.017***			0.030***			0.001			0.003***
			(0.004)			(0.005)			(0.004)			(0.004)			(0.000)			(0.001)
ppi_{t-1}				0.005***						0.005***						0.000		
				(0.001)						(0.001)						(0.000)		
$unempl_t$					-0.045***	-0.079***					-0.036***	-0.069***					-0.008***	-0.010***
					(0.013)	(0.014)					(0.012)	(0.013)					(0.002)	(0.002)
$freq\_up$	-0.014	0.007				-0.010	-0.011	0.008				-0.007	-0.002*	-0.001				-0.002**
	(0.009)	(0.006)				(0.007)	(0.008)	(0.005)				(0.006)	(0.001)	(0.001)				(0.001)
$freq\_down$	0.002	-0.007				0.015	0.003	-0.005				0.013	-0.001	-0.001				0.001
	(0.011)	(0.011)				(0.009)	(0.010)	(0.011)				(0.009)	(0.002)	(0.002)				(0.001)
trend	-0.000***	-0.000**	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	0.000	0.000	0.000	0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.200***	0.150**	0.190***	0.155**	0.348***	0.806***	0.220***	0.173***	0.210***	0.174***	0.311***	0.744***	-0.010	-0.012	-0.010	-0.008	0.042***	0.071***
	(0.068)	(0.066)	(0.069)	(0.066)	(0.100)	(0.117)	(0.070)	(0.066)	(0.069)	(0.062)	(0.093)	(0.112)	(0.007)	(0.008)	(0.007)	(0.008)	(0.015)	(0.019)
Adj. R^2	0.52	0.48	0.52	0.50	0.50	0.64	0.52	0.48	0.52	0.49	0.47	0.63	0.32	0.32	0.31	0.32	0.41	0.45

Notes: Sample from January 2012 to December 2023, i.e. 144 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Bootstrapped standard errors in brackets. All regressions include a constant, a linear time trend, and calendar month dummies.

Table C.2.2: Regression results for alternative model specifications: Frequency of increases in product size

	All						Downgrades						Upgrades					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
cpi_t	-0.002						-0.000						-0.002					
	(0.004)						(0.002)						(0.002)					
ppi_t		0.002**						0.001**						0.001*				
		(0.001)						(0.000)						(0.001)				
cpi_{t-1}			0.000			0.004**			0.000			0.002**			-0.000			0.002**
			(0.001)			(0.002)			(0.001)			(0.001)			(0.001)			(0.001)
ppi_{t-1}				0.002**						0.001***						0.001**		
				(0.001)						(0.000)						(0.000)		
$unempl_t$					-0.031***	-0.036***					-0.015***	-0.017***					-0.016***	-0.019***
					(0.009)	(0.010)					(0.005)	(0.005)					(0.005)	(0.005)
$freq\_up_t$	0.003	-0.003					0.001	-0.002					0.002	-0.001				
	(0.006)	(0.003)					(0.003)	(0.002)					(0.003)	(0.002)				
$freq\_do_t$	-0.009*	-0.002					-0.004*	-0.000					-0.006*	-0.002				
	(0.005)	(0.004)					(0.002)	(0.002)					(0.003)	(0.002)				
trend	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.100***	0.131***	0.099***	0.143***	0.305***	0.379***	0.024**	0.038***	0.023**	0.044***	0.122***	0.160***	0.073***	0.091***	0.073***	0.096***	0.186***	0.222***
	(0.025)	(0.030)	(0.024)	(0.030)	(0.065)	(0.079)	(0.010)	(0.012)	(0.010)	(0.012)	(0.033)	(0.042)	(0.016)	(0.017)	(0.016)	(0.018)	(0.035)	(0.041)
Adj. R^2	-0.01	0.02	-0.00	0.04	0.10	0.12	-0.08	-0.05	-0.08	-0.03	0.03	0.05	0.08	0.10	0.08	0.11	0.18	0.19

Notes: Sample from January 2012 to December 2023, i.e. 144 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Bootstrapped standard errors in brackets. All regressions include a constant, a linear time trend, and calendar month dummies.

Table C.2.3: Regression results for alternative independent variables: Frequency of decreases in product size

	All					Downgrades					Upgrades				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ma_cpi_{t-1}	0.027^{***}					0.024^{***}					0.003^{**}				
	(0.008)					(0.007)					(0.001)				
ma_ppi_{t-1}		0.005^{**}					0.004^{**}					0.001^{*}			
		(0.002)					(0.002)					(0.000)			
ma_unempl_{t-1}			-0.057^{***}					-0.048^{***}					-0.008^{***}		
			(0.013)					(0.011)					(0.002)		
$business\_conf_{t-1}$				-0.006^{**}					-0.006^{**}					-0.000	
				(0.003)					(0.003)					(0.000)	
$cons\_conf_{t-1}$					-0.006^{**}					-0.007^{**}					0.000
					(0.003)					(0.003)					(0.001)
$freq\_up$	-0.008	0.004	0.021^{***}	0.011^{**}	0.008	-0.005	0.005	0.021^{***}	0.012^{**}	0.009^{*}	-0.003^{**}	-0.002^{*}	0.001	-0.001	-0.001
	(0.007)	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$freq\_down$	-0.005	-0.006	-0.008	-0.022^{**}	-0.017	-0.004	-0.005	-0.007	-0.019^{**}	-0.016	-0.001	-0.001	-0.001	-0.002^{*}	-0.002
	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
trend	-0.000^{***}	-0.000^{**}	-0.000^{***}	-0.000^{*}	-0.000^{*}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{**}	-0.000^{**}	0.000	0.000	-0.000^{**}	0.000^{**}	0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.201^{***}	0.165^{**}	0.547^{***}	0.118^{*}	0.123^{*}	0.217^{***}	0.184^{***}	0.508^{***}	0.143^{**}	0.148^{**}	-0.008	-0.009	0.048^{**}	-0.016^{**}	-0.016^{**}
	(0.075)	(0.069)	(0.117)	(0.066)	(0.067)	(0.072)	(0.067)	(0.102)	(0.063)	(0.061)	(0.007)	(0.009)	(0.021)	(0.007)	(0.008)
Adj. R^2	0.52	0.49	0.54	0.49	0.48	0.51	0.48	0.52	0.48	0.48	0.33	0.33	0.39	0.31	0.31

Notes: Sample from January 2012 to December 2023, i.e. 144 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. "ma_cpi_{t-1}: lagged 12-months moving average of CPI rate, "ma_ppi_{t-1}: lagged 12-months moving average of PPI rate, "ma_unempl_{t-1}: lagged 12-months moving average of unemployment rate, "$retail\ sales_{t-1}$: lagged year-on-year change in retail sales index, "$business\ conf_{t-1}$: lagged year-on-year change in business confidence index. "$cons\ conf_{t-1}$: lagged year-on-year change in consumer confidence index; Bootstrapped standard errors in brackets. All regressions include a constant, a linear time trend, and calendar month dummies.

Table C.2.4: Regression results for alternative independent variables: Frequency of increases in product size

	All					Downgrades					Upgrades				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ma_cpi_{t-1}	-0.004					-0.002					-0.003				
	(0.005)					(0.002)					(0.003)				
ma_ppi_{t-1}		0.004**					0.002***					0.002*			
		(0.002)					(0.001)					(0.001)			
ma_unempl_{t-1}			-0.037***					-0.018***					-0.020***		
			(0.011)					(0.005)					(0.005)		
$business\_conf_{t-1}$				0.004**					0.002**					0.002**	
				(0.002)					(0.001)					(0.001)	
$cons\_conf_{t-1}$					-0.001					-0.001					-0.000
					(0.002)					(0.001)					(0.001)
$freq\_up$	0.004	-0.006	0.007**	0.002	0.000	0.002	-0.003	0.003**	0.001	-0.000	0.002	-0.002	0.003**	0.001	0.000
	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
$freq\_down$	-0.009**	-0.001	-0.003	-0.004	-0.008*	-0.004**	0.001	-0.001	-0.002	-0.004*	-0.005**	-0.001	-0.002	-0.002	-0.004*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
trend	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000*	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
constant	0.093***	0.144***	0.392***	0.103***	0.108***	0.020*	0.047***	0.165***	0.024**	0.027***	0.071***	0.095***	0.230***	0.077***	0.079***
	(0.026)	(0.033)	(0.090)	(0.026)	(0.026)	(0.010)	(0.014)	(0.044)	(0.011)	(0.010)	(0.016)	(0.019)	(0.044)	(0.016)	(0.015)
Adj. R^2	-0.00	0.04	0.12	0.02	-0.01	-0.08	-0.02	0.05	-0.06	-0.08	0.08	0.10	0.19	0.11	0.08

Notes: Sample from January 2012 to December 2023, i.e. 144 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. "ma_cpi_{t-1}: lagged 12-months moving average of CPI rate, "ma_ppi_{t-1}: lagged 12-months moving average of PPI rate, "ma_unempl_{t-1}: lagged 12-months moving average of unemployment rate, "$retail\ sales_{t-1}$: lagged year-on-year change in retail sales index, "$business\ conf_{t-1}$: lagged year-on-year change in business confidence index. "$cons\ conf_{t-1}$: lagged year-on-year change in consumer confidence index; Bootstrapped standard errors in brackets. All regressions include a constant, a linear time trend, and calendar month dummies.

C.3 Sectoral-level regressions

Table C.3.1 presents regression results for the baseline OLS model at the sectoral level (COICOP2 level). The findings indicate that the aggregate results are primarily driven by dynamics in the Food sector. Specifically, reductions in product size – both all reductions and downgrades – exhibit a strong procyclical behavior in the Food sector. In contrast, they do not show a systematic business cycle pattern in the other sectors. For example, reductions are positively correlated only with lagged CPI in the Recreation and Furnishing sectors, and negatively correlated only with unemployment in the Personal Care and Health sectors.

Table C.3.1: Regression results: COICOP2-level

	Food			Alc. beverages			Restaurants			Personal care			Recreation			Furnishing			Health		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Dependent variable: Frequency of product size decreases																					
cpi_{t-1}	0.083***			-0.001			0.000			0.011			0.012***			0.013***			-0.002**		
	(0.026)			(0.002)			(0.001)			(0.010)			(0.005)			(0.002)			(0.001)		
ppi_{t-1}		0.028***			0.001*			0.000			-0.000			-0.005***			-0.000			-0.000	
		(0.007)			(0.001)			(0.000)			(0.003)			(0.001)			(0.001)			(0.000)	
$unempl_t$			-0.261***			-0.007			0.002			-0.113***			0.005			0.001			-0.006***
			(0.056)			(0.005)			(0.002)			(0.019)			(0.009)			(0.004)			(0.001)
Adj. R^2	0.41	0.41	0.45	0.04	0.06	0.05	0.34	0.34	0.34	0.25	0.24	0.40	0.14	0.18	0.06	0.57	0.39	0.39	0.03	-0.01	0.10
Dependent variable: Frequency of product size increases																					
cpi_{t-1}	-0.003			-0.035			0.007**			-0.001			0.002**			-0.000			-0.001***		
	(0.004)			(0.040)			(0.003)			(0.001)			(0.001)			(0.001)			(0.000)		
ppi_{t-1}		-0.000			0.039***			-0.001			-0.000			-0.001			-0.001***			-0.000***	
		(0.001)			(0.013)			(0.001)			(0.000)			(0.000)			(0.000)			(0.000)	
unempl			-0.014*			-0.462***			0.029***			-0.006***			0.000			0.003**			-0.002***
			(0.007)			(0.112)			(0.008)			(0.002)			(0.002)			(0.001)			(0.001)
Adj. R^2	0.29	0.29	0.30	-0.10	-0.04	0.08	0.16	0.14	0.22	0.07	0.07	0.14	0.03	0.02	-0.01	0.09	0.16	0.12	0.05	0.09	0.05
Dependent variable: Frequency of downgrades from product size decreases																					
cpi_{t-1}	0.077***			-0.002			0.000			0.011			0.013***			0.009***			-0.002**		
	(0.024)			(0.002)			(0.001)			(0.010)			(0.005)			(0.002)			(0.001)		
ppi_{t-1}		0.025***			0.001**			-0.000			-0.000			-0.005***			-0.000			-0.000	
		(0.007)			(0.001)			(0.000)			(0.003)			(0.001)			(0.001)			(0.000)	
unempl			-0.210***			-0.010**			0.001			-0.105***			0.005			-0.001			-0.005***
			(0.054)			(0.005)			(0.002)			(0.018)			(0.009)			(0.003)			(0.001)
Adj. R^2	0.40	0.41	0.43	0.03	0.06	0.06	0.29	0.29	0.29	0.24	0.23	0.38	0.13	0.20	0.05	0.54	0.39	0.39	0.03	-0.00	0.11

Dependent variable: Frequency of downgrades from product size increases																					
cpi_{t-1}	0.001			-0.012			0.001*			-0.000			0.001***			-0.000			-0.000**		
	(0.001)			(0.019)			(0.000)			(0.001)			(0.000)			(0.000)			(0.000)		
ppi_{t-1}		-0.000			0.018***			0.000			0.000*			-0.000***			-0.000			-0.000***	
		(0.000)			(0.006)			(0.000)			(0.000)			(0.000)			(0.000)			(0.000)	
unempl			0.007**			-0.225***			0.003***			-0.005***			0.000			0.000**			-0.001**
			(0.003)			(0.056)			(0.001)			(0.001)			(0.001)			(0.000)			(0.000)
Adj. R^2	0.07	0.07	0.13	-0.10	-0.05	0.07	0.09	0.06	0.17	-0.03	-0.01	0.12	0.12	0.13	0.06	-0.07	-0.06	-0.04	0.01	0.07	0.02
Dependent variable: Frequency of upgrades from product size decreases																					
cpi_{t-1}	0.006			0.001**			-0.000			0.000			-0.000			0.004***			-0.000		
	(0.004)			(0.000)			(0.000)			(0.001)			(0.001)			(0.001)			(0.000)		
ppi_{t-1}		0.003**			-0.000			0.000**			0.000			0.001***			0.000			0.000	
		(0.002)			(0.000)			(0.000)			(0.000)			(0.000)			(0.000)			(0.000)	
unempl			-0.049***			0.004***			0.000			-0.007***			-0.001			0.003**			-0.000*
			(0.009)			(0.001)			(0.001)			(0.002)			(0.001)			(0.001)			(0.000)
Adj. R^2	0.22	0.24	0.35	0.09	0.07	0.21	0.06	0.08	0.07	0.11	0.11	0.20	0.09	0.13	0.08	0.43	0.21	0.23	-0.03	-0.04	-0.01
Dependent variable: Frequency of upgrades from product size increases																					
cpi_{t-1}	-0.004			-0.024			0.006**			-0.001			0.001			-0.000			-0.001***		
	(0.004)			(0.023)			(0.003)			(0.001)			(0.001)			(0.001)			(0.000)		
ppi_{t-1}		-0.000			0.021***			-0.001			-0.000*			-0.000			-0.001***			-0.000***	
		(0.001)			(0.007)			(0.001)			(0.000)			(0.000)			(0.000)			(0.000)	
unempl			-0.022***			-0.240***			0.025***			-0.001			-0.000			0.003**			-0.002***
			(0.006)			(0.059)			(0.007)			(0.001)			(0.002)			(0.001)			(0.001)
Adj. R^2	0.29	0.28	0.33	-0.09	-0.03	0.08	0.16	0.14	0.22	0.12	0.14	0.11	0.01	0.00	-0.00	0.10	0.18	0.13	0.06	0.09	0.07

Notes: Sample from January 2012 to December 2023, i.e. 143 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant, a linear time trend, calendar month dummies and the frequencies of nominal price increases and decreases.

C.4 Alternative standard errors

Table C.4.1 reports the OLS estimates and alternative standard errors for the baseline OLS model. In addition to the OLS standard errors, the table provides results for robust standard errors, bootstrapped standard errors and Newey West standard errors. To account for possible serial correlation and/or heteroskedasticity in the residuals, the Newey-West standard errors allow for a maximum autocorrelation of four lags.

To account for potential small property problems, especially in the smaller sample from 2009-2022, I compute bootstrapped standard errors. This involves the following steps: (i) draw 5,000 independent samples (with replacement) from the whole sample; (ii) estimate the standard errors for each bootstrap sample; (iii) compute the average standard errors across all 5,000 samples.

Table C.4.1: Alternative standard errors

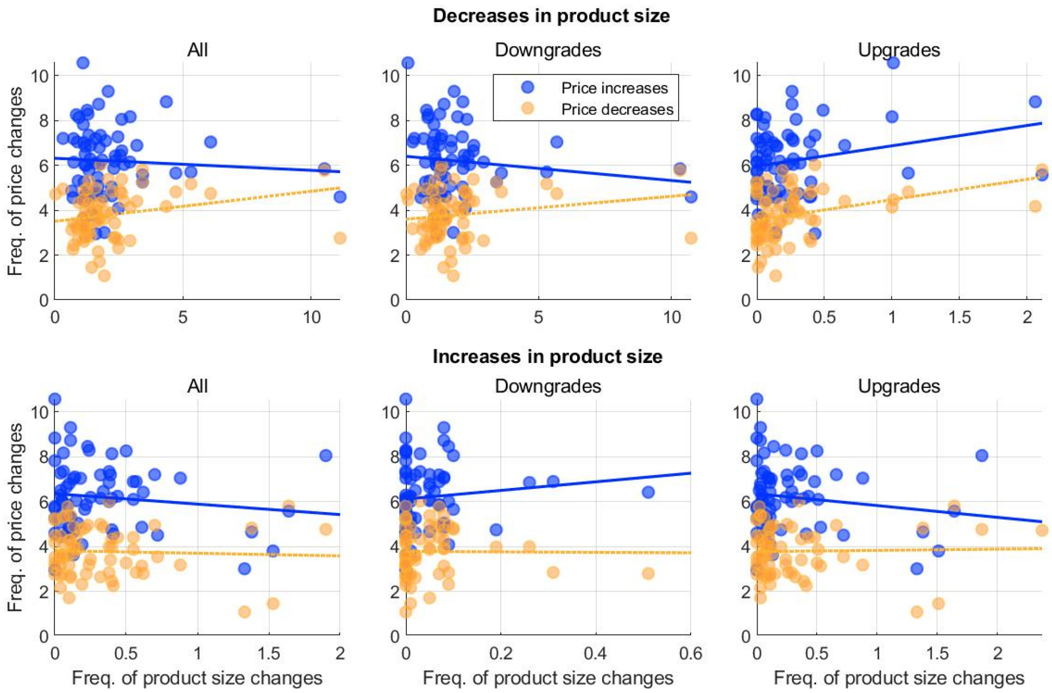
	Frequency of product size decreases					**Frequency of product size increases**				
		Standard errors					Standard errors			
	OLS estimate	OLS	Robust	BS	NW	OLS estimate	OLS	Robust	BS	NW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
All										
cpi_{t-1}	0.025	0.007***	0.007***	0.007***	0.008***	0.007	0.005	0.004**	0.004*	0.004
ppi_{t-1}	0.007	0.002***	0.002***	0.003***	0.003**	0.001	0.002	0.001	0.001	0.002
unempl	-0.064	0.013***	0.014***	0.014***	0.022***	-0.037	0.009***	0.010***	0.010***	0.021*
Downgrades										
cpi_{t-1}	0.023	0.006***	0.006***	0.006***	0.007***	0.000	0.002	0.002	0.002	0.002
ppi_{t-1}	0.006	0.002**	0.002**	0.002**	0.003*	0.002	0.001**	0.001***	0.001***	0.001
unempl	-0.053	0.012***	0.013***	0.012***	0.020***	-0.017	0.004***	0.005***	0.005***	0.010*
Upgrades										
cpi_{t-1}	0.002	0.001**	0.001**	0.001**	0.001**	-0.002	0.003	0.002	0.003	0.003
ppi_{t-1}	0.001	0.000***	0.000***	0.000***	0.000***	0.003	0.001***	0.001***	0.001***	0.002*
unempl	-0.011	0.002***	0.002***	0.002***	0.003***	-0.020	0.005***	0.006***	0.006***	0.011*

Notes: Aggregate level data, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, NW: Newey-West, BS: Bootstrapped

C.5 Price adjustment vs. product size adjustment

This section explores the relationship between price and product size adjustments for individual goods in the CPI. Figure C.5.1 plots the frequencies of product size decreases and increases against the frequencies of posted price increases (blue dots) and decreases (yellow dots) for individual products. The top panels focus on decreases in product size. It is difficult to discern clear patterns in the two sets of dots; neither price increases nor price decreases appear to be systematically related to the frequency of product size reductions. In fact, the linear trend lines are essentially flat or driven by a few large values. The same applies to downgrades from product size reductions. Regarding upgrades from size reductions, there appears to be some positive correlation, although this may again be driven by outliers. The bottom panels show scatter plots for increases in product size. Once more, no clear patterns emerge between product size increases and either price increases or decreases.

Figure C.5.1: Item-level: frequency of product size changes vs. frequency of posted price changes



Notes: in per cent. Monthly averages from 2012-2023

Table C.5.1 shows the results of a regression analysis based on the following specification: $y_t = \alpha + \beta_1 x_t + \beta_2 x_t^2 + error_t$, where y_t denotes the frequency of product size decreases, increases, downgrades, or upgrades in month t, and x_t is the frequency of price increases or decreases.

The analysis reveals no clear relationship between the frequencies of product size and price adjustments. Most coefficients are statistically insignificant, and the adjusted R-squared values are small or even negative. Only the frequency of product size increases is negatively correlated with the frequency of price cuts at the 5% significance level, but the overall model fit is weak.

Table C.5.1: Regression results

	Frequency of decreases in product size						Frequency of increases in product size					
	All		Downgrades		Upgrades		All		Downgrades		Upgrades	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
freq_up	0.606		0.866		-0.283		-0.131		0.063^{*}		-0.193	
	(0.687)		(0.634)		(0.197)		(0.278)		(0.034)		(0.285)	
freq_up^2	-0.054		-0.080^{*}		0.027		0.008		-0.005^{*}		0.012	
	(0.054)		(0.047)		(0.018)		(0.021)		(0.003)		(0.021)	
freq_do		-1.605		-1.630		-0.015		-0.790^{**}		0.032		-0.813^{**}
		(1.249)		(1.282)		(0.294)		(0.372)		(0.033)		(0.397)
freq_do^2		0.273		0.260		0.019		0.104^{**}		-0.004		0.107^{**}
		(0.185)		(0.191)		(0.043)		(0.049)		(0.004)		(0.052)
Constant	0.585	3.995^{*}	-0.243	4.014^{*}	0.910^{*}	0.023	0.831	1.706^{**}	-0.163	-0.007	0.988	1.694^{**}
	(2.160)	(2.078)	(2.133)	(2.109)	(0.522)	(0.463)	(0.918)	(0.683)	(0.101)	(0.064)	(0.938)	(0.736)
Adj. R^2	-0.02	0.08	0.01	0.05	0.08	0.10	-0.01	0.11	0.01	-0.03	-0.00	0.12

Notes: N = 67. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Bootstrapped standard errors in brackets.

C.6 Properties of C-flag

The ”indicator_box” variable in the ONS data also reports product replacements using the letter ”C”. This C-flag indicates that a product has been replaced with a comparable one in a given month. Unlike product size changes (W-flag), these replacements may involve substitutions with similar items that differ not only in packaging or size but also in other characteristics, such as the brand. Replacements can occur for various reasons, such as the original product being out of stock or either temporarily or permanently removed from the assortment. Product replacements are substantially more common than product size changes in the U.K., averaging around 5% per month from 2012 to 2023. Their prevalence is consistent with evidence from other countries (e.g., Nakamura and Steinsson (2008)).