Temporary Sales and Cyclicality*

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Abstract

This paper provides novel evidence from U.K. CPI microdata from 1996–2023 on the role of temporary markdowns (”sales”) for aggregate price flexibility. Sales are used as a tool to adjust *regular prices*: (i) Around 45% of sales occur immediately before or after a regular price increase or decrease, seemingly to divert attention from regular price hikes or to stimulate demand when regular prices are reduced. (ii) These ”strategic sales” are strongly *countercyclical*, while all other sales are acyclical. (iii) Sales-related regular price increases (decreases) account for 9% (11%) of all regular increases (decreases) and are 1 percentage point (0.6 percentage points) larger in absolute size. (iv) Lastly, sales-related price hikes (cuts) tend to flatten (steepen) the slope of the aggregate Phillips curve.

Keywords: Aggregate price dynamics, temporary sales, price stickiness, inflation
JEL-Codes: E31, E32, E52, E71, L11, M37

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1 Introduction

Temporary markdowns, or "sales," are arguably the most visible and pervasive source of nominal consumer price fluctuations. A typical sale involves a large but temporary price reduction. Macroeconomists have long debated the role of sales for aggregate price adjustment in response to aggregate shocks. Yet, the question remains unresolved. Some studies argue that sales are special events that can be disregarded by macroeconomists.[1] Conversely, others find that sales are an important margin for temporary price reductions over the business cycle.[2] This paper provides new evidence on the macroeconomic relevance of sales from U.K. consumer micro-price data. The evidence offers a consistent answer to the debate, reconciling the opposing views in the literature.

The starting point of the paper is the idea that firms offer sales for various reasons – some of which may be relevant over the cycle, while others are not. To investigate this, I use the publicly available microdata underlying the Consumer Price Index (CPI) from the Office for National Statistics (ONS). The sample contains monthly price quotes for a wide range of consumer goods and services from 1996 to 2023. It also features a "sales flag," which enables the identification of sales periods for individual items in the data.

The data reveal an interesting stylized fact about sales: around 45% of sales occur immediately before or right after a change in the regular price. For example, suppose a product is temporarily offered at a discount during a sale. After the sale ends, the price does not return to its pre-sale level but instead adjusts to a new, higher (or lower) level than before. Similarly, there are cases where the regular price of a product increases (or decreases) first, followed by a sales offer in the subsequent month. Anecdotal evidence from the media suggests a *strategic* motive behind this close timing between sales and regular price changes.[3] Firms may use sales to divert attention from regular price hikes or to stimulate demand when regular prices are lowered.

Against this background, I analyze the macroeconomic relevance of different types of sales by decomposing aggregate sales in the data into three major groups. The first group consists of sales where a regular price change – either an increase or decrease – is observed immediately in the month before or after the sale, as described earlier. In line with the anecdotal evidence, I refer to these sales as *strategic sales*. The second group includes sales where the regular price reverts exactly to its pre-sale level, with no regular price change observed prior to the sale. These are referred to as v-sales, as the price trajectory resembles the letter "V." V-sales account for 55% of all sales from 1996 to 2023. Lastly, the third group consists of sales that cannot be categorized into either group,[4] referred to as "other sales." Their share is negligible, making up less than 1%.

The data show significant variation in the incidence of the different sales types over time. Specifically, I find that the frequency of strategic sales is strongly *countercyclical*: a 1-percentage-point rise in the unemployment rate is associated with a 0.140-percentage-point (0.107-percentage-point)

[1] For example, Nakamura and Steinsson (2008), Kehoe and Midrigan (2015), or Anderson et al. (2017).

[2] For example, Kryvtsov and Vincent (2021), or Eden et al. (2021).

[3] See e.g., The Washington Post (2023), CBS News (2023), The Wallstreet Journal (2023), or Wired (2024).

[4] In particular, this applies to products where the first or the last observation of the time series is a sale.

increase in the fraction of strategic sales linked to regular price increases (decreases). Strategic sales closely follow fluctuations in the unemployment rate, peaking during economic downturns such as the Great Recession and the Covid-19 pandemic. In contrast, v-sales and other sales are mostly acyclical, showing no significant relationship with unemployment over the sample period.[5]

Unlike the frequency of sales, the average size of strategic sales is less volatile and generally acyclical. For v-sales, there is a mild positive correlation between the average absolute size and the unemployment rate, suggesting that they tend to be larger during periods of higher unemployment. Meanwhile, the duration of sales remains remarkably stable across all sales types throughout the sample period.

At the aggregate level, I find that sales generally display countercyclical behavior, with a 1-percentage-point increase in the unemployment rate linked to a 0.266-percentage-point rise in aggregate sales. However, this correlation has weakened in recent years. From around 2010 to 2020, the comovement between aggregate sales and the unemployment rate has significantly diminished, primarily due to an increase in v-sales during this period.

What do these findings imply for the macroeconomic relevance of sales? Previous research has mostly viewed sales as a tool for firms to temporarily lower prices, suggesting they might serve as a substitute for regular price cuts in response to aggregate shocks. However, the evidence in this paper points to a different role. I find that *only* strategic sales – linked to increases or decreases in regular prices – consistently respond to changes in economic conditions. This indicates a close connection between sales and regular price adjustments. Rather than serving as a separate margin for price changes, sales appear to be a tool to implement regular price adjustments.

Why would retailers use this tactic? The marketing literature suggests that sales can significantly shape consumers' perceptions of prices and influence their expectations of regular prices.[6] A plausible explanation is that retailers employ this strategy more frequently during economic downturns, when consumer demand is generally more elastic. This is particularly evident for sales associated with increases in regular prices. The countercyclical nature of these sales suggests that firms systematically use sales when raising regular prices during recessions.

That said, to understand the impact of sales on aggregate pricing, it is important to consider both the direct effects of sales and the regular price changes associated with them. I begin by calculating the share of sales-related regular price changes. This share is quite substantial: sales-related regular price increases (decreases) accounted for about 6% (8%) of all regular price hikes (cuts) until the mid-2000s and have since risen to around 12% (14%). Moreover, sales-related regular price changes tend to be larger in absolute terms compared to their non-sales-related counterparts, significantly affecting the aggregate size of regular price adjustments. For instance, from 1996 to 2010, sales-related price hikes increased the aggregate mean by approximately 0.7 percentage points, and from 2010 to 2021, by as much as 1.2 percentage points. Similarly, sales-related price

[5] The patterns for strategic sales and v-sales are highly robust across various model specifications, alternative standard errors, and at a more disaggregated level, including different sectors and retailer types.

[6] For example, Lichtenstein et al. (1993), Grewal et al. (1998), Pedrajaiglesias and Guillén (2000), and Villas-Boas and Villas-Boas (2008).

cuts consistently raised the aggregate absolute mean by around 0.6 percentage points throughout the entire sample period.

Next, I analyze the contribution to aggregate inflation by decomposing monthly inflation into its regular price change component and sales component. Most of the variation in inflation is driven by non-sales-related regular price increases and decreases. Monthly inflation from these price increases averages around 1% until 2020, rising to 1.6% thereafter. Inflation from non-sales-related price cuts is around -0.8% for most of the sample period, briefly dropping to -1.5% during the COVID-19 pandemic. Sales-related regular price changes contribute a smaller, yet still significant, portion to aggregate inflation. Inflation from sales-related regular price increases (decreases) is around 0.1% (-0.11%) until 2010, rising to 0.18% (-0.17%) afterward. Sales themselves, however, have little direct impact on inflation: price decreases at the start of the sales period and price increases at the end tend to cancel each other out, consistent with evidence from other studies.[7]

Finally, I examine how sales-related price adjustment affect the slope of the aggregate Phillips curve. The Phillips curve illustrates the inverse relationship between inflation and economic activity: in a booming economy with low unemployment, firms raise wages to attract workers, leading to higher prices as they pass on increased costs. The slope of the Phillips curve represents the extent to which inflation responds to changes in the unemployment rate.

To analyze the impact of sales on the Phillips curve, I estimate the relationship between unemployment and the *difference* between aggregate inflation and an inflation measure that excludes sales-related regular price changes. The estimated coefficients effectively capture the *difference* in the slopes of two Phillips curves – one for aggregate inflation and one for inflation excluding sales-related price changes.[8]

I find that these relative slopes are non-zero and significant at the 1% level, indicating that sales-related price adjustments do impact the Phillips curve. Moreover, the sign of the coefficient is negative when excluding sales-related price increases and positive when excluding sales-related decreases. The negative coefficient suggests that the aggregate Phillips curve would be steeper in the absence of sales-related price increases. This aligns with earlier findings: the countercyclical nature of sales linked to regular price increases – and, consequently, sales-related price hikes – partly offsets the negative relationship between inflation and unemployment at the aggregate level. Conversely, the positive coefficient for sales-related price cuts indicates that these adjustments contribute to a steeper aggregate Phillips curve. Here, the countercyclical behavior of strategic sales and sales-related regular price cuts is consistent with the overall behavior of regular price decreases over the cycle.

In sum, the findings emphasize that sales and regular prices cannot be viewed in isolation; rather, certain types of sales play a crucial role for regular price adjustments over the business cycle. This insight helps clarify some of the conflicting results in the literature. For instance, Kryvtsov and Vincent (2021) find a positive relationship between the frequency of aggregate sales

[7] For example, Chevalier and Kashyap (2019) and Guimaraes and Sheedy (2011).

[8] Under certain assumptions, estimating these relative slopes avoids common issues associated with the estimation of the Phillips curve. For a summary of these issues, see, for example, Furlanetto and Lepetit (2024).

and the unemployment rate for the U.S. and the U.K. in a sample from 1996 to 2013. They interpret their findings using a theoretical model, suggesting that cyclical sales emerge as a strategy for firms to temporarily lower prices and attract bargain hunters. My analysis, using a sample from 1996 to 2023, generally confirms the main empirical results in Kryvtsov and Vincent (2021), but also shows that the correlation between aggregate sales and unemployment has weakened over the last 15 years due to an increase in acyclical v-sales.

Anderson et al. (2017) analyze U.S. grocery and general merchandise microdata from 2006 to 2009 and find that sales are generally unresponsive to identified wholesale and commodity cost shocks. However, they observe that sales sometimes increase temporarily with rising production costs, suggesting that retailers use sales to mask regular price increases. I also examine the relationship between sales and producer prices. Unlike Anderson et al. (2017), I focus on unconditional correlations but reach similar conclusions: the frequency of strategic sales linked to regular price increases is positively correlated with PPI inflation, while other sales types show no correlation with changes in producer prices.

Using scanner data from U.S. grocery stores, Coibion and Gorodnichenko (2015) find that temporary discounts for grocery products are acyclical and do not significantly impact the effective prices paid by consumers. My robustness analysis provides a potential explanation for this result: I find that most sales in the household nondurable goods sector are acyclical v-sales. In contrast, strategic sales in this sector exhibit a clear countercyclical pattern.

Overall, this paper offers a new perspective on the longstanding question in the literature of whether "regular" and "sales" prices should be treated differently (e.g., Nakamura and Steinsson, 2008; Klenow and Kryvtsov, 2008; Kehoe and Midrigan, 2015; Eichenbaum et al., 2011). A consistent conclusion is that sales act as complements to regular price changes, making sales an integral part of firms' price-setting behavior. These sales-related regular price adjustments matter at the aggregate level, affecting overall pricing and inflation dynamics. However, sales themselves have a negligible effect on inflation. Thus, sales may have limited impact on macro-level dynamics, but they play an important role in firms' pricing strategies at the micro level.

A limitation of the findings is the potential influence of sales regulations and other institutional factors. For instance, Berardi et al. (2015) find limited business cycle variation in sales using French CPI microdata, which they attribute to regulations on sales and promotions in EU member states (European Commission, 2021). Additionally, temporary sale decisions are often negotiated between wholesalers and retailers. Typically, both parties agree in advance on specific sale periods and the cost-sharing arrangement (Aguirregabiria, 1999). Anderson et al. (2017) provide further institutional evidence, showing that sales frequently involve complex contingent contracts established well in advance.

The remainder of the paper is organized as follows. Section 2 provides an overview of the U.K. CPI micro price dataset and outlines the methodology for the decomposition into sales types. Section 3 presents the main findings of the paper, including basic sales statistics and an analysis of their business cycle behavior. Section 4 explores the implications of strategic sales for aggregate price and inflation dynamics. Section 5 presents a detailed robustness analysis. Finally, Section 6 concludes.

2 Data and definitions: ONS price microdata

The section provides an overview of the ONS data and describes how different types of sales are identified in the data.

2.1 The ONS price quote data

This paper presents evidence from the public monthly price micro dataset underlying the Consumer Price Index (CPI) for the United Kingdom, provided by the Office for National Statistics (ONS).[9] To construct the CPI, the ONS surveys the prices of goods and services included in the household final consumption expenditure of the U.K. national accounts. Each month, ONS staff collects prices for over 1,000 individual goods and services through telephone inquiries or store visits to more than 14,000 retail stores across the U.K. The same goods and services are surveyed continuously over months or years until they are either replaced or removed from the sample, reflecting changes in the representative household's consumption basket. This panel structure of the data enables tracking the price evolution of individual items over time.

The public dataset covers approximately two-thirds of the total CPI by weight.[10] Goods and services in the CPI are categorized into COICOP (Classification of Individual Consumption by Consumption Purpose) categories such as "Food", "Clothing", or "Transportation." Each category is further divided into groups like "Bread" or "Garment", and then into more specific "items" like "large loaf, white, sliced (800g) bread" or "T-Shirt for men."[11] For each item and stratum (given by the region and shop type pairing), the ONS provides sampling weights reflecting its relative importance in the households' consumption expenditures. These weights are updated annually to reflect changes in consumption patterns. For more details on the ONS data, refer to Appendix A.

2.2 Definition of sales

The ONS defines a sale as either (i) a temporary price reduction expected to revert to its regular price or (ii) an end-of-season discount (ONS, 2019). The ONS data includes a "sales flag," represented by the "indicator_box" variable. This variable is marked with "S" if an item is on sale in a specific month and with "R" for "recovery price" when the sale has concluded.

In this paper, I will use the ONS sales flag to identify sales in the data. The literature has employed various methods to identify sales in price microdata. For example, Nakamura and Steinsson

[9] `https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/consumerpriceindicescpiandretailpricesindexrpiitemindicesandpricequotes`. This link provides the latest year's data, while historical data can be accessed through their online archives.

[10] The public data does not include nationally determined prices (i.e., administrative prices) and housing costs like mortgage interest payments or housing-related insurance.

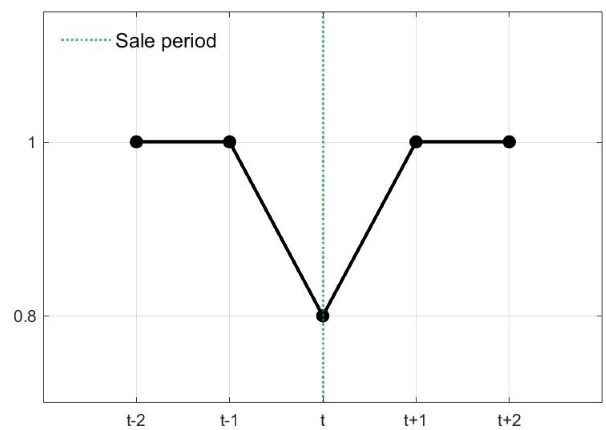
[11] Note that an item refers to a specific expenditure item or product, but not to a brand.

(2008) define a sale episode in U.S. CPI microdata as a period that begins with a price drop and ends with a price increase within a three-month window, a method they refer to as a "v-shaped" sales filter. Alternatively, Eichenbaum et al. (2011) suggest identifying sales periods based on deviations from a reference price, calculated as the modal price within a specific time window. Kryvtsov and Vincent (2021) find that different sales filters yield similar results, particularly for sales of at least 10%.

Using the panel structure of the data, I identify four types of sales based on the following criteria:

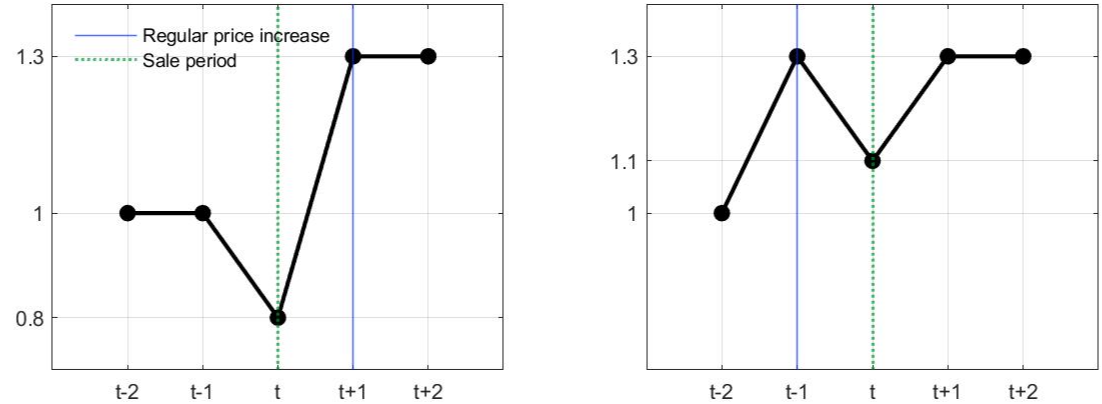
1. **v-sales** (or common sales): These are sales where (i) the sales flag indicates a sales incidence, and (ii) the price reverts exactly to its pre-sale level. There are no changes in the regular price in the month before or after the sale episode. Figure 1 illustrates an example: The price is 1 before and after the sale in period t. During the sale in t, the price temporarily drops from 1 to 0.8, and then returns to 1 in $t+1$, resembling the shape of the letter "V".

Figure 1: Price trajectory of v-sale



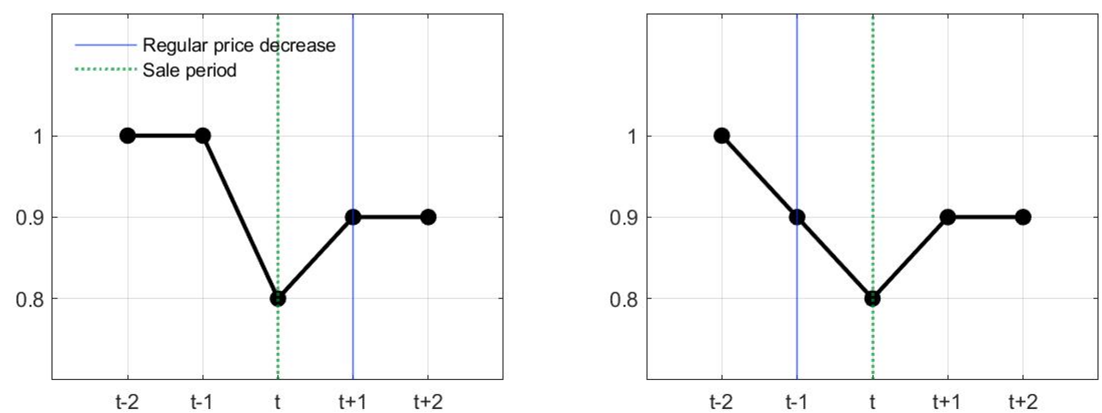
2. **Sales linked to regular price increase**: These are sales where (i) the sales flag indicates a sales incidence and (ii) an increase in the regular price is observed in the month before or after the sales period. Figure 2 illustrates an example: In the first panel, the price drops from 1 to 0.8 during the sale in t but then permanently increases to 1.3 after the sale in $t+1$. Alternatively, in the second panel, the regular price first increases from 1 to 1.3 in $t-1$ right before the sale, and reverts back to 1.3 after the sale in $t+1$.

Figure 2: Sales linked to reg. price increase after (left) and before (right)



3. **Sales linked to regular price decrease**: These are sales where (i) the sales flag indicates a sales incidence and (ii) a decrease in the regular price is observed in the month before or after the sales period. For example, in the left panel of Figure 3, the price drops from 1 to 0.8 during the sale in t and then permanently decreases to 0.9 after the sale in $t+1$. Alternatively, in the second panel, the regular price first decreases from 1 to 0.9 in $t-1$ right before the sale and reverts back to 0.9 after the sale in $t+1$.

Figure 3: Sales linked to regular price decrease after (left) and before (right)



4. **Other sales**: These are sales where (i) the sales flag indicates a sales incidence but (ii) they cannot be categorized into any of the types above.

Three points warrant further explanation. Firstly, throughout the paper, I will use the term "strategic sales" to denote sales linked to increases or decreases in the regular price. The fact that these sales effectively coincide with regular price adjustments suggests a potential strategic motive behind them. Previous research suggests that sales can help attract demand and influence consumers' perceptions of prices (e.g., Kalwani and Yim (1992), Lichtenstein et al. (1991), Jacobson and Obermiller (1990)). For example, Mulhern and Padgett (1995) and Mela et al. (1997) show that sales can influence purchasing behavior and brand choices long after the end of a promotion. This could explain why firms combine a reduction in the regular price with a sale. Additionally, Villas-Boas and Villas-Boas (2008) find that sales tend to change consumers' regular price expectations, making them more likely to forget regular prices during a sale and less sensitive to subsequent price hikes. In other words, sales may serve as a tactic to divert attention from regular price increases.

Secondly, for the main analysis, strategic sales are identified based on observing a regular price adjustment in the month before *or* after the sale. In the robustness section, I will examine each case separately. I find that regular price increases and decreases occurring right *after* the sale play the main role in explaining the aggregate dynamics of strategic sales.

Finally, there are some sales that cannot be classified as either v-sales or strategic sales, which are referred to as "other sales." These sales typically include end-of-season sales, where the item is replaced with a non-comparable item after the sale, or sales that occur at the beginning or end of an item's observation period.

2.3 Data cleaning and sample period

The sample period spans 330 months, from June 1996 to December 2023.[12] I make several adjustments to the data to ensure its suitability for analysis. First, I remove all invalid observations and those not used for the construction of the CPI. Second, I correct implausible price obserit is most likely an imputation error. Finally, in some cases, the sales flag indicates a sale, but the price remains constant or even increases. This could be due to sales being available only in conjunction with other promotions, such as "buy two, get one free," or due to misreporting. To address this, I adopt a conservative approach and focus only on sales incidents where the item's price temporarily decreases. The final dataset contains around 46 million observations.

Unless stated otherwise, all weighted statistics are calculated using the CPI consumption expenditure weights. For more detailed information, refer to Appendix A.2.

3 Empirical findings

This section analyzes the aggregate behavior of temporary sales and presents the main results of the paper.

3.1 Key statistics and time series

To begin, Table 1 presents key statistics on sales. From June 1996 to December 2023, the average monthly frequency of aggregate sales is 3.79%. This frequency is calculated as the fraction of sales observations relative to all price observations in a given month, weighted with CPI weights.

[12] The ONS sales flag has been available since the early 1990s. However, before 1996, there are instances where prices temporarily change without being marked by the sales flag. This inconsistency suggests that the sales flag may not have been applied consistently during that period.

Overall, the majority of sales are v-sales (2.16%). The frequencies of strategic sales linked to regular price increases and decreases are 0.95% and 0.72%, respectively. The fraction of "other sales" is negligible. That said, the rest of the discussion will mainly focus on the other types.

Table 1: Key statistics for sales

	All sales	v-sales	Strategic sales		Other sales
			Reg. price up	Reg. price down	
	1996-2023				
Frequency	3.79	2.16	0.95	0.72	0.07×10^{-1}
Size: mean	-25.7	-25.5	-24.8	-27.9	-19.8
median	-23.1	-22.9	-21.7	-25.0	-16.7
Duration: mean	1.55	1.46	1.65	1.76	1.98
median	1.00	1.00	1.00	1.00	1.00
	Great Recession (2008Q2-2009Q3)				
Frequency	3.70	1.69	1.19	0.90	0.09×10^{-1}
Size: mean	-26.3	-27.4	-24.5	-26.9	-18.2
median	-23.9	-25.0	-21.6	-25.0	-16.9
Duration: mean	1.55	1.48	1.61	1.65	1.59
median	1.00	1.00	1.00	1.00	1.00
	Post-Covid (2021-2023)				
Frequency	4.11	2.42	1.16	0.58	0.03×10^{-1}
Size: mean	-25.4	-25.2	-24.7	-28.3	-24.2
median	-23.1	-23.1	-21.9	-25.3	-24.8
Duration: mean	1.47	1.39	1.56	1.72	1.82
median	1.00	1.00	1.00	1.00	1.00

Notes: Frequency and size in percent, duration in months.

The mean and median size of sales are 24.4% and 22% on aggregate. Strategic sales linked to regular price increases tend to be slightly smaller (24.8% and 21.7%). Conversely, those linked to regular price cuts are slightly larger than the average (27.9% and 25%). However, overall, the differences across the groups are relatively small.

Lastly, the table also shows the duration of sales, calculated as the average length of a sales episode per year. Sales tend to be fairly short, with the mean duration ranging from around 1.5 to 1.8 months and a median duration of 1 month for all sales types.

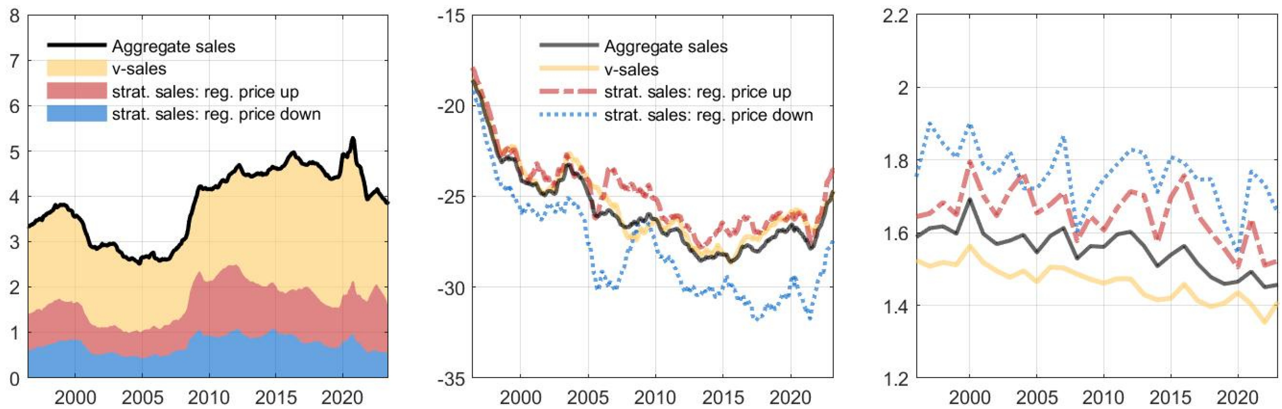
In addition, Table 1 also presents statistics for two specific periods: the Great Recession of 2008–2009[13] and the post-COVID period from 2021–2023. During the post-COVID period, the U.K. and other countries experienced the largest surge in inflation since the 1980s. In both periods, there was a noticeable shift in the composition of sales. During the Great Recession, the proportion of

[13]This is based on official recession dates for the U.K.

strategic sales was significantly higher (1.19% for increases and 0.90% for decreases), while v-sales decreased relatively (1.69%). At the recent end of the sample, the frequency of strategic sales linked to regular price increases remains elevated, although those linked to regular price cuts have declined. Meanwhile, the frequency of v-sales is higher than average.

Figure 4 shows the times series for sales, all represented as 12-month moving averages around each month. The left panel displays the monthly frequencies. Notably, aggregate sales increased significantly during the late 2000s, around the time of the Great Recession, rising from approximately 3% to 4.5% between 2008 and 2010. Since then, the frequency has remained elevated, stabilizing around 4.5%.

Figure 4: Mean monthly frequency (left), size (middle) and duration (right) of sales



Notes: "Strat. sales: reg. price up (down)": sales linked to regular price increases (decreases). Frequency and size as 12-month moving averages around each month, in percent. Annual mean duration in months.

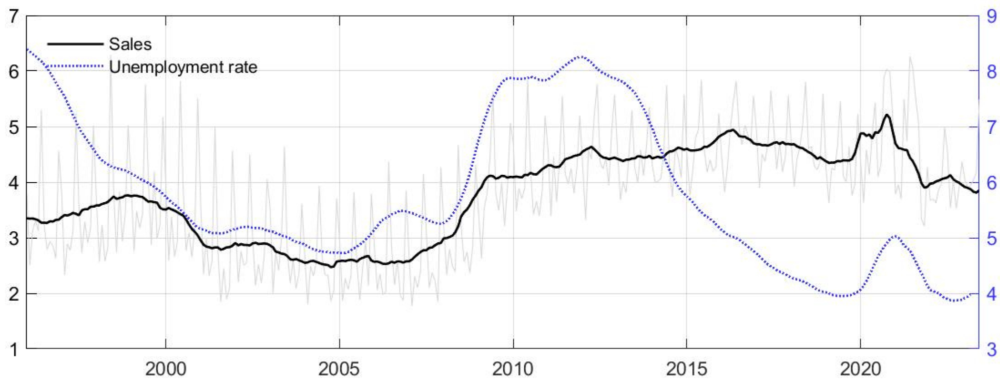
The middle panel illustrates the mean size of sales. All time series show a clear downward trend, indicating that sales have become larger in absolute terms over time. Interestingly, the relative size across different groups has remained stable, suggesting that all types of sales experienced a similar trend. On average, the size of sales increased by approximately 10 percentage points in absolute terms from 1996 to 2023.

Finally, the right panel shows the average duration of sales. The duration has remained relatively stable across all groups throughout the sample period, with only a slight downward trend. This stability in duration suggests that the increase in sales frequency is primarily due to firms offering more sales, rather than extending the length of sales periods.

3.2 The business cycle behavior

To analyze the business cycle behavior of sales, I begin with a visual examination of the relationship between sales and aggregate fluctuations. Figure 5 compares the frequency of aggregate sales with the U.K. unemployment rate. The gray line represents the raw monthly data for sales, while the black line shows the 12-month moving average. The figure reveals that the fraction of aggregate sales closely tracks the unemployment rate during certain periods. From around 2000 to 2012, there is a clear co-movement, with sales decreasing in the early 2000s and increasing during the Great Recession.[14] However, the correlation becomes less pronounced in the mid-2010s, as unemployment declines while sales remain elevated. There is some visible co-movement again since the onset of the COVID-19 pandemic in 2020.

Figure 5: Frequency of aggregate sales (left axis) vs. unemployment rate (right axis)



Notes: in percent. Gray lines: monthly data, black lines: 12-month moving averages.

Figure 6 displays the frequencies of the different types of sales separately.[15] The key insight from these graphs is that there is significant variation in the frequencies across sales types. V-sales move in tandem with the unemployment rate from around 2000 to 2010 but seem largely unrelated to it afterward. In contrast, both types of strategic sales exhibit clear countercyclical behavior throughout the entire sample period: their frequencies closely track the unemployment rate, rising sharply during the Great Recession and declining in the 2010s during the recovery. The correlation with strategic sales linked to regular price increases appears slightly weaker in the late 2010s. For instance, the frequency spiked in 2016, despite a decline in unemployment.

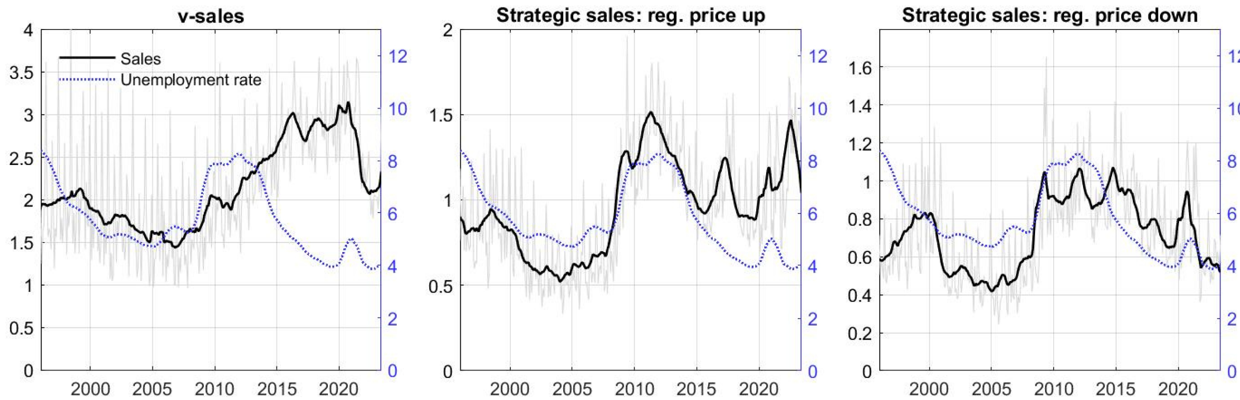
The decomposition sheds light on several aspects of the aggregate data. Notably, the apparent breakdown in the correlation between aggregate sales and the unemployment rate since the early 2010s is entirely driven by the upward trend in v-sales that started around that time. In contrast, both types of strategic sales show no clear trend over the sample period.

Furthermore, Figure 7 compares sales frequencies with the year-on-year change in the producer price index (PPI). V-sales and strategic sales linked to regular price decreases show no clear relationship with PPI. However, there is a noticeable positive co-movement between strategic sales linked to regular price increases and PPI inflation. Their frequency closely tracks PPI inflation, particularly since the 2010s. For example, the spike in sales in 2016 coincides with a sharp rise in the PPI during that period. Overall, the evidence suggests that strategic sales linked to regular price increases are influenced by both the unemployment rate and PPI, with PPI playing a more

[14]This observation aligns with Kryvtsov and Vincent (2021), who study sales using ONS data from 1996-2013.

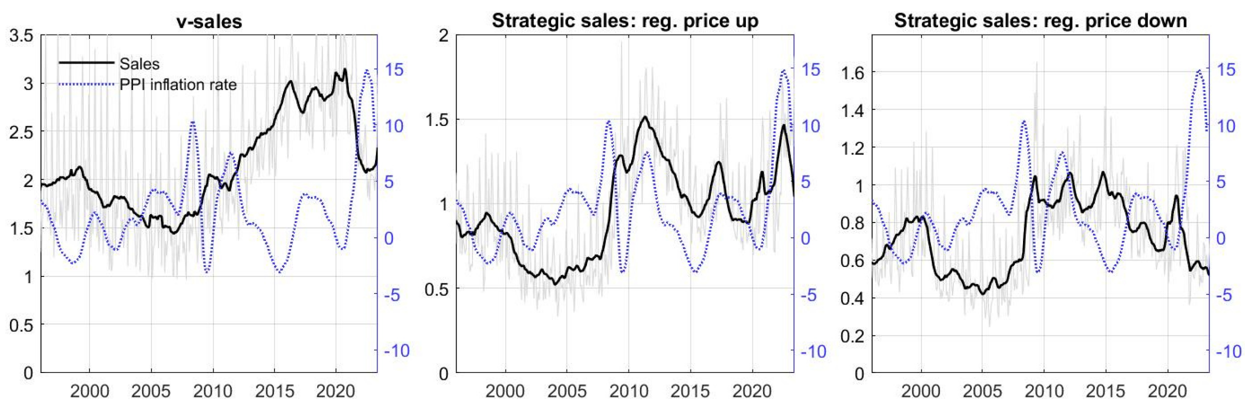
[15]Appendix A.3 provides figures for the type "other sales".

Figure 6: Frequency of sales (left axis) vs. unemployment rate (right axis)



Notes: in percent. Gray lines: monthly data, black lines: 12-month moving averages.

Figure 7: Frequency of sales (left axis) vs. PPI inflation rate (right axis)



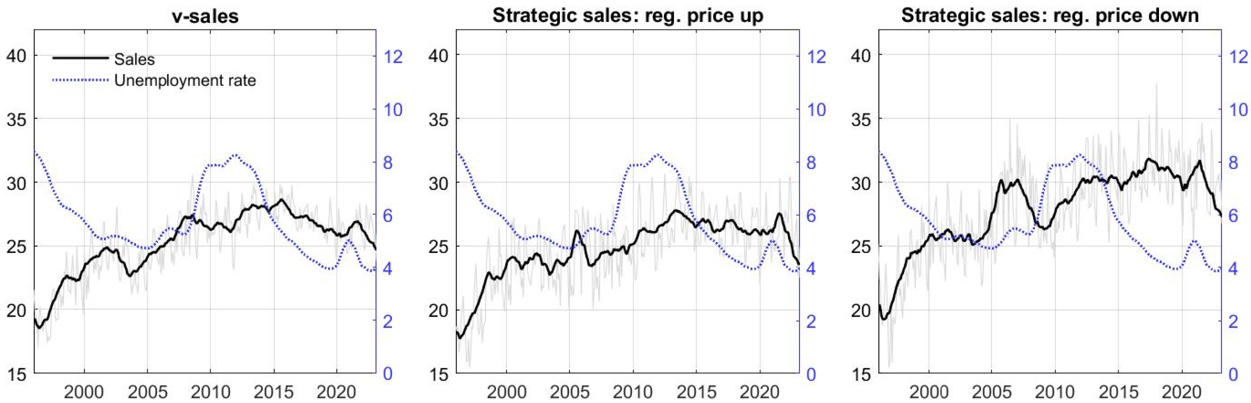
Notes: in percent. Gray lines: monthly data, black lines: 12-month moving averages.

prominent role since the 2010s.

The relationship between the average size of sales and aggregate variables is less clear. Figure 8 plots the absolute mean size of sales against the unemployment rate. There appears to be some correlation between the absolute size of v-sales and unemployment, particularly since the late 2010s. In contrast, the correlation for strategic sales is less evident, except for brief periods during the Great Recession and the COVID-19 pandemic.

Next, I conduct a regression analysis to investigate the business cycle behavior of the different sales types in more detail. Specifically, I employ OLS time-series regressions based on the empirical specification: $y_t = \alpha + \beta x_t + X_t' \gamma + error_t$, where y_t is either the frequency or absolute mean size of sales, and x_t is either the unemployment rate or PPI inflation in month t. X_t is a set of control variables, including the frequency or absolute mean size of regular price increases and decreases, a linear year time trend, and calendar month dummies. Controlling for the frequency and size of regular price changes is necessary because strategic sales inherently capture some variation in

Figure 8: Absolute mean size of sales (left axis) vs. unemployment rate (right axis)



Notes: in percent. Gray lines: monthly data, black lines: 12-month moving averages.

regular prices over the cycle. The linear time trend accounts for general trends, while the calendar month dummies adjust for seasonal sales patterns. Appendix B.1 provides results for alternative model specifications.

Table 2: Regression results: Frequency of sales

	All sales		v-sales		Strategic sales: Reg. price up		Strategic sales: Reg. price down		Other sales	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
unempl	0.266***		0.022		0.138***		0.107***		0.000	
	(0.020)		(0.015)		(0.008)		(0.006)		(0.000)	
PPI		-0.061***		-0.053***		0.007*		-0.017***		-0.000*
		(0.009)		(0.006)		(0.004)		(0.003)		(0.000)
freq_up	-0.041***	0.008	-0.045***	-0.013	0.017***	0.020***	-0.010***	0.004	0.000	0.000
	(0.010)	(0.015)	(0.009)	(0.008)	(0.004)	(0.006)	(0.003)	(0.005)	(0.000)	(0.000)
freq_down	0.018	0.031**	-0.000	-0.003	0.014***	0.024***	0.011	0.017**	0.000	0.000
	(0.013)	(0.014)	(0.011)	(0.012)	(0.005)	(0.008)	(0.007)	(0.008)	(0.000)	(0.000)
trend	0.001***	0.001***	0.000***	0.001***	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	0.028***	0.040***	0.029***	0.027***	-0.002**	0.007***	0.002***	0.008***	0.000***	0.000***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
N	330	330	330	330	330	330	330	330	330	330
Adj. R^2	0.68	0.63	0.61	0.70	0.70	0.45	0.52	0.31	0.06	0.07

Notes: Sample period Jun 1996–Dec 2023. Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. "freq_up (do)": frequency of regular price increases (decreases). All regressions include a constant and calendar month dummies.

Table 2 presents the regression results for the frequency of sales as the dependent variable, with individual regressions conducted for each type of sale. Aggregate sales are positively correlated with unemployment at the 1% significance level: a 1-percentage-point increase in the unemployment rate is associated with a 0.266-percentage-point increase in total sales.[16] Interestingly, this countercyclicality is entirely driven by strategic sales. The coefficients for sales linked to either increases or decreases in the regular price are positive at the 1% significance level: a 1-percentage-point increase in the unemployment rate corresponds to a 0.138-percentage-point (0.107-percentage-point) increase in the frequency of sales linked to regular price increases (decreases). In contrast, the coefficients for v-sales and other sales are not significant and close to zero.

Furthermore, aggregate sales and PPI inflation are negatively correlated at the 1% significance level: a 1-percentage-point increase in PPI inflation is associated with a 0.061-percentage-point decrease in sales. This negative relationship is primarily driven by the negative coefficients for v-sales and strategic sales linked to regular price cuts. In contrast, the coefficient for strategic sales associated with regular price hikes is positive, though relatively small.

Generally, the control variables capture some variation in sales frequencies. The frequencies of regular price changes explain some variation in strategic sales and also seem to account for fluctuations in aggregate sales and v-sales. The linear time trend is significant in all regressions, though its magnitude is essentially zero. Lastly, "other sales" appear to have no role in explaining sales dynamics, as their regression coefficients are zero and the Adjusted R-squared is very low.

Furthermore, Table 3 presents regression results for the absolute mean size of sales as the dependent variable. From 1996 to 2023, the absolute size of aggregate sales is positively correlated with unemployment at the 5% significance level: a 1-percentage-point increase in the unemployment rate corresponds to a 0.167-percentage-point increase in the absolute size of sales. This effect is entirely driven by v-sales. Only the absolute size of v-sales shows a positive correlation with unemployment, while the size of all other sales types remains largely unaffected.

Appendix B provides additional regression results. For instance, in Appendix B.1, I explore alternative model specifications, including one without control variables. Overall, the main results are highly robust and remain largely unchanged across different specifications. Another potential concern is small sample bias. To address this, Appendix B.2 reports alternative standard errors for the regressions, such as Newey-West standard errors for heteroskedasticity or non-parametric bootstrapped errors. Again, the main findings are very robust and remain largely unaffected by different standard error specifications.

[16] This figure is slightly lower than that in Kryvtsov and Vincent (2021), who estimated a coefficient of 0.36 for aggregate sales using a similar regression setting with a sample from 1996 to 2013.

Table 3: Regression results: Absolute size of sales

					Strategic sales:					
	All sales		v-sales		Reg. price up		Reg. price down		Other sales	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
unempl	0.167**		0.298***		0.140		-0.014		-0.353	
	(0.077)		(0.083)		(0.085)		(0.084)		(0.391)	
PPI		-0.014		0.043		-0.072**		0.007		0.076
		(0.026)		(0.032)		(0.028)		(0.029)		(0.140)
abs_size_up	-0.130	-0.181**	-0.157	-0.293***	-0.173	-0.178*	-0.128	-0.127	-0.727*	-0.647
	(0.100)	(0.091)	(0.105)	(0.101)	(0.112)	(0.103)	(0.101)	(0.094)	(0.428)	(0.417)
abs_size_do	0.511***	0.490***	0.422***	0.543***	0.699***	0.540***	0.649***	0.663***	0.916*	1.070*
	(0.099)	(0.127)	(0.107)	(0.148)	(0.120)	(0.149)	(0.103)	(0.139)	(0.505)	(0.579)
trend	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.003***	0.003***	0.001*	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
constant	0.194***	0.211***	0.195***	0.218***	0.189***	0.207***	0.226***	0.224***	0.232***	0.194***
	(0.010)	(0.008)	(0.011)	(0.009)	(0.012)	(0.009)	(0.011)	(0.008)	(0.050)	(0.040)
N	330	330	330	330	330	330	330	330	330	330
Adj. R^2	0.57	0.56	0.51	0.49	0.58	0.58	0.63	0.63	0.04	0.04

Notes: Sample period Jun 1996–Dec 2023. Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. "abs_size_up (do)": absolute mean size of regular price increases (decreases). All regressions include a constant and calendar month dummies.

4 Implications for aggregate price dynamics

This section explores the implications of strategic sales for aggregate price and inflation dynamics, aiming to assess the macroeconomic significance of strategic sales and sales-related regular price changes. In doing so, I document key features of sales-related regular price adjustments in the data.

4.1 Sales-related regular price changes

The focus of this section is on sales-related regular price changes. As defined in Section 2, sales-related regular price increases (decreases) refer to regular price hikes (cuts) observed in the month immediately before or after a sale. This definition is straightforward for regular price changes that occur before a sale. For example, suppose the regular price of a product increases from £1 to £1.30 in period $t-1$ and is then offered on sale for £1.10 in period t. In this case, the sales-related regular price increase is the jump from £1 to £1.30 in period $t-1$.

Now, consider a situation where the regular price change occurs after the sale. Suppose a product with a regular price of £1 is offered on sale for £0.80 in period t. After the sale ends in period $t+1$, the new regular price is £1.30. Here, the sales-related price increase is the change from the regular price before the sale to the regular price after the sale, i.e., from £1 to £1.30. Of course, the same logic applies to sales-related regular price decreases as well.

Table 4 shows key statistics for all regular price changes, as well as statistics for regular prices changes when sales-related regular price adjustments are excluded.

Table 4: Statistics for regular price adjustment

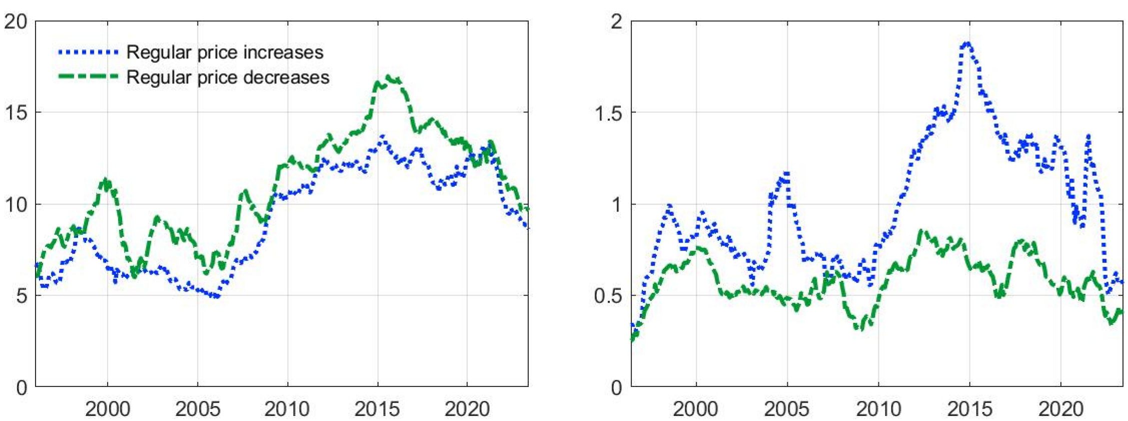
	All		Excl. sales-related	
	increases	decreases	increases	decreases
Frequency	8.0	4.6	7.3	4.1
Size: mean	14.2	-13.8	13.2	-13.2
median	6.2	-9.1	5.9	-8.6

Notes: Sample period Jun 1996 – Dec 2023. In percent.

From 1996 to 2023, the average monthly frequency of regular price increases (decreases) is 8.0% (4.6%). Naturally, excluding sales-related regular price changes reduces these frequencies: without sales-related increases (decreases), the frequency of regular price hikes (cuts) drops to 7.3% (4.1%). Additionally, the overall (absolute) size of price changes is smaller when sales-related regular price adjustments are excluded. The mean and median sizes of regular increases (decreases) are 14.2% (-13.8%) and 6.2% (-9.1%) in the aggregate, compared to 13.2% (-13.2%) and 5.9% (-8.6%) without sales-related changes.

Next, I analyze the contribution of sales-related price changes in more detail. The left panel of Figure 9 displays the shares of sales-related regular price increases and decreases relative to all regular price increases and decreases, respectively. Both shares have grown over time: sales-related regular increases (decreases) accounted for 6% (8%) of all regular increases (decreases) until the mid-2000s, then rose significantly in the late 2000s and have since stabilized at around 12% (14%).

Figure 9: Share of sales-related regular price changes (left) and difference in mean size (right)

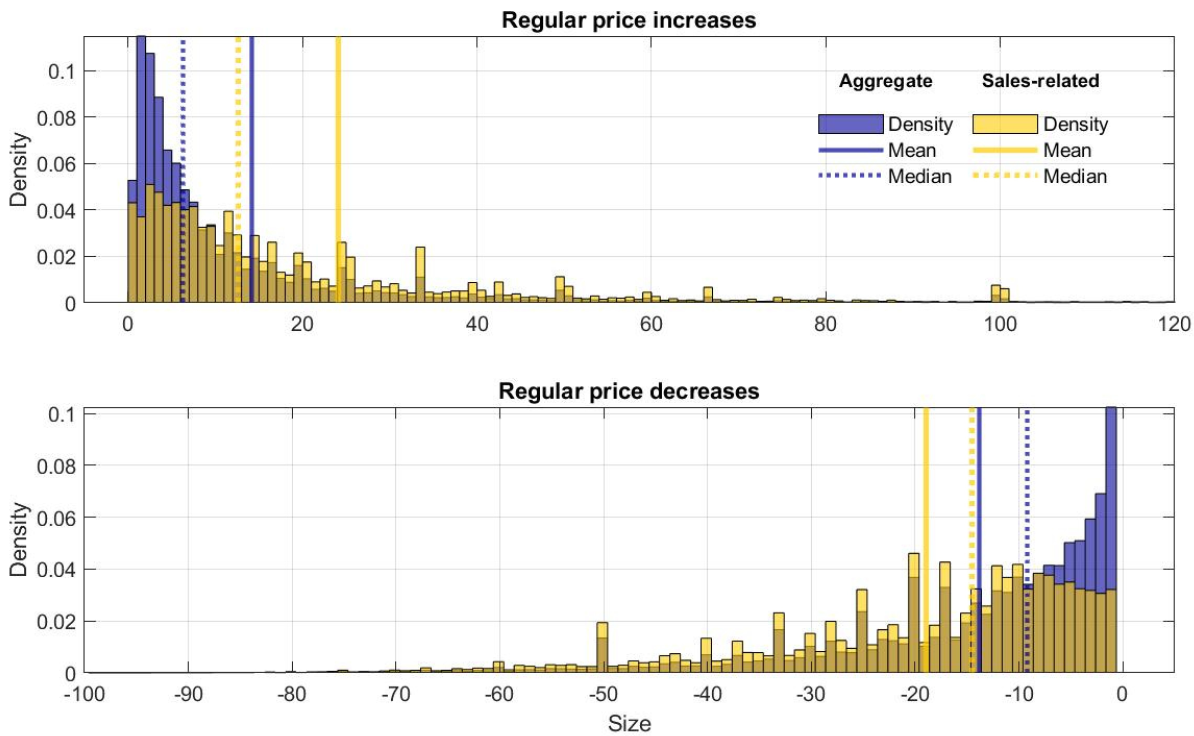


Notes: Left: share of sales-related regular price changes relative to all regular changes in percent. Right: Difference between aggregate mean size and mean size of non-sales-related regular price changes, in percentage points. All in 12-months moving averages.

The right panel of Figure 9 illustrates the difference between the aggregate mean size and the mean size of regular price changes excluding sales-related adjustments. This difference is consistently positive, indicating that sales-related regular price changes raise the aggregate (absolute) mean throughout the sample period. Specifically, sales-related price cuts added about 0.6 percentage points to the overall absolute size from 1996 to 2023. Sales-related price hikes increased the aggregate mean size by approximately 0.7 percentage points from 1996 to 2010 and by up to 1.2 percentage points from 2010 to 2021. Recently, this difference has declined to around 0.5 percentage points.

To assess whether the differences in the mean size of sales-related regular price changes are broad-based or driven by a few extreme observations, Figure 10 plots the distributions of regular price change sizes. Most regular price increases and decreases are relatively small, with modes around 5% and -2%, respectively. In contrast, the size of sales-related changes is much more dispersed, with a higher concentration of price changes exceeding 10% in absolute terms. The size differences are particularly pronounced for sales-related price increases, indicating that firms may systematically use sales to implement larger-than-average price hikes.

Figure 10: Histograms of the size of regular price changes



Notes: in percent. Sample period Jun 1996 – Dec 2023.

4.2 Implications for aggregate inflation

This section analyzes the contribution of sales-related regular price changes and strategic sales to aggregate inflation dynamics. To do this, I decompose monthly inflation into its individual components as follows: Let p_{it} represent the log price for product i, I_{it} indicate whether a price change has occurred, and ω_{it} denote the CPI weight for the product. Inflation is then calculated as the weighted average of log price changes:

$$\pi_t^m \equiv \sum_{i=1}^{N} \omega_{it} I_{it}(p_{it} - p_{it-1}) \tag{1}$$

Altogether, I distinguish six types of price changes:[17]

$$\pi_t^m = \pi_t^{reg+} + \pi_t^{sales\ reg+} + \pi_t^{reg-} + \pi_t^{sales\ reg-} + \pi_t^{sales-} + \pi_t^{sales+} \tag{2}$$

where π_t^{reg+} and π_t^{reg-} represent inflation from regular price increases and decreases from period $t-1$ to t that are not related to sales. These are regular price changes that do not occur within one month of a sales period. $\pi_t^{sales\ reg+}$ and $\pi_t^{sales\ reg-}$ represent inflation from sales-related regular price increases and decreases. Note that if the regular price change occurs immediately after the sale (i.e., the regular price does not return to its pre-sale level but adjusts to a new regular price), I calculate the difference between the new regular price and the *pre-sale* regular price.

π_t^{sales-} are price reductions from the pre-sale regular price to the sales price at the beginning of the sales period. Finally, π_t^{sales+} represents price increases from the sales price back to the *pre-sale* regular price at the end of the sales period. Using the pre-sale regular price ensures that any regular price changes occurring after a sale are decomposed into $\pi_t^{sales\ reg+}$ or $\pi_t^{sales\ reg-}$ and π_t^{sales+}.

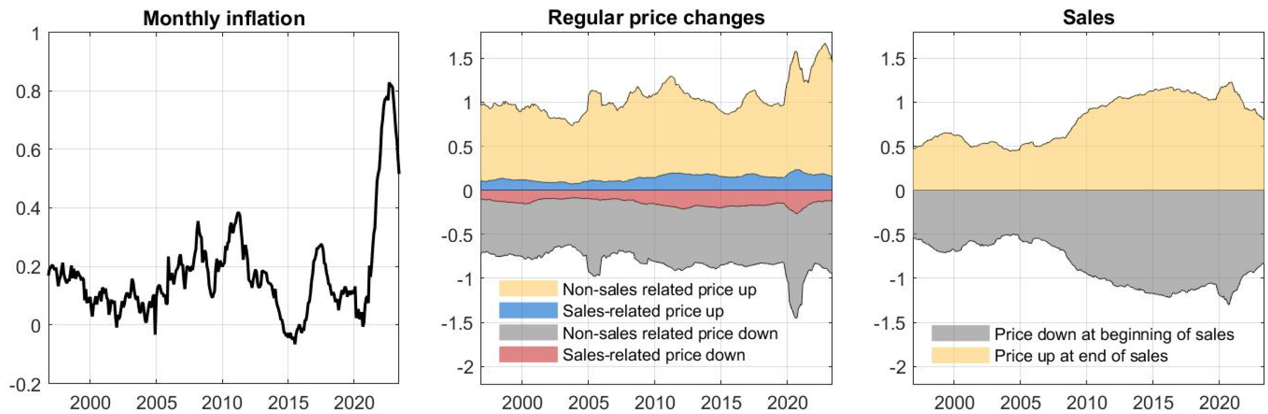
Figure 11 illustrates aggregate monthly inflation and its individual components, represented as 12-month moving averages. Monthly inflation rates ranged between 0% and 0.2% for most of the sample period but have risen to approximately 0.8% since 2021 (left panel). Most variation in inflation is attributed to regular price increases and decreases not linked to sales (middle panel). Inflation due to regular price increases averaged around 1% per month until 2020, rising to 1.6% thereafter. Conversely, inflation due to regular price decreases averages around -0.8% per month for most of the sample period, briefly dropping to -1.5% during the COVID-19 pandemic.

Sales-related regular price changes contribute a smaller but still significant portion to aggregate inflation. Inflation from sales-related increases (decreases) averaged around 0.1% (-0.11%) until 2010 and rose to 0.18% (-0.17%) thereafter. Finally, the sales components increased significantly in the late 2000s (right panel), coinciding with a sharp rise in v-sales. Since around 2010, these components average around -1% at the start of a sale and 1% at the end.

Lastly, I examine the implications for the slope of the Phillips curve, which traditionally describes the relationship between inflation and unemployment. The Phillips curve suggests an inverse

[17] The decomposition is similar to Cavallo and Kryvtsov (2024) who broadly distinguishes between regular price inflation and sale-related inflation.

Figure 11: Aggregate inflation (left) and inflation components (middle and right)



Notes: In percent. Middle: Inflation from regular price increases and decreases, right: inflation from sales. All represented as 12-month moving averages.

relationship between the two. This reflects the common intuition that in a booming economy with low unemployment, higher demand leads firms to raise wages to attract workers, resulting in higher prices as they pass on increased costs. A well-known formulation of this relationship is the New Keynesian Phillips curve (Woodford, 2003):

$$\pi_t = \beta E_t \pi_{t+1} - \kappa(u_t - u_t^n) + \nu_t \tag{3}$$

where $E_t\pi_{t+1}$ represents one-period-ahead inflation expectations, $u_t - u_t^n$ is the difference between unemployment and its natural rate, i.e., the output gap, and ν_t are supply side shocks. The coefficient κ represents the slope of the Phillips curve and measures the trade-off between inflation and real activity.

Another common approach is to solve the Phillips curve forward:[18]

$$\pi_t = E_t \pi_{t+\infty} - \kappa E_t \sum_{k=0}^{\infty} \beta^k u_{t+k} + \omega_t \tag{4}$$

where $\omega_t \equiv E_t \sum_{k=0}^{\infty} \beta^k \kappa u_{t+k}^n + E_t \sum_{k=0}^{\infty} \beta^k \kappa u_{t+\infty} + \nu_t$. This formulation of the Phillips curve highlights the importance of long-run expectations, $E_t\pi_{t+\infty}$, in determining the overall level of aggregate inflation. These long-run expectations are typically influenced by the private sector's beliefs about the central bank's long-term monetary policy regime, such as its long-run inflation target (e.g., Hazell et al. (2022)).

The challenges in estimating the slope of the Phillips curve, κ, are well-documented in the literature.[19] First, there is a potential endogeneity bias from the shock ν_t, which may simultaneously affect both π_t and u_t. Second, controlling for long-run expectations is difficult; but failing to account

[18]Assuming that shocks to u_t^n and ν_t are transitory, Equation (3) implies that $E_t\pi_{t+\infty} = -\frac{\kappa}{1-\beta} E_t u_{t+\infty}$ (e.g. Hazell et al. (2022)).

[19]For a summary of these challenges and the current state of research, see Furlanetto and Lepetit (2024).

for $E_t\pi_{t+\infty}$ can lead to biased estimates if variations in long-run expectations are correlated with u_t.[20] Third, finding an appropriate instrument for the infinite sum of future unemployment rates is challenging. Hazell et al. (2022) suggest using the one-year lagged unemployment rate, given the slow-moving nature of unemployment.

In this section, I focus on estimating *relative* slopes, rather than the absolute value of κ. Specifically, let $\pi_{-j,t}$ denote the inflation rate excluding component j, where j is one of the components in Equation (2). For example, $\pi_{-j,t}$ could represent the inflation rate excluding inflation from sales-related regular price increases. The Phillips curve for $\pi_{-j,t}$ can be represented as:

$$\pi_{-j,t} = E_t\pi_{-j,t+\infty} - \kappa_{-j}E_t\sum_{k=0}^{\infty}\beta^k u_{t+k} + \omega_{-j,t} \tag{5}$$

where $\omega_{-j,t} \equiv E_t\sum_{k=0}^{\infty}\beta^k\kappa_{-j}u^n_{t+k} + E_t\sum_{k=0}^{\infty}\beta^k\kappa_{-j}u_{t+\infty} + \nu_t$. In this framework, assume that long-run expectations are entirely driven by expectations about the monetary policy regime, so that $E_t\pi_{-j,t+\infty} = E_t\pi_{t+\infty}$. This assumption implies that subtracting $\pi_{-j,t}$ from aggregate inflation cancels out both the long-run expectations and the supply-side shock, resulting in:

$$\pi_t - \pi_{-j,t} = -(\kappa - \kappa_{-j})E_t\sum_{k=0}^{\infty}\beta^k u_{t+k} + \tilde{\omega}_t \tag{6}$$

where $\omega_t = E_t\sum_{k=0}^{\infty}\beta^k(\kappa - \kappa_{-j})u^n_{t+k} + E_t\sum_{k=0}^{\infty}\beta^k(\kappa - \kappa_{-j})u_{t+\infty}$.

For the purposes of this paper, it is sufficient to focus on the relative slopes $\kappa - \kappa_{-j}$: assuming that κ is generally positive ($\kappa > 0$), the sign of $\kappa - \kappa_{-j}$ provides valuable insights into how the cyclical behavior of inflation changes when specific components are excluded. I estimate Equation (6) using data from 1996 to 2023 as follows: First, I annualize inflation rates to reduce measurement errors and eliminate seasonality. Second, I instrument the forward sum $E_t\sum_{k=0}^{\infty}\beta^k u_{t+k}$ with the one-year lagged unemployment rate.

Table 5 shows the estimation results.[21] The first column shows the estimate for $\kappa - \kappa_{-j}$ when $\pi_{-j,t}$ excludes inflation from sales-related regular price increases. The coefficient is negative (-0.298), indicating that $\kappa < \kappa_{-j}$ given that $\kappa > 0$. In other words, the slope of the aggregate Phillips curve is steeper when sales-related regular price increases are excluded. This finding complements the results of previous sections: the positive relationship between sales linked to regular price increases and unemployment – and therefore between sales-related price increases and unemployment – partly offsets the negative relationship between inflation and unemployment at the aggregate level.

The second column of Table 5 presents results for $\pi_{-j,t}$, excluding both inflation from sales-related regular price increases and the corresponding sales. Excluding these sales does not significantly alter the outcome, suggesting that they have little additional effect on the slope of the

[20] For instance, in the early 1980s, Paul Volcker's willingness as Federal Reserve Chairman to tolerate high unemployment may have credibly signaled his commitment to reducing inflation.

[21] The results are shown for annual inflation rates. Typically, estimates in the literature are based on quarterly data. To convert these to quarterly estimates, the coefficients would need to be divided by 4 (Hazell et al. (2022)).

Phillips curve beyond that of sales-related regular price increases.

Finally, the relative slope $\kappa - \kappa_{-j}$ is positive (0.314) when inflation from sales-related regular price decreases is excluded (third column), suggesting that $\kappa > \kappa_{-j}$. Again, this finding is consistent with the previous results. The countercyclical behavior of sales linked to regular price cuts – and consequently, sales-related price reductions – aligns with the aggregate relationship between regular price cuts and unemployment over the cycle.

Table 5: Regression results for relative Phillips curves: $\pi_t - \pi_{-j,t}$

	Sales-related			
$j =$	reg. prices up	reg. prices up + sales	reg. prices down	reg. prices down + sales
	(1)	(2)	(3)	(4)
unempl_{t-12}	-0.298***	-0.286***	0.314***	0.318***
	(0.004)	(0.005)	(0.004)	(0.004)
N	307	307	307	307
Adj. R^2	0.91	0.89	0.92	0.92

Notes: Standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. $\pi_t - \pi_{-j,t}$: difference in annual inflation rates, "Sales-related reg. prices up (down) + sales": sales-related regular price increases (decreases) and strategic sales linked to regular price increases (decreases),

5 Robustness analysis

This section investigates the robustness of the main findings in Section 3 and documents additional features of temporary sales at a more disaggregated level.

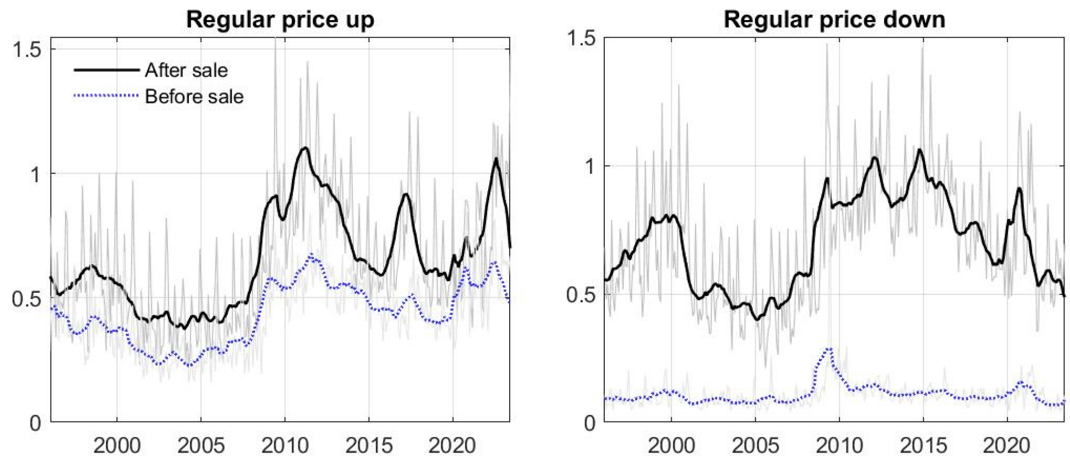
5.1 Regular price changes after vs. before sale

In the previous sections, strategic sales are identified based on regular price changes observed in the month surrounding a sale. Figure 12 further breaks down strategic sales into those with regular price changes occurring before or after the sale. The majority of sales-related regular price changes occur *after* a sale. This pattern is particularly pronounced for sales-related price cuts, with approximately 86% of all cuts, on average, taking place post-sale. For sales-related price hikes, around 60% of the increases are implemented immediately after the sale.

The business cycle properties of strategic sales vary slightly depending on when the regular price change occurs. Table 6 presents regression results based on individual regressions for the frequency of strategic sales. Strategic sales with regular price increases are negatively correlated with the unemployment rate in both cases, although the coefficient is slightly larger for post-sale price hikes. In terms of PPI inflation, a positive and significant correlation is found only for post-sale price hikes, while pre-sale price increases show no significant relationship.

The differences are even more pronounced for sales-related regular price decreases. The positive

Figure 12: Frequency of strategic sales: reg. price change after vs. before sale



Notes: in percent. Gray lines: monthly data, black solid and blue dotted lines: 12-month moving averages.

correlation with unemployment is primarily driven by strategic sales with post-sale price cuts. In contrast, the relationship between unemployment and pre-sale price decreases is relatively weak and exhibits a poorer model fit. The correlation with PPI inflation is negative for both types, but close to zero for pre-sale price cuts, again with a significantly weaker model fit.

5.2 Retailer type: multiples vs. independents

The ONS micro price data includes information on prices from three main outlet types: (i) multiples, which are chains or shops with more than 10 branches, (ii) independents, or shops with fewer than 10 branches, and (iii) more recently, other outlets such as online retailers. In the late 1980s, around 35% of all goods and services in the CPI were sampled from multiples. Over time, this share increased, reflecting a growing trend of consumer purchases at these stores. By 2023, goods and services from multiples account for around 70% of the CPI.

Figure 13 illustrates the time series for the frequency of sales offered by multiples and independents, respectively. Note that adding the sales frequencies from both multiples and independents would yield the aggregate measures. Overall, the dynamics of sales across firms differ primarily in the case of v-sales. The positive trend in v-sales since the 2010s is entirely driven by sales offered by multiples, while v-sales among independents have remained relatively stable over time. In contrast, strategic sales have followed a fairly similar pattern across both types of firms.

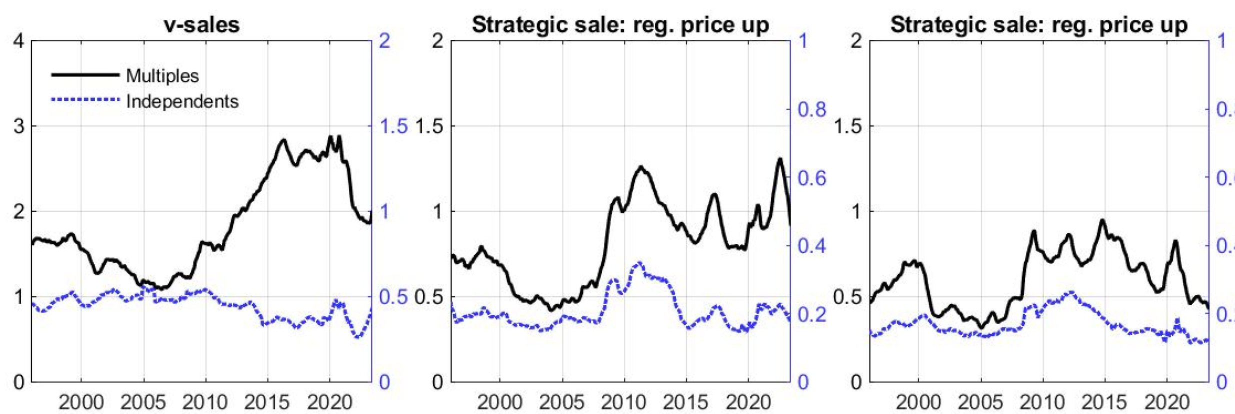
Appendix B.3 provides regression results by retailer type. The results for both multiples and independents largely align with the aggregate findings. For both retailer types, strategic sales are strongly countercyclical, with a positive correlation to the unemployment rate at the 1% significance level. In contrast, v-sales are acyclical in all cases. In sum, although multiples post more sales overall, the strategic motive behind sales appears equally important for both large and smaller firms.

Table 6: Regression results: Frequency of strategic sales: reg. price change after vs. before sale

	Regular price up				Regular price down			
	After sale		Before sale		After sale		Before sale	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
unempl	0.096***		0.062***		0.103***		0.016***	
	(0.007)		(0.004)		(0.006)		(0.002)	
PPI		0.009***		0.001		-0.015***		-0.004***
		(0.003)		(0.002)		(0.003)		(0.001)
freq_up	0.015***	0.015***	0.005**	0.007**	-0.012***	0.002	0.001	0.004**
	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)	(0.004)	(0.001)	(0.002)
freq_down	0.009***	0.017***	0.007***	0.012***	0.008	0.013*	0.006*	0.006*
	(0.004)	(0.006)	(0.002)	(0.004)	(0.008)	(0.008)	(0.003)	(0.003)
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)
constant	-0.002***	0.004***	-0.000	0.003***	0.002***	0.008***	0.000	0.001***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
N	330	330	330	330	330	330	330	330
Adj. R^2	0.62	0.43	0.65	0.40	0.52	0.31	0.20	0.16

Notes: Sample period Jun 1996–Dec 2023. Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. "freq_up (do)": frequency of regular price increases (decreases). All regressions include a constant and calendar month dummies.

Figure 13: Frequency of sales by firm type



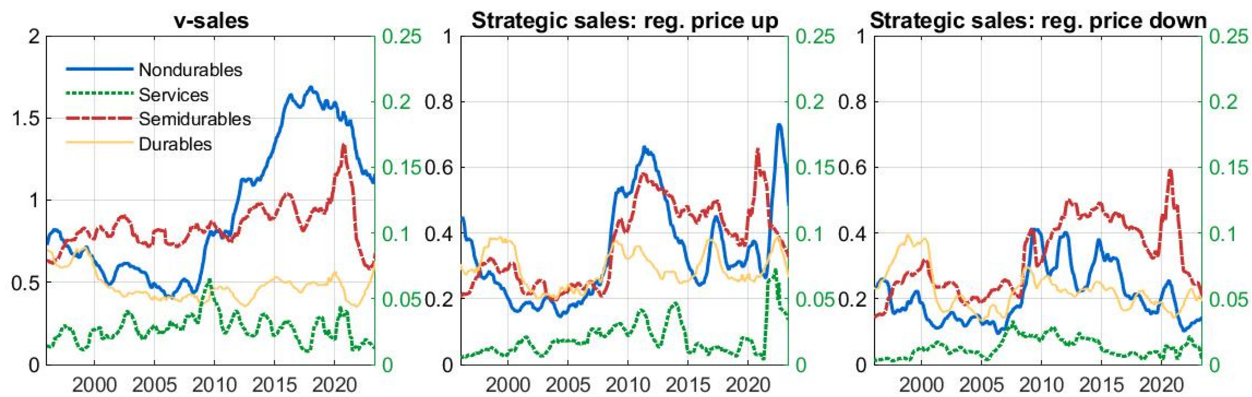
Notes: in percent. 12-month moving averages around each month. Fraction of sales refers to the share of sales observations relative to all sales observations. Left axis: sales of multiples. Right axis: sales of independents.

5.3 Major consumer goods categories

Next, I examine the business cycle behavior of sales across major consumer goods categories: nondurable goods (e.g., food, nondurable household items), services (e.g., restaurants, recreational services), semidurables (e.g., clothing, footwear), and durables (e.g., furniture, jewelry). As of 2023, the proportions in the CPI are approximately 36% for nondurables, 33% for services, 21% for semidurables, and 10% for durables. These shares remained relatively stable throughout the sample period.

Figure 14 shows the time series for sales across different categories. Note that combining the sales frequencies of these groups results in the aggregate measures. Several key observations emerge from the figure. First, the frequency is lowest for services (right axis), while the frequencies for the other groups are relatively similar. Second, the positive trend in v-sales since the 2010s is mainly driven by sales of nondurables, and to a lesser extent, semidurables. In contrast, v-sales for services and durables show no discernible trend. Finally, the dynamics of strategic sales are fairly consistent across nondurables, semidurables, and durables but differ somewhat for services.

Figure 14: Frequency of sales by major goods categories



Notes: in percent. 12-month moving averages around each month. Fraction of sales refers to the share of sales observations relative to all sales observations. Left axis: nondurables, semidurables and durables. Right axis: services.

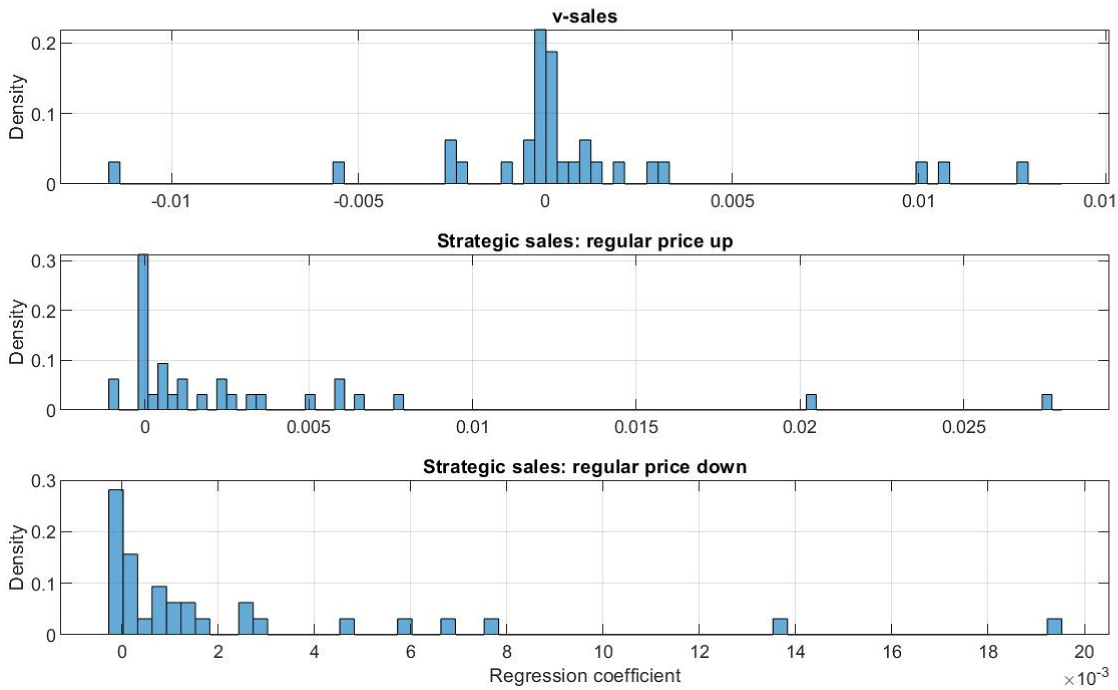
Appendix B.4 provides regression results for each major goods category. Overall, the disaggregated results closely align with those at the aggregate level: strategic sales are positively correlated with the unemployment rate at the 1% significance level across all categories, although the model fit is notably weaker for services. For v-sales, the coefficient is insignificant for nondurables and semidurables but positive for services and negative for durables.

5.3.1 Product group level

Lastly, I analyze sales at a more granular product level. I focus on products at the COICOP3 level, such as food, non-alcoholic beverages, tobacco, and clothing. The analysis covers 33 product categories from 1996 to 2023.

Figure 15 shows the distribution of coefficients on the unemployment rate from separate regressions by product type. The distributions are weighted by the average CPI weights for each product type from 1996 to 2023. The results at the product group level are largely consistent with the baseline findings. The coefficients for v-sales are mostly centered around zero, with observations on both the positive and negative sides. In contrast, the coefficients for strategic sales are skewed toward positive values. Additional results are provided in Appendix B.5.

Figure 15: Distribution of regression coefficients at product group level



Notes: Coefficients for unemployment rate from regressions with frequency of sales as dependent variable, sample period Jun 1996-Dec 2023. OLS regressions include the frequencies of regular price increases and decreases, a linear time trend and calendar month dummies.

6 Conclusion

The paper provides new evidence on the macroeconomic relevance of temporary sales. Using U.K. CPI microdata from 1996 to 2023, I find that sales are used as a way to implement regular price changes: (i) Around 45% of sales occur immediately before or after a regular price increase or decrease. This close timing suggests a strategic motive, where firms may use sales to mask price hikes or boost demand when regular prices are lowered. (ii) These *strategic sales* are strongly countercyclical, rising closely in tandem with the unemployment rate. In contrast, other types of sales are largely acyclical. As a result, aggregate sales exhibit countercyclical patterns driven entirely by strategic sales. (iii) Strategic sales significantly influence aggregate price and inflation dynamics. On average, sales-related regular price increases (decreases) account for 9% (11%) of all regular price hikes (cuts) and are 1 percentage point (0.6 percentage points) larger in absolute size. Furthermore, sales-related regular price hikes tend to flatten the slope of the aggregate Phillips curve, partly offsetting the negative relationship between aggregate inflation and unemployment. Conversely, sales-related regular price cuts contribute to a steepr Phillips curve.

These findings can be interpreted more broadly in the context of how prices function in a market economy. Prices signal the relative scarcity of goods, helping to balance demand and supply. However, strategic sales may distort this signaling mechanism. For instance, when firms pair regular price increases with sales, consumers may not fully perceive the magnitude of the price change, preventing them from adjusting their consumption behavior accordingly. This distortion can influence how consumers respond to aggregate shocks, potentially leading to inefficiencies in the market.

Strategic sales are just one way firms can influence perceived price signals. Other practices, such as product downsizing (reducing a product's size without lowering its price) or altering product quality, can similarly impact how consumers perceive prices. Future research should explore the broader implications of these strategies for resource allocation in the economy and their effects on consumer welfare.

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Appendix

A ONS price quote data

This section provides a more detailed overview of the public CPI micro dataset provided by the U.K.'s Office for National Statistics (ONS).[22] More information can be found 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. Over 1,000 individual goods or services are surveyed each month, with prices collected from more than 14,000 retail stores across the U.K. Each good or service is classified by month and year, shop type, and region. The shop type classification distinguishes between "multiples," which are chain stores with 10 or more outlets, and "independents," referring to shops with fewer than 10 outlets. The region 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 referred to as the "stratum," which further stratifies the data based on shop type, region, or both. Each stratum is then divided into "stratum cells" for more detailed analysis and representation. To ensure a comprehensive coverage of the country and aggregate consumption expenditures, the ONS employs complex sampling procedures that involve sampling across different regions, shops within a location, items within a product category, and product varieties within categories.

Typically, items have broad specifications (e.g., 1 kg of potatoes or women's jeans). The ONS staff selects products that match these specifications and are representative of consumer purchases. For products available in various pack sizes, the ONS provides a specified range. Most prices are collected monthly, except for certain household and leisure services, as well as seasonal items.

Goods and services in the CPI follow the European classification of household expenditure, known as the Classification of Individual Consumption by Purpose (COICOP). Prices of individual items are first aggregated into subclasses and then into classes. These classes are further summarized into groups, divisions, and ultimately, the aggregate level. Here are a few examples:

- Items: potatoes 1kg; women's jeans
- Subclass: potatoes; garments for women
- Class (COICOP4): vegetables; garments
- Group (COICOP3): food; clothing
- Division (COICOP2): food and non-alcoholic beverages; clothing and footwear

In addition, the variable *indicator_box* stores several attributes of the item. For example, $indicator\_box = S$ indicates that an item is on sale in a specific month, while $indicator\_box = R$

[22] `https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/consumerpriceindicescpiandretailpricesindexrpiitemindicesandpricequotes`. This link provides the latest years' data, while historical data can be accessed through their online archives.

indicates that a sales period has ended. The value "C" implies that an item has been substituted with a comparable item, whereas "N" indicates that the substitute is non-comparable. A typical example are seasonal items, such as winter jackets or holiday products.

A.1 Processing the data

I made several adjustments to the data to ensure its suitability for the analysis. First, I removed observations not labeled as valid by the ONS, retaining only those with validity codes of $validity = 3$ or 4. Second, entries with zero or negative prices were eliminated. Additionally, instances where the price, relative to its base (January of the same year), increased by more than 400% or decreased by more than 100% without being on sale were also removed, as such extreme price fluctuations suggest possible misreporting (e.g., £1.60 instead of £160). Finally, I constructed a price time series for each item using a set of unique identifiers: *item_id*, *region*, *stratum_cell*, *shop_type*, *shop_code*, *start_date*, and *end_date*.

A.2 CPI weighting

I use the official ONS CPI sampling weights for all weighted statistics in the paper. The individual raw price quote observations are unweighted, but weights at the shop type, stratum, and COICOP5 levels are provided for each month. Shop weights reflect the relative importance of the shop where the price quote was collected for each item within a specific stratum. Stratum weights reflect the relative importance of the stratum where the price was observed. COICOP5 weights indicate the relative importance of the COICOP5 group to which the item belongs. Using these weights, aggregation allows for the calculation of the overall sampling weight for each individual item. More details can be found in the ONS Technical Manual.

The following outlines the procedure for obtaining the aggregate sampling weights. For example, consider the item "Large loaf – white sliced – 800g." Price quotes for this item are collected from different shops and strata in a given month. To determine the sampling weights for this item, the first step is to compute relative weights at the elementary level: for each stratum, the relative weight is calculated as the shop weight relative to the sum of all shop weights within that stratum. Most price quotes have a shop weight of 1 or 2. The second level involves aggregating to the stratum level, where the relative weight across all strata for this specific item is computed. The third level is the COICOP5 level, where the relative weight for a narrowly defined product category is determined. In this case, the COICOP5 group is "Bread."

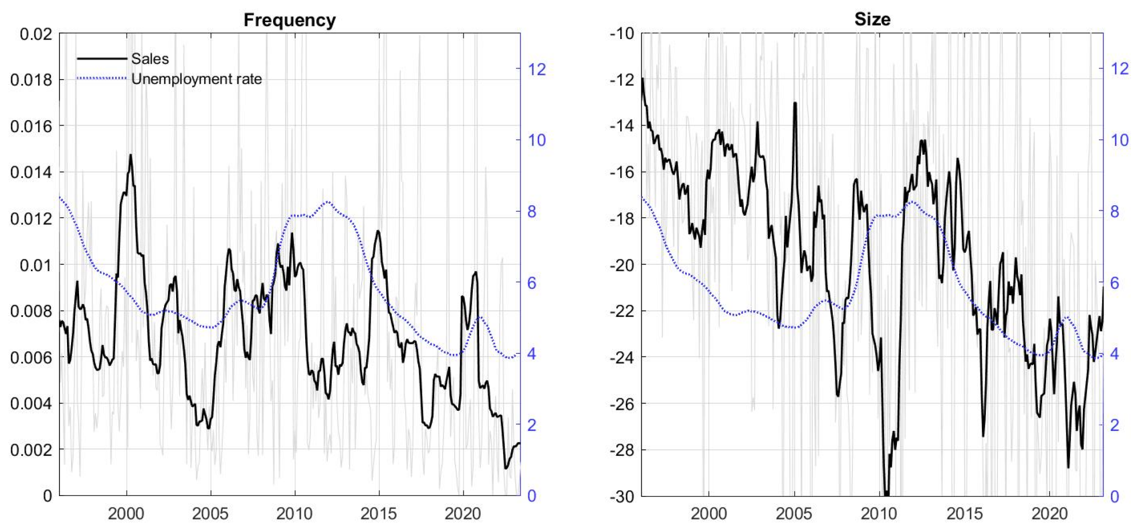
Finally, relative weights are computed at the COICOP4 to COICOP1 levels. For instance, at the COICOP4 level, the relative weight is calculated as the weight from the previous aggregation step relative to the sum of weights in this group. In our example, the COICOP4 group is "Bread and cereals." Therefore, the relative weight at the COICOP4 level is the weight at the COICOP5 level relative to the sum of weights for all goods that belong to the "Bread and cereals" category.

In the paper, I present figures for the size of sales and regular price changes. To compute the moments for the size of these variables, I treat all instances where no change in size is observed as NaN (rather than zero). To obtain aggregate measures such as the mean or median, the final sampling weights are the official aggregate sampling weights, adjusted relative to the sum of weights for observations that are not NaN.

A.3 Time series for other sales

Figure A.1 presents the time series data for the frequency and mean size of "other sales" alongside the unemployment rate. As shown in Table 2, neither the frequency nor the size of these sales is correlated with changes in the unemployment rate. The regression coefficients are essentially zero and/or statistically insignificant.

Figure A.1: Other sales (left axis) vs. unemployment rate (right axis)



Notes: in percent. Gray lines: monthly data, black lines: 12-month moving averages.

B Robustness analysis

B.1 Alternative model specifications

Table B1 presents regression results for alternative model specifications. The findings remain highly robust across different specifications for all sales types. For instance, in columns (2), (5), (8), (11), and (14), I exclude the frequencies of regular price increases and decreases as control variables. Despite these changes, the coefficients on unemployment remain relatively stable. The coefficient for total sales slightly decreases to 0.242, compared to 0.266 in the baseline analysis. As before, strategic sales are the primary drivers of the relationship between unemployment and aggregate sales. The coefficient for v-sales remains insignificant across all specifications.

Table B1: Regression results for alternative models: Frequency of sales

	All sales			v-sales			Strategic sales: Reg. price up			Strategic sales: Reg. price down			Other sales		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Sample period 1996-2022														
unempl	0.242***	0.259***		-0.005	0.010		0.146***	0.145***		0.101***	0.106***		0.000	0.000	
	(0.021)	(0.019)		(0.015)	(0.015)		(0.007)	(0.008)		(0.007)	(0.006)		(0.000)	(0.000)	
ppi	-0.049***		-0.060***	-0.053***		-0.056***	0.014***		0.012***	-0.011***		-0.016***	-0.000		-0.000*
	(0.009)		(0.007)	(0.006)		(0.005)	(0.003)		(0.003)	(0.003)		(0.003)	(0.000)		(0.000)
freq_up	-0.012			-0.013			0.008**			-0.004			0.000		
	(0.012)			(0.008)			(0.004)			(0.003)			(0.000)		
freq_down	0.016			-0.003			0.015***			0.011			0.000		
	(0.013)			(0.012)			(0.005)			(0.007)			(0.000)		
trend	0.001***	0.001***	0.001***	0.001***	0.000***	0.001***	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	0.027***	0.025***	0.043***	0.028***	0.025***	0.026***	-0.001*	0.000	0.010***	0.002***	0.002***	0.009***	0.000***	0.000***	0.000***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
N	330	330	330	330	330	330	330	330	330	330	330	330	330	330	330
Adj. R^2	0.71	0.67	0.63	0.70	0.58	0.70	0.72	0.67	0.41	0.55	0.50	0.30	0.07	0.07	0.07

Notes: Sample period Jun 1996–Dec 2023. Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. "freq_up (do)": frequency of regular price increases (decreases). All regressions include calendar month dummies.

B.2 Alternative standard errors

Table B2 reports the OLS estimates for unemployment and PPI, along with alternative standard errors for the baseline model. In addition to the OLS standard errors, the table includes robust standard errors, Newey-West standard errors, and bootstrapped standard errors. Newey-West standard errors are used to account for potential serial correlation and heteroskedasticity in the residuals, with a maximum autocorrelation of four lags.

To address potential small sample issues, I also compute bootstrapped standard errors using the following procedure: (i) draw 5,000 independent samples (with replacement) from the entire dataset, (ii) estimate the standard errors for each bootstrap sample, and (iii) compute the average standard errors across all 5,000 samples.

Table B2: Alternative standard errors

		Standard errors			
	OLS estimate	OLS	Robust	NW	BS
	(1)	(2)	(3)	(4)	(5)
Unemployment rate					
dependent variable:					
All sales	0.266	0.028***	0.020***	0.019***	0.032***
v-sales	0.022	0.020	0.015	0.016	0.025
Strategic sales: Regular price up	0.138	0.009***	0.008***	0.008***	0.013***
Strategic sales: Regular price down	0.107	0.008***	0.006***	0.007***	0.010***
Other sales	0.000	0.000	0.000	0.000	0.000
PPI					
dependent variable:					
All sales	-0.061	0.009***	0.009***	0.009***	0.014***
v-sales	-0.053	0.006***	0.006***	0.006***	0.008***
Strategic sales: Regular price up	0.007	0.004*	0.004*	0.004*	0.006
Strategic sales: Regular price down	-0.017	0.003***	0.003***	0.003***	0.005***
Other sales	-0.000	0.000**	0.000*	0.000*	0.000

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

B.3 Retailer type

Table B3 provides regression results for the frequency of sales by retailer type, i.e., multiples and independents. The disaggregated results align closely with the aggregate findings, suggesting that the relationship is consistent across retailer types. For both multiples and independents, strategic sales are strongly countercyclical: a 1% increase in the unemployment rate is associated with a 0.224-percentage-point increase in total sales for multiples and a 0.063-percentage-point increase for independents. As before, the overall increase in total sales is entirely driven by strategic sales, which show a strong positive correlation with unemployment for both retailer types. In contrast, v-sales are largely unrelated to the unemployment rate.

Regarding PPI inflation, only sales posted by multiples follow the patterns observed at the aggregate level. In contrast, sales by independents show little to no correlation with PPI inflation. This is because v-sales by these firms are mildly negatively correlated with PPI inflation, while strategic sales linked to regular price hikes are mildly positively correlated. As a result, these opposing effects cancel out at the aggregate level.

B.4 Major consumer good categories

Table B4 presents regression results for the frequency of sales across major goods categories. The disaggregated results largely align with the aggregate findings. Strategic sales show a positive correlation with the unemployment rate for all goods categories at the 1% significance level, although the model fit is relatively weak for services. V-sales show no significant correlation for nondurables and semidurables, but are positively correlated for services and negatively correlated for durables. Overall, total sales exhibit a robust countercyclical pattern for nondurables, services, and semidurables, but remain largely acyclical for durables.

Table B3: Regression results: Frequency of sales by retailer type

	Multiples										Independents									
			Strategic sales:										Strategic sales:							
	All sales		v-sales		reg. price up		reg. price down		Other sales		All sales		v-sales		reg. price up		reg. price down		Other sales	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
unempl	0.224***		0.023		0.115***		0.088***		0.000		0.063***		0.005		0.033***		0.025***		0.000	
	(0.020)		(0.016)		(0.007)		(0.006)		(0.000)		(0.006)		(0.004)		(0.002)		(0.002)		(0.000)	
ppi		-0.063***		-0.053***		0.006*		-0.016***		-0.000		-0.002		-0.003*		0.002*		-0.001		-0.000
		(0.009)		(0.006)		(0.003)		(0.003)		(0.000)		(0.002)		(0.002)		(0.001)		(0.001)		(0.000)
freq_up	-0.047***	-0.000	-0.048***	-0.016*	0.013***	0.015***	-0.011***	0.003	-0.000	0.000	0.003	0.008	0.000	0.003	0.004***	0.005**	-0.001	0.001	0.000	0.000
	(0.010)	(0.013)	(0.010)	(0.008)	(0.004)	(0.005)	(0.003)	(0.004)	(0.000)	(0.000)	(0.003)	(0.005)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
freq_down	-0.011	-0.001	-0.020**	-0.023**	0.008**	0.016**	0.006	0.011	0.000	0.000	0.026***	0.030***	0.017**	0.017**	0.007***	0.009***	0.005**	0.007***	-0.000	-0.000
	(0.015)	(0.015)	(0.008)	(0.009)	(0.004)	(0.008)	(0.006)	(0.007)	(0.000)	(0.000)	(0.006)	(0.005)	(0.007)	(0.007)	(0.001)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)
trend	0.001***	0.001***	0.000***	0.001***	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	0.019***	0.028***	0.021***	0.019***	-0.002***	0.005***	0.001*	0.005***	0.000**	0.000***	0.011***	0.015***	0.009***	0.009***	0.001***	0.003***	0.002***	0.003***	0.000***	0.000***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	330	330	330	330	330	330	330	330	330	330	330	330	330	330	330	330	330	330	330	330
Adj. R^2	0.59	0.57	0.55	0.65	0.63	0.39	0.41	0.23	0.05	0.05	0.86	0.82	0.77	0.78	0.81	0.66	0.74	0.61	0.05	0.06

Notes: Sample period Jun. 1996– Dec. 2023. Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. "freq_up (do)": frequency of regular price increases (decreases). All regressions include calendar month dummies.

Table B4: Regression results: Frequency of sales by major good categories

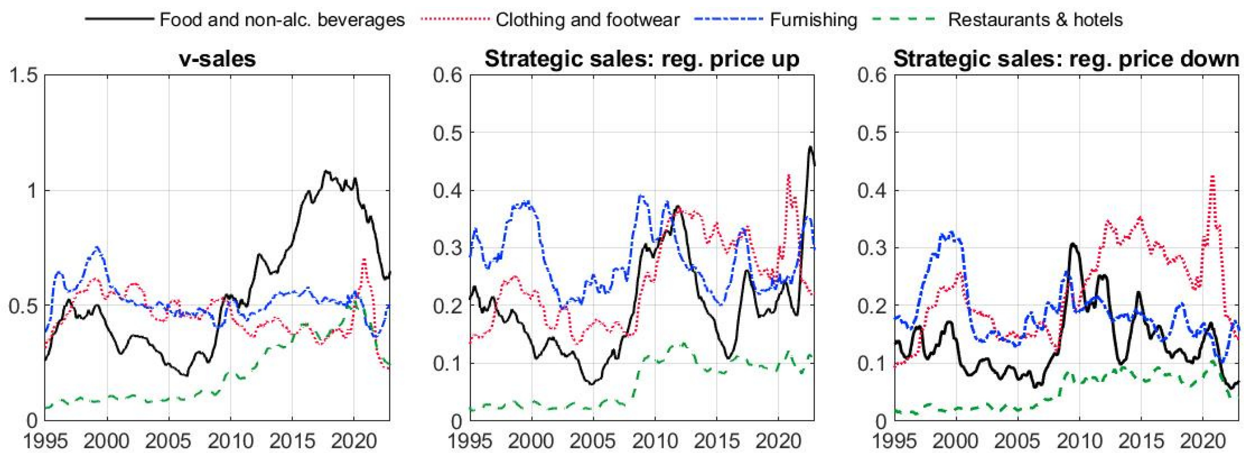
	Nondurables				Services				Semidurables				Durables			
			Strat. sales:				Strat. sales:				Strat. sales:				Strat. sales:	
	All	v-sales	price up	price down	All	v-sales	price up	price down	All	v-sales	price up	price down	All	v-sales	price up	price down
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
unempl	0.144***	0.016	0.076***	0.056***	0.009***	0.004***	0.002**	0.003***	0.104***	0.008	0.052***	0.042***	0.009	-0.010**	0.009***	0.011***
	(0.011)	(0.010)	(0.005)	(0.004)	(0.002)	(0.001)	(0.001)	(0.000)	(0.015)	(0.009)	(0.004)	(0.005)	(0.008)	(0.005)	(0.003)	(0.003)
freq_up	-0.032***	-0.042***	0.018***	-0.006***	0.003	0.000	0.001	0.002***	-0.043	-0.067*	0.058***	-0.018	0.023	-0.059*	0.081***	0.013
	(0.009)	(0.008)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.057)	(0.038)	(0.017)	(0.018)	(0.042)	(0.034)	(0.020)	(0.015)
freq_down	-0.039***	-0.051***	0.019***	-0.003	0.012***	0.008**	0.003**	0.001	0.129**	0.053	0.024**	0.053***	0.146	0.073	0.023	0.050**
	(0.012)	(0.011)	(0.005)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)	(0.061)	(0.033)	(0.011)	(0.019)	(0.090)	(0.050)	(0.018)	(0.023)
trend	0.001***	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	0.000	0.008***	-0.005***	-0.002***	0.000	0.000***	0.000	-0.000*	0.014***	0.013***	0.000	0.001***	0.015***	0.009***	0.004***	0.003***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
N	327	327	327	327	327	327	327	327	327	327	327	327	327	327	327	327
Adj. R^2	0.71	0.65	0.57	0.45	0.23	0.26	0.09	0.12	0.67	0.59	0.71	0.60	0.55	0.53	0.51	0.36

Notes: Sample period Sep. 1996– Dec. 2023. Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. "freq_up (do)": frequency of regular price increases (decreases). All regressions include calendar month dummies.

B.5 COICOP2 level

Figure B.1 illustrates the sales dynamics for selected categories at the COICOP2 level. One key observation is that v-sales for "Food and Non-Alcoholic Beverages" nearly tripled between 2009 and 2020. In contrast, sales in the other categories remained relatively stable over the same period.

Figure B.1: Frequency of sales by COICOP-2 level



Notes: in percent. 12-month moving average around each month.

Table B5 presents the estimated coefficients on unemployment from regressions for the frequency of sales by COICOP2 group. The results at the COICOP2 level are largely consistent with the aggregate findings. Strategic sales exhibit countercyclical behavior in most sectors, except for the service sectors "Health," "Communication," and "Restaurants and Services." The coefficients for v-sales vary significantly across sectors. Specifically, they are positive in some sectors ("Food and Beverages," "Recreation and Culture," "Restaurants and Hotels," and "Personal Care"), negative in "Alcoholic Beverages and Tobacco" and "Health," and insignificant in the remaining sectors. Overall, total sales are positively correlated with unemployment in most sectors, except in those where the positive effects of v-sales and strategic sales offset each other.

Table B5: Frequency of sales at COICOP2-level: estimated coefficients for unemployment rate

	All sales	v-sales	Strategic sales: Reg. price up	Reg. price down
	(1)	(2)	(3)	(4)
Food and beverages	0.079***	0.029***	0.026***	0.026***
	(0.011)	(0.008)	(0.004)	(0.003)
Alcoholic beverages and tobacco	0.038***	-0.008*	0.032***	0.014***
	(0.005)	(0.004)	(0.003)	(0.002)
Clothing and footwear	0.046***	-0.008	0.030***	0.022***
	(0.010)	(0.006)	(0.003)	(0.004)
Housing etc	0.003***	0.001	0.001***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Furnishing	0.011	-0.005	0.009***	0.007***
	(0.007)	(0.005)	(0.003)	(0.002)
Health	-0.001	-0.001**	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Transportation	0.009***	0.001	0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Communication	-0.001**	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Recreation and culture	0.029***	0.007***	0.009***	0.012***
	(0.004)	(0.002)	(0.001)	(0.001)
Restaurants and hotels	0.002	0.002***	-0.001	0.001**
	(0.001)	(0.001)	(0.001)	(0.000)
Personal care	0.036***	0.010***	0.016***	0.010***
	(0.003)	(0.003)	(0.001)	(0.001)

Notes: Sample period Jun. 1996 – Dec. 2022. Robust standard errors in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include a constant, a linear time trend and calendar month dummies.