Price Discounts and Cheapflation During the Post-Pandemic Inflation Surge*

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Abstract

We study how within-store price variation changes with inflation, and whether households exploit it to attenuate the inflation burden. We employ micro price data for food products sold by 92 large multi-channel retailers in ten countries between 2019 and 2023. Based on unit prices within narrowly defined product categories, we analyze two sources of variation in prices within a store: temporary price discounts and differences across varieties of similar products. Price changes associated with discounts grew at a much lower average rate than regular prices, helping to mitigate the inflation burden. By contrast, *cheapflation*—a faster rise in prices of cheaper brands relative to prices of more expensive brands of the same good—exacerbated it. Using Canadian Homescan Panel Data, we estimate that spending on discounts reduced the average unit price by 23%, but expenditure switching to cheaper brands *raised* it by 8.8%.

JEL-Codes: E21, E30, E31, L81.
Keywords: Inflation, Prices, Price dispersion, Expenditure switching, COVID-19 pandemic.

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1 Introduction

The historic surge in inflation following the COVID-19 pandemic has heightened the need to understand the impact of high inflation on household welfare.[1] The burden of inflation depends on the price increases of goods within a household's consumption basket and the household's decisions about which goods to purchase. The existing literature reveals that higher inflation is often accompanied by greater price dispersion for similar goods across different stores.[2] This positive relationship aligns with models that consider market frictions due to firms' costly price adjustments (Sheremirov, 2020) or consumers' costs of obtaining price information (Drenik and Perez, 2020). However, the same literature finds that most of the observed price dispersion is *within* store—due to variation of prices for different brands of the same good or variation of prices for identical goods over time (Kaplan and Menzio, 2015). The impact of inflation on within-store price variation, as well as the extent to which households can utilize this variation to mitigate the effects of rising prices, have not been explored before.

We explore this question by analyzing micro price data from food products offered by 92 large multi-channel retailers across ten countries from 2019 to 2023, including Argentina, Brazil, Canada, France, Germany, Italy, Netherlands, Spain, the United Kingdom, and the United States. Utilizing unit prices from narrowly defined product categories, we examine two primary sources of price variation within stores: temporary price discounts and differences across varieties of similar products. Price changes associated with discounts grew at a much lower average rate than regular prices, thus mitigating the inflation burden. By contrast, *cheapflation*—a faster rise in prices of cheaper brands relative to prices of more expensive brands of the same good—exacerbated it. Using Canadian Homescan Panel Data, we estimate that purchasing products on sale reduced the growth in average unit price by 23%, whereas opting for cheaper brands *increased* it by 8.8%.

We focus on the "Food and Beverages" category because it carries significant weight in household consumption baskets, and it is one of the sectors that experienced the highest price growth during this period. Food products come in many varieties and are relatively easy to

[1]Among the G7 countries, peak year-over-year CPI inflation in 2021–2023 reached 9.1% in the United States, 6.3% in France, 8.8% in Germany, 11.8% in Italy, 4.3% in Japan, 11.1% in the United Kingdom and 8.1% in Canada.

[2]Studies of price dispersion and inflation include Lach and Tsiddon (1992) for Israel, Alvarez et al. (2018); Drenik and Perez (2020) for Argentina, Reinsdorf (1994); Nakamura et al. (2018); Sheremirov (2020) for the United States.

classify and compare across different retailers and countries. We take advantage of the wide variety of package sizes and units and construct *unit prices* by dividing the product's price by its size. Accurately measuring unit prices is crucial for assessing the degree of price dispersion across brands of varying quality within narrowly-defined product categories such as fresh eggs, milk, or dry pasta, and for comparing their relative prices over time.

A major source of variation of prices for similar items within a store is given by temporary price discounts, or "sales". We study the impact of discount events by breaking down inflation into components stemming from regular price changes and sale-related price adjustments. This latter category encompasses variations in the frequency and size of discounts, as well as regular price fluctuations at the start or the end of sales.

We find that sales had only a minor impact on inflation during this period. From January 2020 to July 2023, *regular* food prices in low-inflation countries increased by 14.1% to 20.8%, and in Brazil and Argentina, they rose by 33.0% and 111.7%, respectively. In contrast, the month-to-month inflation attributable to sale events would accrue to only single-digit total price growth, even in Argentina, where it reached 6.2%. We use additional evidence from the U.K. CPI microdata to corroborate that sale-related price changes did not contribute to the inflation surge in neither food nor non-food sectors.

It may come as a surprise that retailers did not directly use discounts to raise their prices, even in countries where discount usage is relatively frequent, such as the United States, United Kingdom, Canada, or Italy. We find, for example, that before the inflation surge, sale-related inflation in these countries accounted for half of the quarterly inflation variance and an even higher share of the monthly inflation variance. However, although fluctuations in the number and size of discounts can cause volatile month-to-month inflation swings (as Jaravel and O'Connell (2020b) document for the United Kingdom in 2020), they cannot support a sustained rise in prices. Retailers cannot simply keep scaling down their sales over extended periods when they need to increase their prices. And the end-of-sale regular price increases are not large enough to compensate for zero regular price growth during sales.

A second major source of variation in prices within a store is due to price differences across varieties of different quality within narrowly-defined categories. We find that retailers systematically raised regular prices of cheaper (lower-quality) products at a faster rate than prices of premium products. For each narrow category, we rank products in quartiles of their average regular unit price in 2019. For each quartile, we construct price indexes and compare their cumulative changes between January 2020 and October 2023. Even in the low-inflation countries in our sample, regular prices for the cheapest products (first quartile) grew by an additional 9 to 23 percentage points over prices of premium products (fourth quartile).

While *posted* prices rose differently across varieties of goods or for regular/discounted prices, the effective inflationary burden for households depends on allocation of expenditures across transactions. Consumers can generate much needed savings by shifting their spending toward cheaper goods, either by finding a lower price for their preferred product, or by buying a lower quality product. We analyze expenditure switching along both of these dimensions using Canadian Nielsen Homescan Panel data. We find that the shift of spending toward sale-related prices lowered the varying-weight price index by 4.5 percentage points, shaving off 23% of the price increase since January 2020 against the increase for regular prices. At the same time, expenditures shifted from more expensive to cheaper brands, *raising* the varying-weight price index relative to the fixed-weight index by an additional 1.7 percentage points—an 8.8% larger increase. Hence, while households switched to cheaper product varieties, their savings were somewhat offset by the higher relative price growth for cheaper varieties.

Over time, sales and cheapflation can have opposite effects on the dispersion of unit prices within stores. Because discounts are associated with sticky regular prices and slower price growth, they increase price dispersion similar to what sticky price models would predict (Sheremirov, 2020). Since prices of cheaper products catch up with prices of more expensive products, cheapflation compresses price dispersion. Using posted prices in the United States and transaction prices in Canada, we measure price dispersion by the interquartile range of unit prices within retailer and narrow product category over time. Although in a given month there is a substantial spread in the degree of unit price dispersion across products, the *median* within-product price dispersion appears either flat or decreasing, suggesting the cheapflation effect dominates.

The main contribution of this paper is to provide new evidence on the relationship between within-store unit price variation and inflation. Documenting price variation within stores requires us to control for variation in product size and packaging. The data employed in this paper meet this challenge. Moreover, the scale and scope of the data used in the paper—across 10 countries, countries with normally high and low inflation, countries with normally high and low use of discounts, observations for posted prices and transaction prices—supports comprehensive analysis of the relationship between within-product price variation and inflation.

Our results provide new insights into the costs of inflation. Cheapflation represents a double whammy of the inflation burden. Households who substitute their favorite products with cheaper counterparts to save cash, incur the utility cost of consuming less preferred products. In addition, some of the saved cash is later offset by a faster rise in prices of cheaper brands, and therefore, their lower *real* consumption. On the other hand, because prices associated with temporary discounts rise much more slowly, they present an opportunity for substantial savings for those households willing to invest extra time and effort in finding these discounts. Future research will further dissect these mechanisms and quantify the burden of inflation they impose.

The paper is structured as follows: Section 2 introduces international micro price data, Section 3 documents changes in price indexes for regular and discounted prices, Section 4 analyzes inflation segmented by unit price quartiles, Section 5 discusses the Canadian Homescan Panel dataset and examines the impact of expenditure switching on effective prices, Section 6 presents evidence of within-firm dispersion of posted and transaction prices. Section 7 concludes.

2 Data from large multi-channel retailers

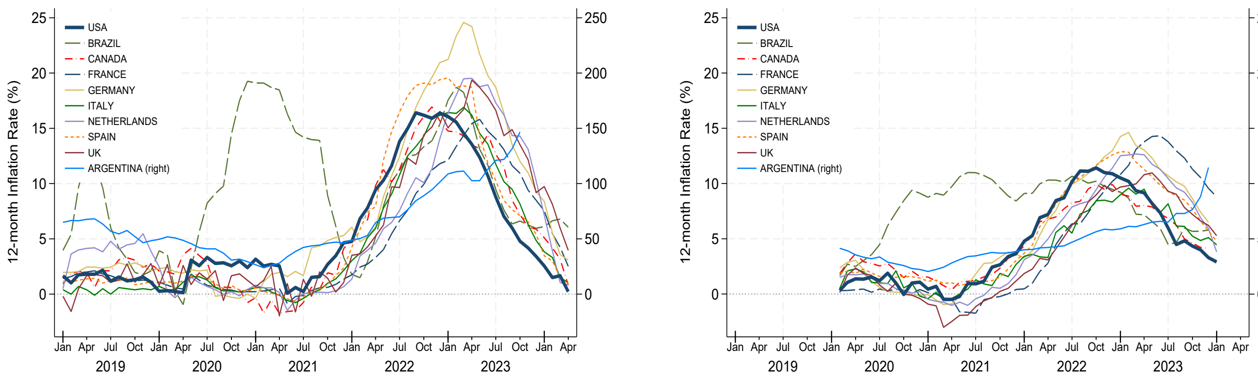
We use micro price data provided by PriceStats, a private company affiliated with The Billion Prices Project (Cavallo and Rigobon, 2016). Our dataset encompasses daily posted prices for all products sold by ninety-two major retailers across ten countries: Argentina, Brazil, Canada, France, Germany, Italy, the Netherlands, Spain, the United Kingdom, and the United States. This information is gathered daily using web-scraping methods and includes product details such as IDs, prices, categories, and sale flags. For a subset of products, we also observe unit prices, i.e., price per measurement unit, such as grams or fluid ounces. Table 1 displays the number of retailers, the number of narrowly-defined product categories, the number of individual products and products with unit prices for each country. The dataset spans from January 1, 2019, to November 27, 2023.

	# Retailers	# Categories	# Products	# Unit Prices	% Unit Prices
ARGENTINA	9	6,832	170,923	72,816	42.6
BRAZIL	12	8,891	228,497	1,632	.71
CANADA	12	11,317	271,890	55,939	20.57
FRANCE	12	17,396	364,920	268,583	73.6
GERMANY	7	8,743	178,152	91,050	51.11
ITALY	5	3,578	80,711	68,674	85.09
NETHERLANDS	7	22,472	161,145	55,565	34.48
SPAIN	9	12,159	177,025	99,887	56.43
UK	10	21,728	193,521	145,719	75.3
USA	8	13,366	296,108	155,786	52.61

Table 1: Multi-channel retail data by country.

The data are collected using consistent methodologies across various countries, ensuring high comparability for similar categories of goods over identical time periods. The frequent updates and detailed nature of the data help mitigate measurement errors commonly associated with other sources, particularly those errors stemming from the time aggregation of average revenue (Cavallo, 2018). Additionally, studies have shown that web-scraped prices closely align with those found in the physical stores of the same retailers (Cavallo, 2017). For the purpose of this paper, we focus on the "Food and Beverages" category due its significant weight in the goods component of the Consumer Price Index (CPI) for most countries and the high quality and comparability of the data across different countries.

Food prices experienced one of the highest inflation rates during this period. Figure 1 and Table 2 summarize recent food inflation for countries in our sample. In Europe and North America, inflation surged in late 2021–early 2022 and took a bit over a year to reach its peak, registering double-digit annual rates. The surge in European countries started and peaked a few months after North America, and was several percentage points higher, with Germany's food clocking nearly a 20% inflation rate by February 2023. Food inflation among multi-channel stores in the dataset displays broadly similar behavior, although inflation rates tend to be a bit lower. Inflation in two largest South American economies was already high in 2019: 59% in Argentina and 5.9% in Brazil. Yet, it reached even higher levels during and after the pandemic: 122% in Argentina in June 2023, and 21.8% and 18.8% in Brazil in December 2020 and August 2022, respectively.



(a) CPI - Annual Inflation (b) Multi-channel retailers - Annual Inflation

Figure 1: Inflation rates for food products.

Notes: Panel A shows the annual inflation rate for the official food CPI in each country. Panel B shows annual inflation rates constructed using the multi-channel retailers data used in the paper.

	Start surge	Peak surge	Months to peak	Peak annual food inflation	
				CPI	Multi-channel
GERMANY	Oct 2021	Feb 2023	16	19.6	14.9
CANADA	Nov 2021	Oct 2022	11	11.4	10.0
USA	Nov 2021	Oct 2022	11	13.1	12.7
SPAIN	Dec 2021	Jan 2023	13	15.9	13.1
NETHERLANDS	Jan 2022	Jan 2023	12	16.7	13.2
ITALY	Jan 2022	Apr 2023	15	13.3	10.5
UK	Mar 2022	May 2023	14	18.8	12.4
FRANCE	May 2022	Jun 2023	13	14.9	16.3

Table 2: Inflation surge for food products.

Notes: Inflation surge is defined to start with two consecutive months of at least 3% year-on-year inflation in food for retailers in the sample. Peak is the week with highest year-on-year rate.

2.1 Unit prices and price discounts

An advantage of collecting prices online is that retailers often show details on unit prices and sale discounts next to each individual product, as shown in Figure 2. When unit prices are not displayed by the retailer, we can calculate them by dividing the total price by the package size shown in the product's description. Similarly, if a sale flag is not available, we can use a price algorithm to identify them.

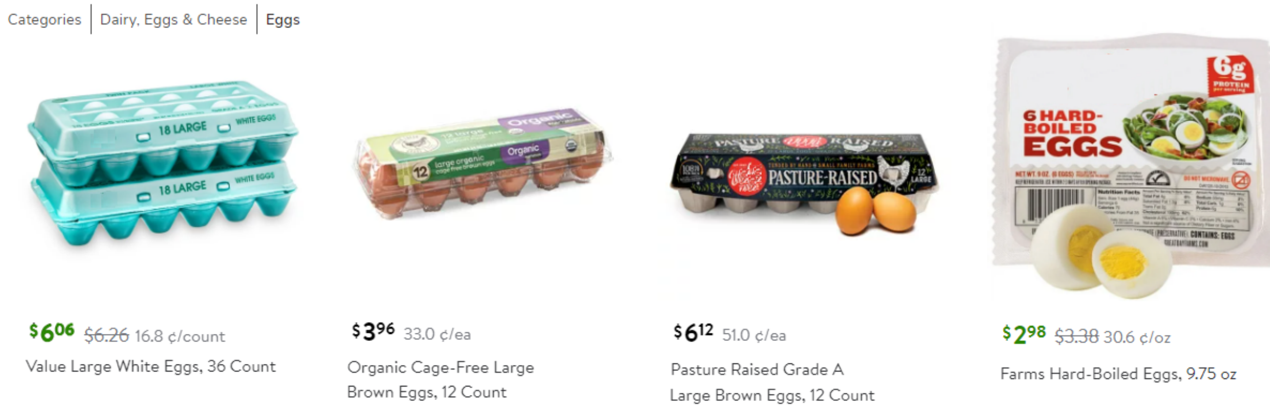
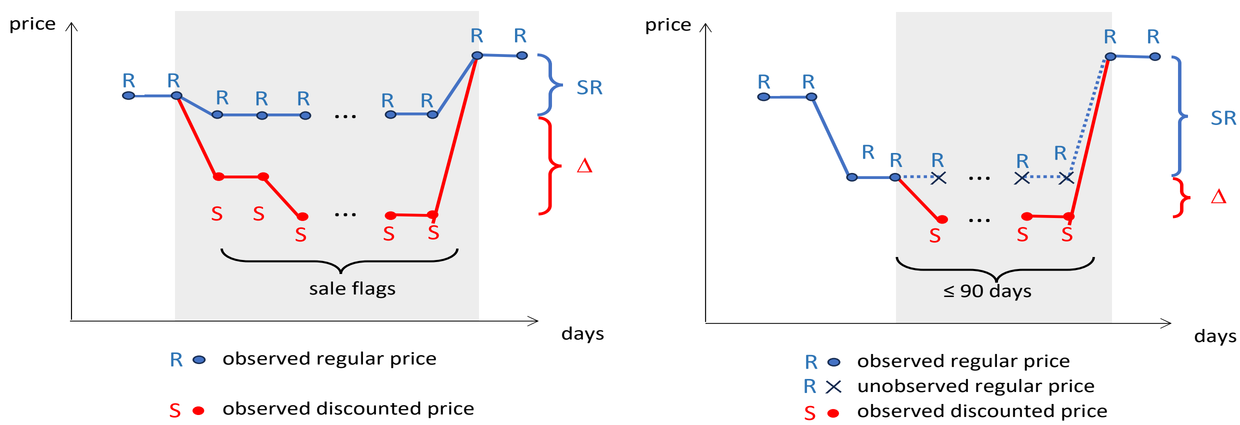


Figure 2: Example of a sale flag and unit price on a retailer's website.

Unit prices allow us to control for package sizes and distinguish between "cheap" and "premium" varieties of narrowly-defined categories, such as "fresh eggs". To construct these categories, we rely on three product characteristics available in the dataset. First, all products are categorized using the Classification of Individual Consumption According to Purpose (COICOP) at 3-digit level, which is commonly used by statistical agencies to construct price indices. In the example above, the corresponding code would be 114 corresponding to "Milk, other dairy products and eggs". Second, the dataset contains a variable that uniquely identifies the web address (URL) where the data was collected. Within retailers, these URLs are typically created to group together different varieties of similar products, such as "eggs". For example, a typical URL that shows the products in Figure 2 would be: https://www.retailername.com/browse/food/eggs. Third, we further distinguish products using the packaging unit in which they are sold, such as count, weight, or volume. In the example above, fresh egss are sold by unit (count), while hard-boiled eggs in the same URL as sold by weight (ounces). Our categories are therefore COICOP-URL-unit groupings of highly similar products, for which there can still be a wide range of unit prices reflecting varieties of different quality, from the cheapest "Value Eggs" to the most expensive "Pasture raised" in our example.

Sale discounts are identified either by retailers' sale flags, which are discount advertisements posted alongside the product's price (as illustrated in Figure 2), or through the application of an ad-hoc V-shape filter. This filter detects a price decrease followed by a price increase within 90 days, effectively identifying temporary price reductions (Nakamura and Steinsson, 2008). Figure 3 illustrates hypothetical price observations corresponding to two definitions of sales. Sale advertisements typically include not only the discounted price but also the regular (undiscounted) price, which means that sale flags provide observations of both sale and regular prices. For V-shape sales, in contrast, the regular price is unobserved during the sale period; we therefore define it as the last observed price before the sale began. For both definitions, if no discount is applied, the regular price level is the recorded price level. During a flag sale, both the regular and sale prices may change, whereas in a V-shape sale, they are fixed by definition. Additionally, the duration of a V-shape sale is defined as less than 90 days, while the duration of a flag sale is directly observed.



(a) Flag discounts (b) V-shape discounts

Figure 3: Definitions of sale-related price changes.

Notes: Charts show hypothetical price paths during a flag sale (Panel a) and V-shaped sale (Panel b). Sale-related price changes are regular or discounted price changes occuring during the sale, marked by the shaded area. The end of sale price change comprises discount ("Δ") and the end-of-sale regular price change ("SR").

We define *sale-related* price changes as those occurring over the duration of the sale (shaded areas in Figure 3). Sale-related price changes include regular price changes at the beginning and the end of sales. Figure 3 exemplifies how the total price change at the end of sale combines the discount itself (the difference between the regular and discounted price levels) and the "S-to-R" regular price change.

Table 3 summarizes the share and magnitude of price discounts in 2019. On average, price discounts are between 18% and 35%. They are more frequent in North America and the United Kingdom, between one and two in every 10 price observations, and less frequent in Europe or South America, usually between 0.02 and 0.08 of price observations.

	Flag		V-shapes	
	Share	Size, %	Share	Size, %
ARGENTINA	0.06	26.5	0.09	22.7
BRAZIL	0.08	26.5	0.12	25.6
CANADA	0.19	29.1	0.16	31.1
FRANCE	0.02	27.2	0.05	15.7
GERMANY	0.04	34.7	0.03	33.6
ITALY	0.08	32.0	0.08	33.0
NETHERLANDS	0.02	30.4	0.05	25.5
SPAIN	0.06	18.0	0.07	16.3
UK	0.15	35.3	0.12	34.9
USA	0.10	31.2	0.10	30.0

Table 3: Fraction and size of discounts in 2019.

Notes: For each country, columns "Share" provide the weighted mean monthly share of discounted prices in all price observations in 2019, and columns "Size" give the weighted mean size of discounts (the difference between regular and discounted prices during sale). Weights are 3-digit COICOP weights.

3 Inflation for regular and sale-related price changes

To obtain monthly inflation rates, we construct the daily rates, decompose them into components due to regular and sale-related price changes, and time-aggregate the daily time series to monthly frequency.

In each day t, we observe N_t regular price quotes. Let p_{it} denote log price for product i. Let I_{it} denote the indicator of a price change, I_{it}^S be the discount indicator (flag or V-shape), and p_{it}^R be the log of regular price level. Let ω_i denote product weights, equal to 3-digit COICOP weights divided equally among products within 3-digit COICOP categories.

Inflation is the weighted mean of daily log price changes

$$\pi_t \equiv \sum_{i=1}^{N_t} \omega_i I_{it}(p_{it} - p_{it-1}). \tag{1}$$

We distinguish four types of price changes: from regular price on day $t-1$ to regular price on day t when there is no sale (RR), from regular to sale price at the beginning of sale (RS), from sale to sale price during sale (SS), and from sale to regular price at the end of sale (SR). *Regular price inflation* π_t^{RR} sums up RR changes, and *sale-related inflation* sums up RS, SS, and

SR changes:

$$\pi_t \equiv \pi_t^{RR} + \pi_t^{Sales}, \tag{2}$$

$$\pi_t^{RR} = \sum_{i=1}^{N_t} \omega_i I_{it}(1 - I_{it}^S)(1 - I_{it-1}^S) dp_{it}^{RR},$$

$$\pi_t^{Sales} = \sum_{i=1}^{N_t} \omega_i I_{it} \left[I_{it}^S(1 - I_{it-1}^S)(dp_{it}^{RS} - \Delta_{it}) + I_{it}^S I_{it-1}^S dp_{it}^{SS} + (1 - I_{it}^S) I_{it-1}^S (dp_{it}^{SR} + \Delta_{it-1}) \right],$$

where the $dp_{it}^X = (p_{it}^R - p_{it-1}^R)$, $X = \{RR, RS, SR\}$, denotes the *regular* price change of type X, $dp_{it}^{SS} = p_{it} - p_{it-1}$ is the SS price change, and $\Delta_{it} = p_{it}^R - p_{it}$ is the absolute size of discount. Note that RS and SR changes combine discounts and start- or end-of-sale regular prices changes. The total RS price change (the beginning of sale) is the sum of the discount itself $-\Delta_{it}$ and the concurrent change in the regular price dp_{it}^{RS} (for V-shapes the latter is zero by definition). Similarly, at the end of sales, the SR price change is the sum of the discount Δ_{it-1} and the additional change in the regular price dp_{it}^{SR}. We make these distinctions to gauge retailers' adjustments of regular prices at the start and the end of sales. Appendix A provides decomposition details.

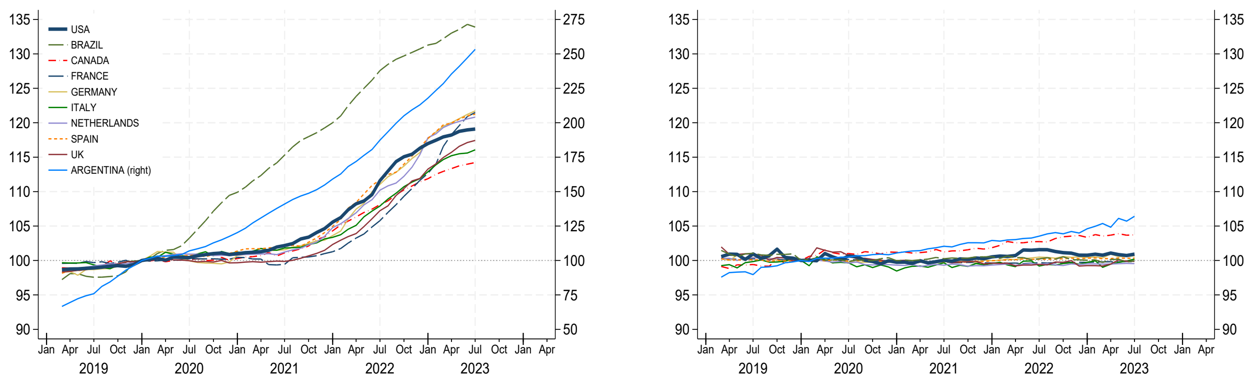
We time-aggregate the daily time series to monthly frequency to facilitate visualization of the results. Monthly inflation rate is the sum of daily rates for each month. Monthly fractions of price adjustments (increases or decreases) are defined as probabilities of adjusting price at least once a month computed from daily fractions of adjustments.[3] The monthly average size of price changes is the ratio of corresponding monthly inflation rate and monthly fraction of adjustments.[4]

Figure 4 and Table 4 summarize the cumulative month-to-month inflation rates for regular and sale-related price changes over the period between January 2020 and July 2023. In all countries, price growth over this period reflected mainly regular price adjustments. Figure 4(a) shows that regular food prices grew by 14.1% to 20.8% in low-inflation countries, and by 33.0% and 111.7% in Brazil and Argentina. In Appendix C we show that retailers attained higher regular price growth by raising the proportion of price increases to decreases from roughly balanced to

[3] Under assumptions that daily fraction of adjustments, F_d, represents probability of adjustments on day d of the month, and that adjustments are independent across days, monthly probability of adjusting price at least once is $1 - \prod_d (1 - F_d)$.

[4] Since sale-related inflation is much more transitory than RR inflation, time aggregation lowers the contribution of sale-related inflation to fluctuations in total inflation. For example, aggregation from monthly to quarterly frequency reduces the share of inflation variance contribution due to sale-related inflation by more than half in the pooled sample for low-inflation countries, from 0.28 to 0.12 (see Appendix B).

about 2 to 1. The magnitude of price changes diminished, especially the magnitude of increases, reflecting their higher frequency. These patterns are present in all countries in our data and in non-food sectors in the U.K. CPI data.



(a) Regular price changes

(b) Sale-related price changes

Figure 4: Cumulative monthly inflation rates for regular and sale-related price changes.

Notes: Figure provides cumulative monthly inflaiton rates, normalized to 100 in Jaunary 2020. Panel A shows the cumulative rates for monthly regular price changes. Panel B provides them for sale-related price changes, defined as the difference between the rates for all price changes and regular price changes. Discounts are defined by a sale flag.

In contrast to regular prices, Figure 4(b) shows that the month-to-month inflation during sales would accrue to below single digits, even in Argentina (6.2%). To gauge whether these results also apply for non-food sectors, we compute this decomposition for food and non-food goods in the U.K. CPI micro data (Appendix D). While food CPI inflation in the United Kingdom was expectedly the highest across goods, increasing by 27.7% since January 2020, it surged in other sectors as well (24.2% in Nondurables, 20.5% in Durables, 21.4% in Semi-durables, and 19.9% in Services). In line with evidence from multi-channel food retailers, sale-related changes contributed little to the inflation surge in food and non-food sectors, with the exception of Semi-durables, where discounts almost entirely offset regular price growth. This is not very surprising, given frequent occurrence of sales, especially clearance sales, in Semi-durables sector (Kryvtsov and Vincent, 2020).

	Flag				V-shapes			
	Regular	Sales			Regular	Sales		
		Total	Discounts	Regular		Total	Discounts	Regular
ARGENTINA	153.3	6.4	0.4	6.0	155.3	4.4	0.5	3.8
BRAZIL	33.9	0.0	-0.3	0.3	31.8	2.1	0.3	1.8
CANADA	14.2	3.7	0.1	3.6	15.0	3.0	1.9	1.1
FRANCE	21.5	-0.2	0.0	-0.2	21.7	-0.4	0.2	-0.6
GERMANY	21.7	0.7	0.0	0.7	21.0	1.4	0.4	1.0
ITALY	16.1	0.2	-1.0	1.2	13.6	2.7	1.2	1.4
NETHERLANDS	20.8	-0.5	-0.7	0.2	18.9	1.4	0.9	0.5
SPAIN	21.2	0.3	0.0	0.3	20.1	1.5	0.4	1.1
UK	17.4	-0.1	-0.2	0.1	13.5	3.8	2.4	1.5
USA	19.1	0.9	-0.3	1.2	17.0	3.0	1.3	1.7

Table 4: Cumulative monthly inflation rates between January 2020 and July 2023, % change.

Notes: The table provides cumulative inflation rates (in %) for regular and sale-related price changes between January 2020 and July 2023. Price growth during sale-related changes is in column "Total" (cumulative π_t^{Sales} in (3)), due to discounts and SS price changes is in column "Discounts" (cumulative $\pi_t^{\Delta} + \pi_t^{SS}$), and due to RS and SR regular price changes is in column "Regular" (cumulative $\pi_t^{reg,end} + \pi_t^{reg,start}$).

The fact that retailers did not directly use discounts to raise their prices may be surprising. In countries with relatively frequent use of discounts (United States, United Kingdom, Canada, Italy) sale-related inflation accounted for half of quarterly inflation variance before the inflation surge, and even higher share for monthly inflation rates (Appendix E). This includes early months of the pandemic period when inflation was still low. Indeed, Jaravel and O'Connell (2020b) report that the sharp fall in the share of discounts contributed half of the 2.4% inflation for fast-moving products over the first month of the lockdown in the United Kingdom at the end of March 2020.[5]

To clarify why discounts contribute so little to inflation, we look at how sale-related price changes accrue over time. Let H_t denote the share of discounts in price quotes, i.e., $H_t = \sum_{i=1}^{N_t} \omega_i I_{it}^S$, where I_{it}^S is a sales indicator. Based on definitions in (2), inflation from sales π_t^{Sales} can be decomposed as follows (see Appendix A):

$$\pi_t^{Sales} = \underbrace{-(H_t - H_{t-1})\Delta_t}_{\pi_t^{\Delta}} + \underbrace{H_{t-1}F_t(1-H_t)D_t^{SR}}_{\pi_t^{reg,end}} + \pi_t^{reg,start} + \pi_t^{SS}. \tag{3}$$

The first term on the right-hand side of (3) represents the discounts inflation:

$$\pi_t^{\Delta} \equiv F_t^{SR}\Delta_t^{+} - F_t^{RS}\Delta_t^{-} = -(H_t - H_{t-1})\Delta_t, \tag{4}$$

[5] As households were panic-buying consumer staples amid lockdowns and uncertainty, and delivery chains were disrupted, retailers were facing strains on their stocks. For example, Cavallo and Kryvtsov (2023) document a widespread multi-fold rise in stockouts in nearly all sectors at this time. Under such conditions, it is optimal for retailers to curb their discounts and keep their prices relatively high (Aguirregabiria, 1999).

where $\Delta_t \equiv \frac{F_t^{SR}\Delta_t^+ + F_t^{RS}\Delta_t^-}{F_t^{SR}+F_t^{RS}}$ is the average size of discounts in period t, and the change in the fraction of discounts, $H_t - H_{t-1}$, reflects the balance of sales that start in period t and those that end in the same period:

$$F_t^{SR} - F_t^{RS} = \sum_{i=1}^{N_t} \omega_i I_{it} \left[(1 - I_{it}^S) I_{it-1}^S - I_{it}^S (1 - I_{it-1}^S)\right] = -(H_t - H_{t-1}).$$

According to (4), discount inflation is higher when either the fraction of discounts or their size decrease. Variation in the average size of discounts is much smaller than variation in the change in the share of discounts (see Appendix E), so we can approximate $\Delta_t \approx \Delta$ and write the total change in price level between periods 0 and T:

$$P_T^\Delta - P_0^\Delta \approx -(H_T - H_0)\Delta, \tag{5}$$

which says that the contribution of discounts to price growth between periods 0 and T is approximately the product of the total decrease in the share of discounts in posted prices and the average discount size.

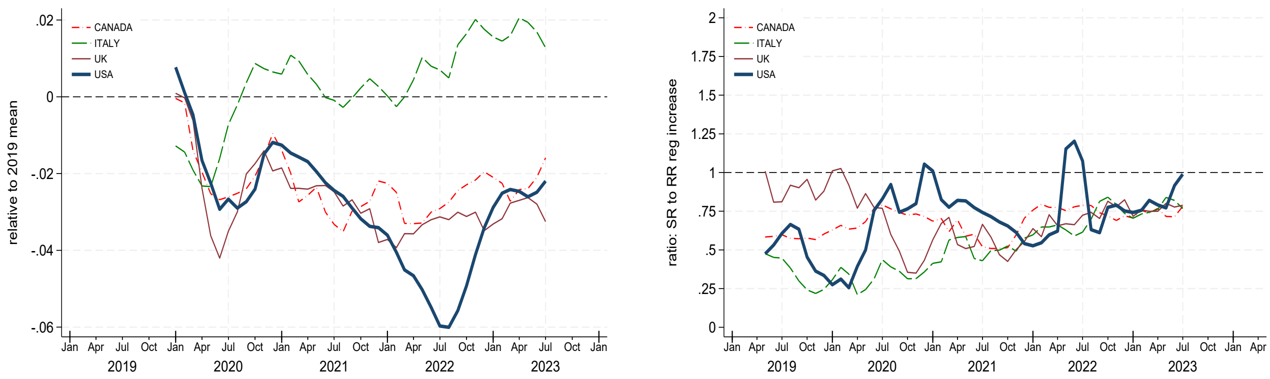
Figure 5(a) shows the evolution of the fraction of discounts relative to their average 2019 levels for four countries with frequent discounts. In all four countries, the share of discounts decreases at the onset of the pandemic, by 0.02 to 0.04 (with the largest decrease in the United Kingdom, in line with Jaravel and O'Connell (2020b)). While such swings in discounts can generate volatile month-to-month inflation swings, they cannot create a sustained rise in prices.[6] For example, even if U.S. retailers completely removed *all* discounts (Table 3), the cumulative rise in the price level would be 3.1% (=0.10 · 31.2). Retailers simply cannot keep shrinking their sales for long stretches of time when they need to raise their prices.

The second term on the right-hand side of (3) stems from regular price changes at the end of sales:

$$\pi_t^{reg,end} \equiv F_t^{SR,reg+} D_t^{SR+} - F_t^{SR,reg-} D_t^{SR-} = H_{t-1} F_t (1 - H_t) D_t^{SR}$$

where $F_t = \sum_{i=1}^{N_t} \omega_i I_{it}$ is the fraction of price adjustments in t, and D_t^{SR} is the average size of regular price changes at the end of sales in period t.

[6] This evidence is in line with the view in the literature that retailers use discounts to respond to unexpected but transient shocks (Kryvtsov and Vincent, 2020) or accommodate anticipated seasonal events (Warner and Barsky, 1995). In contrast to rising prices, sales can help sustain persistent downward price pressures: Nakamura et al. (2018) document a "dramatic" multi-fold increase in the frequency of sales between 1978 and 2014 in sale-intensive product categories.



(a) Monthly share of discounts

(b) Ratio: SR to RR regular price increase

Figure 5: Share price discounts and end-of-sale regular price changes.

Panel (a) provides the monthly share of discounts, H_t relative to its average 2019 levels. Panel (b) provides the ratio of the average magnitude of the regular price increase at the end of sales to the average magnitude of the RR price increase. Averages are weighted means, with 3-digit COICOP weights. Discounts are identified by the sale flag. Series are smoothed by a 3-month backward looking moving average.

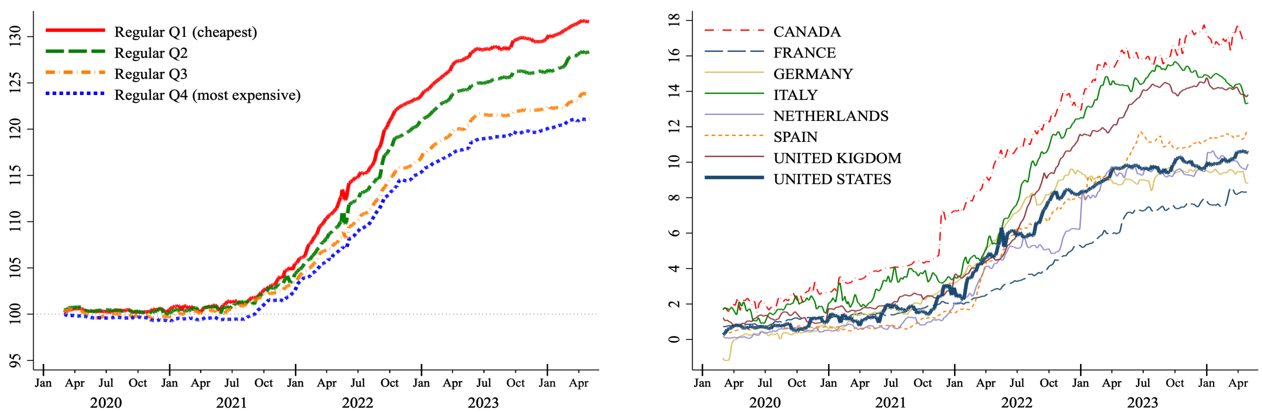
Contribution of this term to inflation is small because when retailers return from discounted to regular prices, they do not "pro-rate" the end-of-sale regular price changes to compensate for zero regular price growth *during* sales. For example, Figure 5(b) shows that on average regular price increases at the end of sales are similar in magnitude to, if not lower than, RR price increases. The implication is that unit prices for products that went through a sale diverge from unit prices of products that did not have a sale.

The remaining two components of sale-related price inflation—beginning-of-sale regular price changes and SS price changes—are quantitatively small for flag sales, and they are zero by definition for V-shape sales. Table 4 breaks down sale-related price changes into components from discounts (together with changes during discounts) and from regular changes around sales.

4 Cheapflation

The second source of variation in prices within a store comes from price differences in narrow categories, defined by a COICOP-URL-unit combination. Within these categories, we group products into quartiles based on their average unit prices in 2019. Products falling into the first quartile are categorized as "cheap," representing the least expensive options available to consumers at the start of the pandemic. Conversely, products whose prices were in the fourth quartile were classified as “premium,” the highest-priced goods within each category. We then construct a matched-model price index for each quartile and country, as visualized in Figure 6(a).

For all 10 countries, there is a significant disparity in inflation rates between the first and last quartiles over the period from January 2020 to May 2024. In most cases, the difference starts to increase in early 2021 and stabilizes by early 2023.



(a) Regular price index, by quartile

(b) Q1 vs Q4 cumulative inflation since Jan 2020

Figure 6: Cheapflation.

Panel (a) provides the matched-model regular price indexes for products in quartiles of average unit price in 2019 for the United States. Indexes are normalized to 100 in January 2020. Panel (b) provides the cumulative inflation rates since January 2020 (i.e., the differences between indexes for the cheapest (Q1) and most expensive (Q4) products) for low-inflation countries in the sample.

To summarize this disparity, Table 5 provides the cumulative inflation differentials for all countries. For instance, in the United States, we find that cheaper products experienced an inflation rate of 30% over this period, while premium product prices increased by only 20%. In other words, there was 1.5 times higher inflation for cheaper products, leading to an additional 10 percentage points relative to premium varieties since January 2020. This difference in cumulative inflation for cheapest products ranges between 7.5 percentage points in France and 17 percentage points in Canada. The differences in price growth—visualized for low-inflation countries in Figure 6(b)—represent convergence of prices within narrowly defined product categories.

	Cumulative Inflation Jan 2020 – Oct 2023 (%)			
	All Products	Cheapest Q1	Most Exp. Q4	Q1–Q4 ppt
CANADA	26.6	35.2	18.2	17.0
FRANCE	22.2	25.9	18.4	7.5
GERMANY	21.0	25.9	16.5	9.5
ITALY	18.0	25.8	10.5	15.3
NETHERLANDS	27.4	31.1	21.8	9.3
SPAIN	28.1	33.3	22.5	10.9
UNITED KINGDOM	21.6	28.1	14.0	14.1
UNITED STATES	24.8	29.8	19.8	10.0

Table 5: Cumulative inflation by unit regular price quartile.

Notes: Table shows the cumulative inflation rate from January 2020 to October 2023. The Q1 (cheapest) and Q4 (most expensive) products are selected based on their average unit regular price in 2019 (flag discounts).

Cheapflation represents a double whammy of inflation burden. By switching from their favorite products to their cheaper counterparts, households incur the utility cost of consuming less preferred products. In the next section, we show that indeed consumers switched their spending toward cheaper brands. But even if households save dollars by consuming cheaper brands, some of the savings will be offset by faster rise in prices of those brands. Therefore, even if inflation has all but returned to its pre-pandemic levels, relative prices of cheaper options are *permanently* higher.

5 Expenditure switching

While most of the increase in measured inflation stemmed from regular price increases, the ultimate inflationary burden depends on reallocation of expenditures along the product spectrum. Consumers can generate much needed savings by shifting their spending toward cheaper goods. For each product in the consumption basket, such an adjustment occurs along both dimensions of the effective price: lower price for the same-quality product, or lower quality product. For example, as the price of Mel's favorite milk brand "NATURES BEST 1% MILK CARTON 2LT" becomes more expensive, she may wait until it is on sale or look for a lower price at another store. This option usually comes at a cost of searching or waiting. Alternatively, she may want to buy a different package of the same brand "NATURES BEST 2% MILK CARTON 2LT" or switch to a cheaper brand of milk in the same store. This option implies the cost of having to buy a less preferred or lower-quality brand of the same product.

In this Section, we analyze expenditure switching along both price and quality dimensions using Canadian Nielsen Homescan Panel data. Our goal is to assess the degree to which such shifts in spending helped households curb the post-pandemic increase in price they paid per unit of product of the same quality. To complement evidence in Sections 3 and 4, we focus on expenditure switching *within* narrow product categories. We present additional evidence on expenditures switching across retailers.

5.1 Canadian Nielsen Homescan Panel data

The data, collected by NielsenIQ, contain information for Canadian households' expenditures on consumer goods, such as food and household goods. Individual transactions have been recorded from 2013 by households from a participating panel of roughly 12,000 households across all provinces (excluding Newfoundland and Labrador, and territories). For this paper, we focus on transactions for 164 fast-moving product categories (104 food and 60 non-food) between 2019 and 2023. For each transaction, we observe: expenditures (dollars paid, quantity purchased, type and use of discount, trip date); Universal Product Code (upc) or other product code (for bulk products); item and package description; retailer (including brick-and-mortar and online shopping); shopping location, given by city or region; household's socio-demographic information (household size, age, children, language, and income). After cleaning, the dataset contains observations for 28,605,666 transactions for 175,155 upcs across 533 retailers and 53 locations. Appendix G provides the list of food products.

5.2 Expenditure switching toward cheaper products

To construct unit prices, we first standardize package sizes for all upcs in the same product category. Most upcs in the same category are measured in units of mass (e.g., grams, kilograms or pounds), liquid volume (e.g., liters or milliliters), or the number of units in a package (most non-food upcs have one unit per package).[7] For example, a "NEILSON 2% CARTON 473ML" milk and "NUTRINOR 1% MILK CARTON 2LT"—both in "MILK" product category—count as 0.473 and 2 standardized units. Peanut butter brands "KRAFT CRUNCHY 2KG" and "EARTHS CHOICE ORGANIC CREAMY JAR 500GM" count as 2 and 0.5 standardized units,

[7] Out of 164 products, 127 have at least 90% of upcs measured in the same unit of measurement, and 20 products have mixed units with more than 10% of mass or liquid units. We treat 1 gram as equivalent to 1 milliliter. For the remaining 38 products, packages are in units per package.

respectevely. Unit transaction price equals dollars spent on transaction (after discounts) per number of standardized units (the product of the number of purchased packages and the number of standardized units per package). Unit *regular* price is defined similarly, but without the discounts.

Define the average monthly unit price as the mean of unit prices across all transactions for each retailer in that month, i.e., across all locations where these transactions occurred in that month. Let P_{it} denote the average unit price for retailer-upc i in month t. To construct the monthly price index, we consider two alternatives for the basket of retailer-upc pairs, Ψ_t. *Matched-model* basket refers to all retailer-upc pairs for which the average unit price is observed in both months t and $t-1$. *Constant basket* contains only retailer-upc pairs for which average unit price is observed in all 60 months between 2019 and 2023. This conservative basket is a strongly balanced panel of unit price observations; for food products, it is roughly 6 times smaller than the matched-model basket.

We are primarily interested in the effect of expenditure switching across groups of transactions, as opposed to individual transactions (e.g., regular vs discounted transactions, cheap vs expensive brands). Therefore, we construct fixed-weight price indexes for each group of interest, combine them with varying group weights—changes in expenditures for respective groups—and study the varying-weight index.[8]

Define month-t fixed-weight inflation rate as

$$\pi_t \equiv \sum_{i \in \Psi_t} \omega_i \left(\ln P_{it} - \ln P_{it-1} \right), \tag{6}$$

where ω_i is the mean expenditure share for retailer-upc i during 2019–2023.

Similarly, define month-t fixed-weight regular inflation rate as

$$\pi_t^{RR} \equiv \sum_{i \in \Psi_t} \omega_i^R \left(\ln P_{it}^R - \ln P_{it-1}^R \right), \tag{7}$$

where P_{it}^R is the average unit regular price for transactions for retailer-upc i in month t, and ω_i^R is the mean expenditure share for retailer-upc i in all regular price transactions during 2019–2023.

[8] A more comprehensive treatment of expenditure switching would require construction of superlative chained indexes (Ivancic, Diewert, and Fox, 2011). Analysis of chained indexes would entail two additional challenges: distinguishing expenditure switching within versus across groups of transactions and the chain drift (Nakamura, Nakamura, and Nakamura, 2011). Jaravel and O'Connell (2020a) use the U.K. scanner data to quantify the effects of expenditure switching in the wake of inflationary spike during the 2020 lockdown.

Following Section 3, sale-related inflation rate is the difference between inflation rates for all and only regular price transactions: $\pi_t^{Sales} \equiv \pi_t - \pi_t^{RR}$.

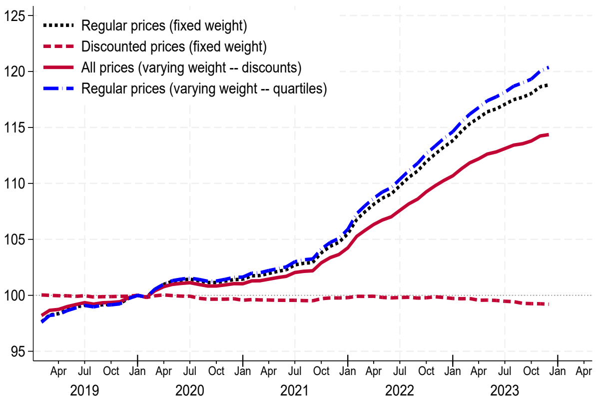
Let s_{it}^{Sales} denote dollars spent on discounted transactions for retailer-upc i in month t, and let s_{it} denote total dollars spent in month t. Expenditure switching from regular to discounted prices is summarized by the share of expenditures on discounted transactions in all expenditures:

$$\omega_t^{Sales} = \frac{\sum_{i \in \Psi_t} s_{it}^{Sales}}{\sum_{i \in \Psi_t} s_{it}}. \tag{8}$$

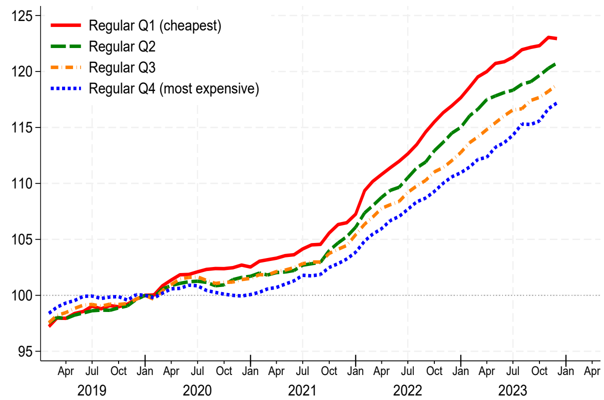
To visualize the impact of expenditure switching from regular to discounted prices, we construct the varying-weight inflation rate as the weighted average of fixed-weight inflation rates with weight equal to the respective expenditure shares:

$$\widetilde{\pi}_t = \left(1 - \frac{\omega_t^{Sales} + \omega_{t-1}^{Sales}}{2}\right) \pi_t^{RR} + \frac{\omega_t^{Sales} + \omega_{t-1}^{Sales}}{2} \pi_t^{Sales}. \tag{9}$$

As before, we visualize the cumulative inflation rates for regular and sale-related changes, which we now call "price indexes" in short. Figure 7(a) provides fixed-weight price indexes for regular and discounted transactions for food products (matched models), π_t^{RR} and π_t^{Sales}. While regular prices grew by 18.8% from January 2020 to December 2023, the cumulative rate of sale-related price changes was roughly zero (Table 6). Figure 7(c) shows that after the initial sharp fall to 0.19 at the onset of the pandemic in 2020, the expenditure share of discounted transactions gradually recovered to its end-2019 level of around 0.25. The shift of spending toward flat sale-related prices, lowered the varying-index price level by 4.4 percentage points (row 2 in Table 6). Hence, expenditure switching to discounts shaved off roughly a quarter of the price increase since January 2020 relative to the increase for regular-price transactions. The results are similar for non-food products and when using constant basket.

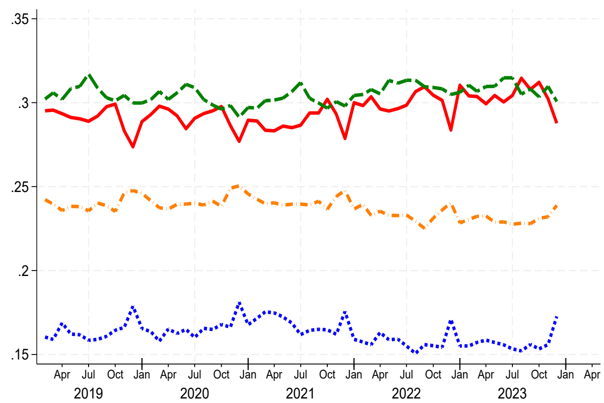


(a) Price indexes with varying group weights



(b) Fixed-weight regular-price indexes, quartiles

(c) Expenditure share: discounted transactions



(d) Expenditure shares: unit price quartiles

Figure 7: Prices and expenditure switching for food (matched models).

Notes: Panel A shows price indexes for matched models: fixed-weight indexes for regular-price and discounted transactions, and variable-weight indexes that apply variation of the expenditure share across groups while keeping within-group weights fixed. Panel B shows fixed-weight price indexes for matched models for regular-price transactions within quartiles of unit price levels. All price indexes are normalized to 100 in January 2020. Panel C and D show expenditure shares for discounted transactions and for transactions by unit price quartiles.

Turning to expenditure switching across groups of regular-price transactions, we rank upcs within each product category into quartiles by their average unit regular price in 2019 (after controlling for retailer-category fixed effects). For upcs in each quartile, we construct fixed-weight inflation rates and corresponding expenditure shares in all regular-price transactions.

Figure 7(b) shows that cheaper brands experienced faster growth of transaction prices, corroborating the facts from multi-channel retailers in Section 4. Figure 7(d) shows that starting in the end of 2021, i.e., when Canadian inflation started its surge, expenditures started to shift from more expensive to cheaper brands. The shift toward faster-growing prices of cheaper brands *raised* the varying-weight regular price index relative to the fixed-weight index by an additional 1.6 percentage points (row 3 in Table 6). Hence, while households switched to cheaper (lower quality) brands their savings were somewhat offset by the higher relative price growth for those brands. This effect is more modest for constant basket due to a smaller number of brands.

		Matched models			Constant basket		
		Food	**Non-food**	**All**	**Food**	**Non-food**	**All**
(1)	**Regular prices (fixed weight), %**	**18.8**	**17.3**	**12.5**	**20.4**	**20.3**	**19.0**
(2)	**Varying weight – discounts, %**	**14.4**	**13.2**	**9.6**	**16.2**	**16.1**	**16.3**
	total savings = (1) – (2)	4.4	4.1	2.9	4.3	4.1	2.7
(3)	**Varying weight – quartiles, %**	**20.4**	**20.1**	**19.2**	**20.6**	**20.5**	**20.1**
	total savings = (1) – (3)	-1.6	-2.8	-6.7	-0.2	-0.2	-1.1
(4)	**Varying weight – retailers, %**	**18.9**	**17.3**	**12.5**	**20.5**	**20.3**	**19.2**
	total savings = (1) – (4)	-0.1	0.0	0.1	-0.1	-0.1	-0.2
	# products	104	59	163	104	56	160
	# upc	113,623	72,427	185,069	17,997	3,170	21,167
	# observations	8,218,723	1,285,666	9,504,389	2,327,994	205,098	2,533,092

Table 6: Unit price changes between January 2020 and December 2023.

Notes: Table provides cumulative monthly inflation rates (in %) from between January 2020 to December 2023. Row (1): change in the fixed-weight index for regular-price transactions; Row (2): change in the index with varying expenditure weight for regular and discounted transactions; Row (3): change in the index with varying expenditure weights for regular-price transactions within quartiles of unit price levels; Row (4): change in the index with varying expenditure weights for regular-price transactions within retailer groups. Columns distinguish upc baskets (continuing models and constant basket of upc's with transactions in all months), and upc groups (food, non-food, and all).

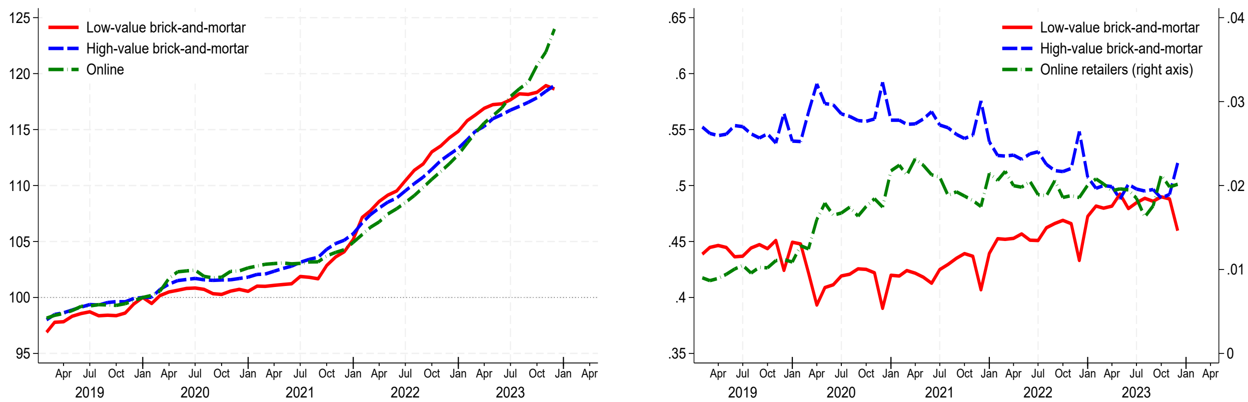
5.3 Expenditure switching across stores

While the paper so far focused on prices and expenditures within retailer and product category, Canadian homescan panel data allow analysis of expenditure switching *across* retailers. Previous literature documented retailer heterogeneity as an important dimension of pricing behavior.[9] We split retailers into three groups: high- and low-value brick-and-mortar (BMO) retailers, and online retailers. High-value retailers include premium grocery stores and specialty stores. Premium grocery stores are grocery stores that do not advertise themselves as discount stores.

[9] Kaplan and Menzio (2015) use the U.S. homescan panel data to estimate that half of variation in prices that household pay is due to differences in expensiveness of retail stores they choose to shop. Coibion, Gorodnichenko, and Hong (2015) employ a different scanner dataset for transactions from U.S. grocery stores to find that during economic slumps consumers move their spending from high- to low-value retailers. Gorodnichenko and Talavera (2017) and Gorodnichenko, Sheremirov, and Talavera (2018) document differences in pricing behavior by online retailers vis-à-vis brick-and-mortar stores.

Specialty stores include pharmacies, convenience stores, gas stations, beer/wine/liquor stores, and other specialty stores. Online retailers include all online platforms and online deliveries.

Figure 8(a) shows fixed-weight price indexes constructed for upcs in each group using matched models basket. Until 2021, prices of low-value BMO retailers grew slower than prices of high-value BMO retailers. As inflation took off at the end of 2021, so did low-value BMO prices; and and they cooled off together with inflation over year 2023. In contrast, high-value BMO prices were rising more steadily. On balance, cumulative price growth between January 2020 and December 2023 was around 19% for both high- and low-value retailers. Online food prices have been rising faster in 2023, ending around 6 ppt higher over 2019–2023 period.



(a) Fixed-weight regular price indexes

(b) Expenditure shares

Figure 8: Transaction prices and expenditures for food, by retailer group (continuing models).

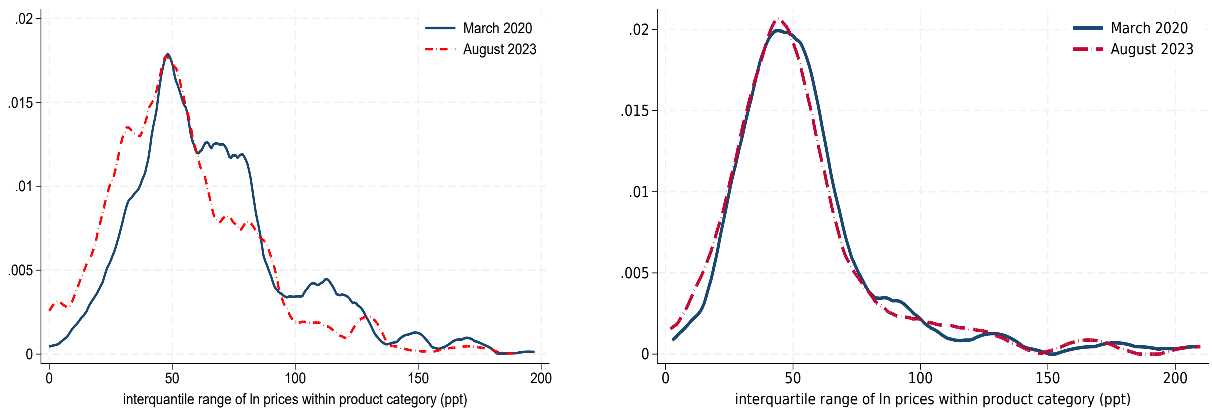
Notes: Panel A shows fixed-weight price indexes for matched models using regular-price transactions for each retailer group. All indexes are normalized to 100 in January 2020. Panel B shows expenditure shares for transactions in each retailer group.

Figure 8(b) shows that when the pandemic hit, around 5% of expenditures switched from low-value BMO retailers to high-value retailers (roughly 4%) and online retailers (1%). The latter doubled the share of food spending online from 1% to 2%, which stayed around 2% since then. But the bulk of spending in high-value BMO stores switched back to low-value retailers, raising their share in regular price expenditures from 0.39 in April 2020 to 0.49 in Fall 2023. This substantial switching did not influence the varying-weight price index since prices for low- and high-value retailers grew by around the same magnitude (row 4 in Table 6).

6 Unit price dispersion

Since regular and discounted prices diverged with inflation and regular prices of cheap products converged to prices of more expensive brands, the effect on within-store price dispersion depends on the balance of these effects.

We measure price dispersion by the interquartile range of unit prices within retailer and narrow product category in each month. Figure 9 shows a substantial variation in unit price dispersion across products in a given month, for both posted prices (in the United States, Panel (a)) and transaction prices (in Canada, Panel (b)).



(a) Posted prices (United States)

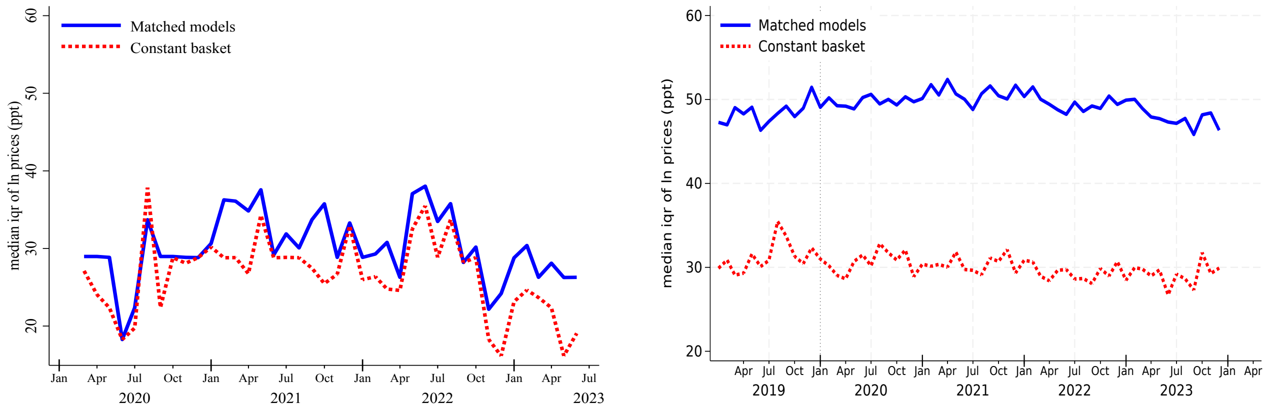
(b) Transaction prices (Canada)

Figure 9: Distribution of within-product unit price dispersion for food.

Notes: Figure provides kernel densities of interquartile range for ln unit prices within retailer-product in a given month. Panel A uses unit posted prices for food sold by multi-channel retailers in PriceStats data for the United States. Panel B uses unit transaction prices for food products (matched models) in the Canadian Homescan Panel Dataset.

The mode interquartile range is around 50 percentage points. We compare distributions at the beginning of the pandemic (March 2020) and after the pandemic (August 2023). For both posted and transaction prices the distribution of within-product price dispersions shifted to the left, indicating a larger number of products with decreased price dispersion in 2023 than in 2020.

Figure 10 visualizes the evolution of the median within-product price dispersion in our sample. In all four cases—unit posted prices in the United States and unit transaction prices in Canada, using all matched models and constant basket—median within-product price dispersion appears to be stable or decreasing (in 2022 and 2023).



(a) Posted prices (United States)   (b) Transaction prices (Canada)

Figure 10: Median within-product unit price dispersion for food.

Notes: Figure provides the time series for the median of interquartile ranges for ln unit prices within retailer-product in a given month. Panel A uses unit posted prices for food sold by multi-channel retailers in PriceStats data for the United States. Constant basket comprises 16,897 unique products that enter before March 2020 and never exit. Panel B uses unit transaction prices for food products in the Canadian Homescan Panel Dataset, for matched-model basket and for constant basket.

This finding contrasts the positive relationship between inflation and price dispersion documented in previous studies.[10] The key focus—and difference—in these studies is on price dispersion *across* firms. The positive correlation of across-firm price dispersion and inflation is in line with models based on frictions in goods markets due to costly price adjustments by firms (Sheremirov, 2020) or the consumers' costs of acquiring price information (Drenik and Perez, 2020). For example, in a standard Calvo sticky price model, prices of adjusting firms drift farther away from prices of non-adjusting firms when inflation is higher.

Documenting price dispersion within stores faces a dual challenge of obtaining micro data for prices within stores-categories and for product parameters that allow controlling for variation in product size and packaging. The data employed in this paper meet this challenge. Moreover, the scale and scope of the data used in the paper—across 10 countries, countries with normally high and low inflation, countries with normally high and low use of discounts, observations for posted prices and transaction prices—supports comprehensive analysis of the relationship between within-product price dispersion and inflation.

[10] Lach and Tsiddon (1992) for food products in Israel (1978–1984), Alvarez et al. (2018) for Argentina (1988–1997), Nakamura et al. (2018) for the United States (1978–2014). Sheremirov (2020) examines U.S. retail scanner data for 2001–2011 and finds positive correlation between regular price dispersion and inflation, but negative correlation when price discounts are included. Reinsdorf (1994) finds that dispersion for 65 products in 9 U.S. in 1980–1982 decreases with inflation but increases with expected inflation.

7 Conclusions

High inflation is associated with significant movements in relative prices within firms and narrow product categories. While price discounts offer a way to lower effective inflation burden, cheapflation implies higher price growth for households favoring lower-quality products. Furthermore, those households who switch from buying their favoring brands to cheaper varieties, incur an additional utility cost consuming less-preferred goods. The degree to which these factors create an additional cost to households remains an open question.

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A Inflation decomposition

In each day t, we observe N_t regular price quotes. Let p_{it} denote log price for product i. Let I_{it} denote the indicator of a price change, I^S_{it} be the discount indicator (flag or V-shape), and p^R_{it} be the log of regular price level. Finally, ω_i denote product weights, equal to 3-digit COICOP weights divided equally among products within 3-digit COICOP categories.

Inflation is

$$\begin{aligned}\pi_t &= \sum_{i=1}^{N_t} \omega_i I_{it}(p_{it} - p_{it-1}) \\ &= \sum_{i=1}^{N_t} \omega_i I_{it}\left[I^S_{it} I^S_{it-1} + I^S_{it}(1 - I^S_{it-1}) + (1 - I^S_{it}) I^S_{it-1} + (1 - I^S_{it})(1 - I^S_{it-1})\right](p_{it} - p_{it-1}) \\ &= \sum_{i=1}^{N_t} \omega_i I_{it}\left[(1 - I^S_{it})(1 - I^S_{it-1})(p_{it} - p_{it-1}) + (1 - I^S_{it}) I^S_{it-1}(p_{it} - p^R_{it-1} + p^R_{it-1} - p_{it-1})\right. \\ &\qquad \left. + I^S_{it}(1 - I^S_{it-1})(p^R_{it} - p_{it-1} + p_{it} - p^R_{it}) + I^S_{it} I^S_{it-1}(p_{it} - p_{it-1}) \quad \right].\end{aligned}$$

Denote the absolute size of discount by $\Delta_{it} = p^R_{it} - p_{it}$, the regular price change by $dp^X_{it} = (p^R_{it} - p^R_{it-1})$, $X = RR, SR, RS$, and the SS price change by $dp^{SS}_{it} = (p_{it} - p_{it-1})$. Note that since we define an unobserved regular price as the last observed regular price, $dp^{SR}_t = 0$. This gives

$$\begin{aligned}\pi_t = \sum_{i=1}^{N_t} \omega_i I_{it}&\left[(1 - I^S_{it})(1 - I^S_{it-1}) dp^{RR}_{it} + (1 - I^S_{it}) I^S_{it-1}(dp^{SR}_{it} + \Delta_{it-1}) + I^S_{it}(1 - I^S_{it-1})(-dp^{RS}_{it} - \Delta_{it})\right. \\ &\left. + I^S_{it} I^S_{it-1} dp^{SS}_{it} \quad \right].\end{aligned} \tag{A.1}$$

We will now distinguish price increases and decreases, by defining $I^+_{it}(I^-_{it})$ denote the indicator of a price increase (decrease), $I^{SR+}_{it}(I^{SR-}_{it})$, an indicator of regular price increase (decrease) at the end of sales, and similarly, $I^{RS+}_{it}(I^{RS-}_{it})$, an indicator of regular price increase (decrease) at the beginning of sales.

Denote fractions of RR, SR, RS and SS price changes by

$$F_t^{RR+} = \sum_{i=1}^{N_t} \omega_i I_{it}^{+}(1 - I_{it}^{S})(1 - I_{it-1}^{S}), \qquad F_t^{RR-} = \sum_{i=1}^{N_t} \omega_i I_{it}^{-}(1 - I_{it}^{S})(1 - I_{it-1}^{S}),$$

$$F_t^{SR} = \sum_{i=1}^{N_t} \omega_i I_{it}(1 - I_{it}^{S}) I_{it-1}^{S},$$

$$F_t^{SR,reg+} = \sum_{i=1}^{N_t} \omega_i I_{it}^{SR+}(1 - I_{it}^{S}) I_{it-1}^{S}, \qquad F_t^{SR,reg-} = \sum_{i=1}^{N_t} \omega_i I_{it}^{SR-}(1 - I_{it}^{S}) I_{it-1}^{S},$$

$$F_t^{RS} = \sum_{i=1}^{N_t} \omega_i I_{it} I_{it}^{S}(1 - I_{it-1}^{S}),$$

$$F_t^{RS,reg+} = \sum_{i=1}^{N_t} \omega_i I_{it}^{RS+} I_{it}^{S}(1 - I_{it-1}^{S}), \qquad F_t^{RS,reg-} = \sum_{i=1}^{N_t} \omega_i I_{it}^{RS-} I_{it}^{S}(1 - I_{it-1}^{S}),$$

$$F_t^{SS+} = \sum_{i=1}^{N_t} \omega_i I_{it}^{+} I_{it}^{S} I_{it-1}^{S}, \qquad F_t^{SS-} = \sum_{i=1}^{N_t} \omega_i I_{it}^{-} I_{it}^{S} I_{it-1}^{S}.$$

The average sizes of those changes are

$$D_t^{RR+} = \frac{1}{F_t^{RR+}} \sum_{i=1}^{N_t} \omega_i I_{it}^{+}(1 - I_{it}^{S})(1 - I_{it-1}^{S}) dp_{it}^{RR},$$

$$D_t^{RR-} = -\frac{1}{F_t^{RR-}} \sum_{i=1}^{N_t} \omega_i I_{it}^{-}(1 - I_{it}^{S})(1 - I_{it-1}^{S}) dp_{it}^{RR},$$

$$D_t^{SR+} = \frac{1}{F_t^{SR,reg+}} \sum_{i=1}^{N_t} \omega_i I_{it}^{SR+}(1 - I_{it}^{S}) I_{it-1}^{S} dp_{it}^{SR},$$

$$D_t^{SR-} = -\frac{1}{F_t^{SR,reg-}} \sum_{i=1}^{N_t} \omega_i I_{it}^{SR-}(1 - I_{it}^{S}) I_{it-1}^{S} dp_{it}^{SR},$$

$$D_t^{RS+} = \frac{1}{F_t^{RS,reg+}} \sum_{i=1}^{N_t} \omega_i I_{it}^{RS+} I_{it}^{S}(1 - I_{it-1}^{S}) dp_{it}^{RS},$$

$$D_t^{RS-} = -\frac{1}{F_t^{RS,reg-}} \sum_{i=1}^{N_t} \omega_i I_{it}^{RS-} I_{it}^{S}(1 - I_{it-1}^{S}) dp_{it}^{RS},$$

$$D_t^{SS+} = \frac{1}{F_t^{SS+}} \sum_{i=1}^{N_t} \omega_i I_{it}^{+} I_{it}^{S} I_{it-1}^{S} dp_{it}^{SS},$$

$$D_t^{SS-} = -\frac{1}{F_t^{SS-}} \sum_{i=1}^{N_t} \omega_i I_{it}^{-} I_{it}^{S} I_{it-1}^{S} dp_{it}^{SS},$$

$$\Delta_t^{+} = \frac{1}{F_t^{SR}} \sum_{i=1}^{N_t} \omega_i I_{it}(1 - I_{it}^{S}) I_{it-1}^{S} \Delta_{it-1},$$

$$\Delta_t^- = \frac{1}{F_t^{RS}} \sum_{i=1}^{N_t} \omega_i I_{it} I_{it}^S (1 - I_{it-1}^S) \Delta_{it}.$$

Total fraction of price changes is $F_t = \sum_{i=1}^{N_t} \omega_i I_{it} = F_t^{RR+} + F_t^{RR-} + F_t^{SR} + F_t^{RS} + F_t^{SS+} + F_t^{SS-}$.

We can rewrite

$$\begin{aligned}
\pi_t = & \underbrace{F_t^{RR+} D_t^{RR+} - F_t^{RR-} D_t^{RR-}}_{\text{regular price changes (no sales), } \pi_t^{RR}} \\
& + \underbrace{F_t^{RS,reg+} D_t^{RS+} - F_t^{RS,reg-} D_t^{RS-}}_{\text{regular price changes (start sales), } \pi_t^{reg,start}} \\
& + \underbrace{F_t^{SR,reg+} D_t^{SR+} - F_t^{SR,reg-} D_t^{SR-}}_{\text{regular price changes (end sales), } \pi_t^{reg,end}} \\
& + \underbrace{\overbrace{F_t^{SR} \Delta_t^+}^{\text{discounts (end sales)}} - \overbrace{F_t^{RS} \Delta_t^-}^{\text{discounts, new sales}}}_{\text{discount inflation, } \pi_t^{\Delta}}, \\
& + \underbrace{F_t^{SS+} D_t^{SS+} - F_t^{SS-} D_t^{SS-}}_{\text{continuing sales, } \pi_t^{SS}}.
\end{aligned}$$

Altogether, inflation decomposition takes the following form

$$\pi_t = \pi_t^{RR} + \underbrace{\pi_t^{reg,start} + \pi_t^{reg,end} + \pi_t^{\Delta} + \pi_t^{SS}}_{\pi_t^{Sales}}.$$

Let H_t denote the share of discounts in price quotes, i.e., $H_t = \sum_{i=1}^{N_t} \omega_i I_{it}^S$, where I_{it}^S is a sales indicator. Based on definitions in (A.1), inflation from sales π_t^{Sales} can be decomposed as follows

$$\pi_t^{Sales} = \underbrace{-(H_t - H_{t-1})\Delta_t}_{\pi_t^{\Delta}} + \underbrace{H_{t-1} FR_t (1 - H_t) D_t^{SR}}_{\pi_t^{reg,end}} + \pi_t^{reg,start} + \pi_t^{SS} \tag{A.2}$$

The first term on the right-hand side of (A.2) represents the discounts inflation:

$$\pi_t^{\Delta} \equiv F_t^{SR} \Delta_t^+ - F_t^{RS} \Delta_t^- = -(H_t - H_{t-1}) \Delta_t$$

where $\Delta_t \equiv \frac{F_t^{SR} \Delta_t^+ + F_t^{RS} \Delta_t^-}{F_t^{SR} + F_t^{RS}}$ is the average size of discounts in period t, and the change in the fraction of discounts, $H_t - H_{t-1}$ reflects the balance between sales that start and end in period t:

$$F_t^{SR} - F_t^{RS} = \sum_{i=1}^{N_t} \omega_i I_{it} \left[(1 - I_{it}^S) I_{it-1}^S - I_{it}^S (1 - I_{it-1}^S) \right] = -(H_t - H_{t-1})$$

The second term on the right-hand side of (A.2) stems from regular price changes at the end of sales:

$$\pi_t^{reg,end} \equiv F_t^{SR,reg+} D_t^{SR+} - F_t^{SR,reg-} D_t^{SR-} = \sum_{i=1}^{N_t} \omega_i I_{it}(1 - I_{it}^S) I_{it-1}^S dp_{it}^{SR}$$
$$= H_{t-1} F_t (1 - H_t) D_t^{SR}$$

where $D_t^{SR} \equiv \frac{\sum_{i=1}^{N_t} \omega_i I_{it}(1-I_{it}^S) I_{it-1}^S dp_{it}^{SR}}{H_{t-1} F_t (1-H_t)}$ is the average size of regular price changes at the end of sale in period t.

B Time series frequency

By definition, inflation is the sum of regular and sale-related inflation: $\pi_t = \pi_t^{RR} + \pi_t^{Sales}$, for any frequency of time series observations. We compute the fraction of π_t variance due to π_t^{Sales} as $\frac{cov(\pi_t^{Sales},\pi_t)}{var(\pi_t)}$. It is equal to the coefficient of regressing π_t^{Sales} on π_t.

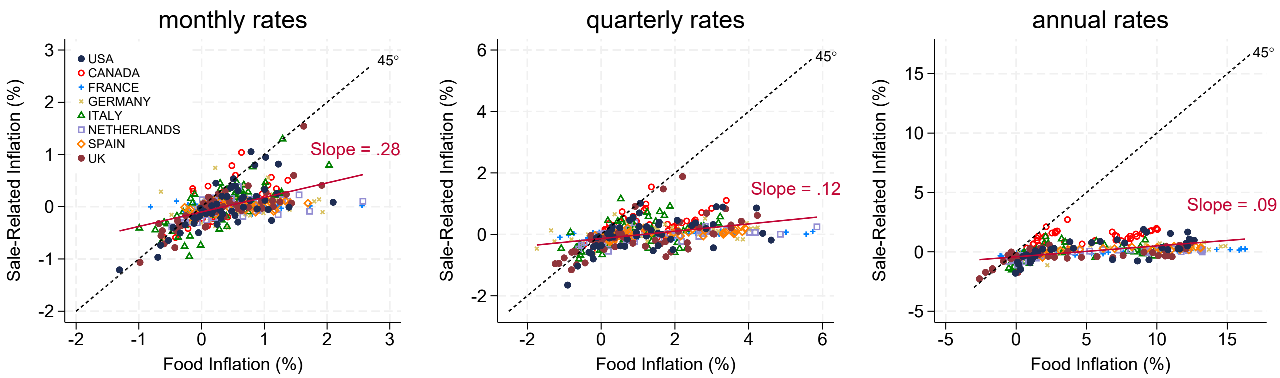


Figure B1: Co-movement of sale-related and overall inflation in food.

Notes: Figure summarizes contribution of sale-related inflation to overall food inflation from February 2019 to July 2023 for pooled sample from USA, Canada, France, Germany, Italy, Netherlands, Spain, and UK. The slope represents the fraction of inflation variance due to sale-related inflation (β_π).

	monthly rates	**quarterly rates**	**annual rates**
ARGENTINA	0.05	0.04	0.04
BRAZIL	0.07	0.00	-0.01
CANADA	0.35	0.23	0.20
FRANCE	0.01	0.01	0.01
GERMANY	0.08	0.04	0.04
ITALY	0.41	0.11	0.03
NETHERLANDS	0.06	0.02	0.01
SPAIN	0.04	0.03	0.03
UK	0.33	0.13	0.01
USA	0.34	0.10	0.06
Pooled (ex. ARG, BRA)	**0.28**	**0.12**	**0.09**
Pooled	**0.08**	**0.05**	**0.04**

Table B1: Summary of discounted price changes.

Notes: Table provides the fraction of inflation variance due to sale-related inflation (β_π) from February 2019 to July 2023. Quarterly (annual) rates are 3-(12-)month backward moving averages.

C Regular price inflation

How do retailers attain high regular price growth during the inflation surge? Before the pandemic, around 55% of all regular price changes in low inflation countries were price increases and 45% of changes were decreases, i.e., increases and decreases were roughly balanced. Such composition of regular price inflation components is representative of price adjustments in low inflation environments well documented in previous studies.[11]

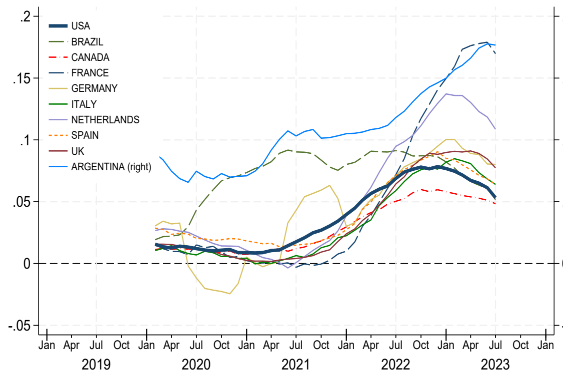
During the inflation surge, retailers accelerated their price growth, raising the proportion of price increases to decreases to about 2 to 1 (Table C1). Figure 1(a) shows that in all countries in our data monthly fraction of upward adjustments increased relative to the fraction of downward changes. At the same time, the magnitude of price changes fell, especially the magnitude of increases, reflecting their higher frequency (Figure 1(b)). We find similar patterns for non-food sectors in the UK CPI data (Appendix D). Such responses of the adjustment frequency and size to higher inflation are consistent with the effects of large inflationary shocks in menu cost models (Cavallo, Lippi, and Miyahara, 2023).

	Before surge				**During surge**			
	FR+	***FR−***	***Size+***	***Size−***	***FR+***	***FR−***	***Size+***	***Size−***
GROUP A (CAN, ITA, UK, USA)	0.083	0.069	19.3	22.2	0.117	0.050	14.4	19.9
GROUP B (FRA, GER, NED, ESP)	0.098	0.078	10.9	12.1	0.196	0.088	10.3	11.2
	Full sample							
GROUP C (ARG, BRA)	0.314	0.145	13.6	14.9				

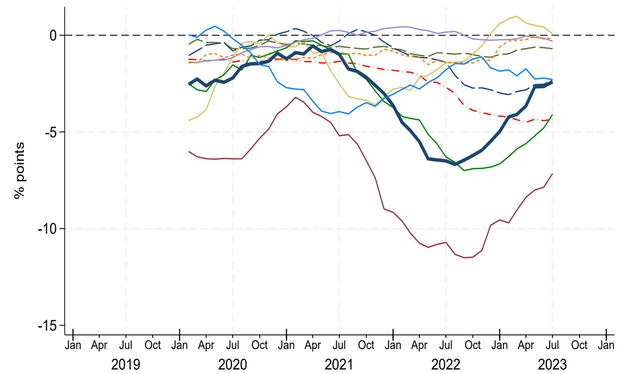
Table C1: Frequency and size of RR increases and decreases.

Notes: Table provides the monthly fraction of price increases/decreases in all observations ($FR+/FR-$) and average absolute size of those changes ($Size+/Size-$). Discounts are identified by a sale flag. All statistics are weighted by corresponding country's 3-digit COICOP weights and smoothed by 3-month backward moving average. Group A (Group B) countries have relatively high (small) share of discounts. For each country in Groups A and B, statistics are computed for the sample prior to ("Before surge") or after the start of the surge ("During surge"). For Group C countries statistics are computed over the entire sample. For each group (A,B,C) statistics are means of corresponding statistics for countries in the group.

[11]Studies of pricing behaviour include, for the United States: Klenow and Kryvtsov (2008); Nakamura and Steinsson (2008); Klenow and Malin (2010); Argentina: Alvarez et al. (2018); Brazil: Barros et al. (2009); Euro area: Álvarez et al. (2006); Gautier et al. (2024); Canada: Kryvtsov (2016); United Kingdom: Dixon and Tian (2017).



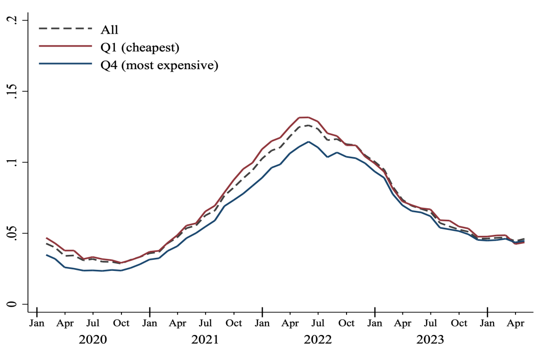
(a) FR+ v FR–



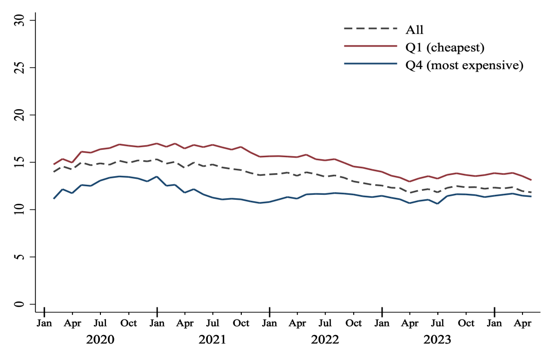
(b) Size+ v Size–

Figure C1: Monthly fraction and size of RR increases relative to decreases.

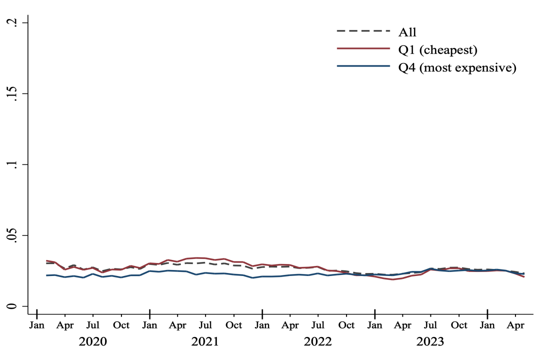
Notes: Figures provide the difference between average monthly fraction of RR increases and decreases (Panel a), and the difference between average absolute size of RR increases and decreases (Panel b). Discounts are identified by a sale flag. Time series are 12-month backward moving averages. Monthly averages are weighted means, with 3-digit COICOP weights.



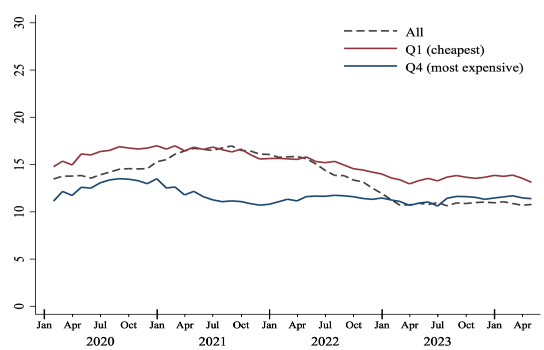
(a) Fraction of reg price increases



(b) Size of reg price increases



(c) Fraction of reg price decreases



(d) Abs Size of reg price decreases

Figure C2: Fraction and size of regular price increases and decreases.

Notes: Figures provide the average monthly fraction of RR increases and decreases (Panels a and c), and the average absolute size of RR increases and decreases (Panels b and d). Discounts are identified by a sale flag. Monthly averages are weighted means, with 3-digit COICOP weights.

Figure C2 shows that to attain higher growth for cheaper brands relative to more expensive goods, retailers primarily used the extensive margin. First, price increases are more frequent for cheaper brands and decreases are less frequent. Moreover, retailers increased the frequency of regular changes for cheaper products more than they did for expensive products.

D Inflation across U.K. goods sectors

To explore generality of the results for goods other than food, we apply our analysis for the U.K. CPI micro data provided publicly by the U.K. Office for National Statistics (ONS). The data contain monthly product prices posted by retail outlets across the United Kingdom from February 1996 to December 2023.[12] We use two definitions of sales to accord with definitions used so far. The first definition uses the sale flag, provided by the ONS, indicating that "sale prices are recorded if they are temporary reductions on goods likely to be available again at normal prices or end-of-season reductions." The second definition identifies a V-sale, whereby a price decrease is followed by a price increase within the next three months. The results are similar for both definitions.

We summarize the results for 5 good sectors: Food and beverages—for direct comparisons with food and beverages in the U.K. PriceStats data, Nondurables (excluding food and fuel), Durables, Semi-durables (mostly clothing and footwear), and Services. The results are summarized in Figure D1 and Table D1 below.

While food CPI inflation was expectedly the highest across goods, increasing by 27.7% since January 2020, it surged in other sectors as well (24.2% in Nondurables, 20.5% in Durables, 21.4% in Semi-durables, and 19.9% in Services). Figure D1 breaks down price growth in each of the sectors into components due to regular and sale-related price changes. In line with evidence from multi-channel food retailers, sale-related changes contributed little to the inflation surge. In fact, sale-related changes are *deflationary* in CPI data, indicating, potentially, a downward bias due to right-censored discount spells.

Unlike in other sectors, in Semi-durables sector, discounts almost entirely offset regular price growth. This is not very surprising, given frequent occurrence of sales, especially clearance sales, in this sector.

[12] Description of the data can be found in Dixon and Tian (2017); Kryvtsov and Vincent (2020).

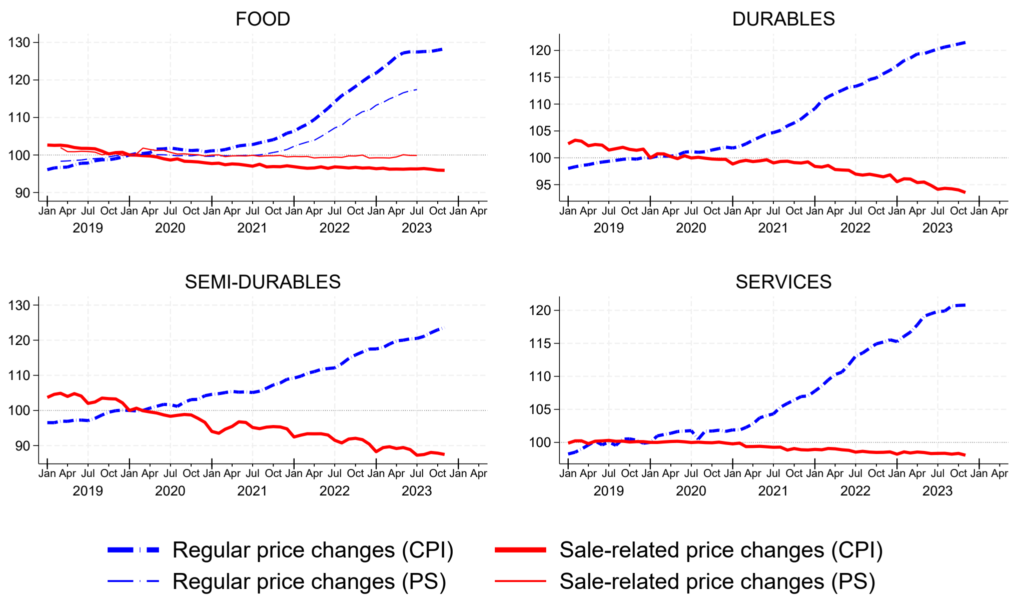


Figure D1: Regular and sale-related inflation across UK sectors.

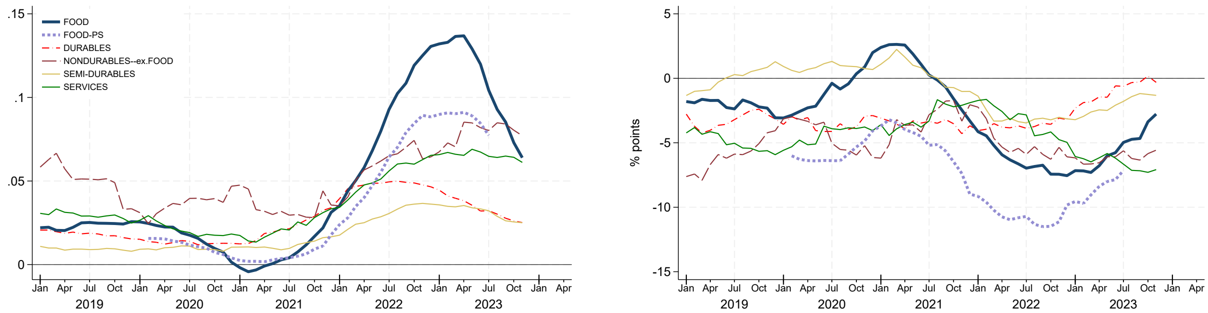
Notes: Figures provides cumulative month-to-month inflation rates for regular and sale-related price changes between January 2019 and July 2023 by sector in the United Kingdom. Discounts are identified by a sale flag. Indexes are normalized to 100 in January 2020. For food and beverages, thin lines provide components computed from PriceStats multichannel retail data for the United Kingdom, plotted in Figure 4.

	Flag		**V-shapes**	
	Regular	Sales	Regular	Sales
FOOD	27.7	-3.5	34.7	-10.6
FOOD-PS	17.4	-0.1	13.5	3.8
NONDURABLES–ex.FOOD	24.2	-5.9	32.6	-14.4
DURABLES	20.5	-5.6	32.4	-17.5
SEMI-DURABLES	21.4	-15.9	38.3	-32.8
SERVICES	19.9	-1.9	33.5	-15.5

Table D1: Price growth between January 2020 and July 2023, % change.

Notes: The table provides cumulative monthly inflation rates (%) for regular and sale-related price changes between January 2020 and July 2023.

Figure D2 shows that regular price adjustments shifted toward price increases, leading to smaller size of those increases. These patterns in the UK CPI sector data seem to be similar across sectors and similar to the patterns found in PriceStats data.



(a) FR+ v FR– (b) Size+ v Size–

Figure D2: Monthly fraction of RR increases relative to decreases in UK CPI data.

Notes: Figures provide the difference between average monthly fraction of RR increases and decreases (Panel a), and the difference between average absolute size of RR increases and decreases (Panel b). Discounts are identified by a sale flag. Time series are 12-month backward moving averages. Monthly averages are weighted means, with CPI expenditure weights.

E Contributions of inflation components

Table E1 contrasts summary statistics before and during country-specific inflation surge: mean, standard deviation, and serial correlation of quarterly inflation rates, and the fraction of inflation variance due to sale-related inflation (β_π).[13]

Based on inflation behavior prior to the surge, countries are clearly divided in three groups. For countries in **Group A** (CAN, UK, USA and ITA)[14] sale-related inflation accounts for a significant portion of inflation dynamics during normal times. Countries in **Group B** (ESP, FRA, GER, NED) do not normally have many discounts. Countries in **Group C** (ARG, BRA) experienced elevated inflation prior to the pandemic.

Before the surge, in Group A countries sale-related inflation accounted for half of quarterly inflation variance ($\beta_\pi = 0.49$ in Table E1). The co-movement of sale-related inflation with inflation is even higher at monthly rates (Figure E1). In all four countries in Group A, the share of discounts decreases at the onset of the pandemic, by 0.02 to 0.04 (with the largest decrease in the United Kingdom, in line with Jaravel and O'Connell (2020b)). Figure E2 shows how the dips in discount rates during lockdowns in Canada and UK contributed to spikes in inflation

[13] Since inflation π_t is the sum of regular and sale-related inflation, the fraction of π_t variance due to π_t^{Sales} is computed as $\frac{cov(\pi_t^{Sales},\pi_t)}{var(\pi_t)}$.

[14] Karadi et al. (2023) provide evidence that supermarket prices in Italy were more responsive to the first wave of COVID-19 lockdowns than prices in Germany.

rates. By contrast, once inflation surged the share of inflation variance due to discounts in these countries fell to a mere 0.09.

	Before surge				During surge			
	mean	***std***	***AR(1)***	$\boldsymbol{\beta_\pi}$	***mean***	***std***	***AR(1)***	$\boldsymbol{\beta_\pi}$
GROUP A (CAN, ITA, UK, USA)								
Inflation, π	0.32	0.66	0.54	1.00	2.32	0.81	0.64	1.00
Regular price inflation, π^{RR}	0.34	0.43	0.68	0.51	2.17	0.67	0.83	0.91
Sale-related inflation, π^{sales}	-0.01	0.52	0.33	0.49	0.15	0.41	0.50	0.09
GROUP B (FRA, GER, NED, ESP)								
Inflation, π	0.31	0.56	0.80	1.00	3.02	1.07	0.79	1.00
Regular price inflation, π^{RR}	0.36	0.53	0.85	0.97	2.95	1.04	0.79	0.98
Sale-related inflation, π^{sales}	-0.06	0.16	0.23	0.03	0.07	0.11	0.12	0.02
	Full sample							
GROUP C (ARG, BRA)								
Inflation, π	6.60	2.91	0.91	1.00				
Regular price inflation, π^{RR}	6.39	2.79	0.93	0.98				
Sale-related inflation, π^{sales}	0.21	0.32	0.19	0.02				

Table E1: Summary table.

Notes: Table provides mean ("mean"), standard deviation ("std"), and serial correlation ("AR(1)") of quarterly inflation rates; β_π is the fraction of π_t variance due to π_t^{Sales} and is computed as $\frac{cov(\pi_t^{Sales},\pi_t)}{var(\pi_t)}$. Discounts are identified by a sale flag. All statistics are weighted by corresponding country's 3-digit COICOP weights. Inflation surge is defined to start with two consecutive months of at least 3% year-on-year inflation in food for retailers in the sample. Country surge dates are given in (2). For each country in Groups A and B, statistics are computed for the sample prior to ("Before surge") or after the start of the surge ("During surge"). For Group C countries statistics are computed over the entire sample. For each group (A,B,C) statistics are means of corresponding statistics for countries in the group.

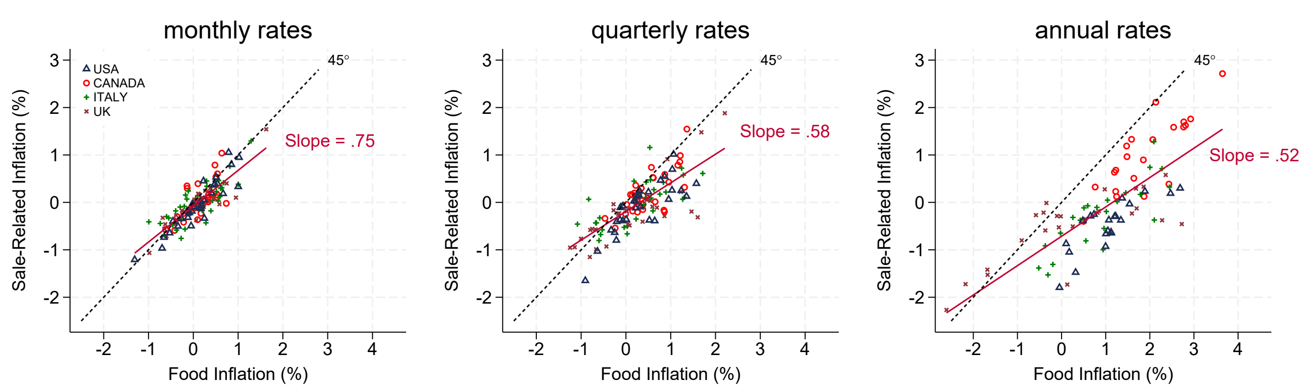


Figure E1: π_t and π_t^{Sales} rates before surge, pooled across USA, UK, CANADA, ITALY.

Notes: Figure summarizes contribution of sale-related inflation to overall food inflation from February 2019 to the date of country-specific beginning of inflation surge for pooled sample from USA, Canada, Italy, and UK. The beginning of the surge is defined as two consecutive months of at least 3% year-on-year inflation rate. The slope represents the fraction of inflation variance due to sale-related inflation (β_π), coefficient in the regression of π_t^{Sales} on π^t and country dummies.

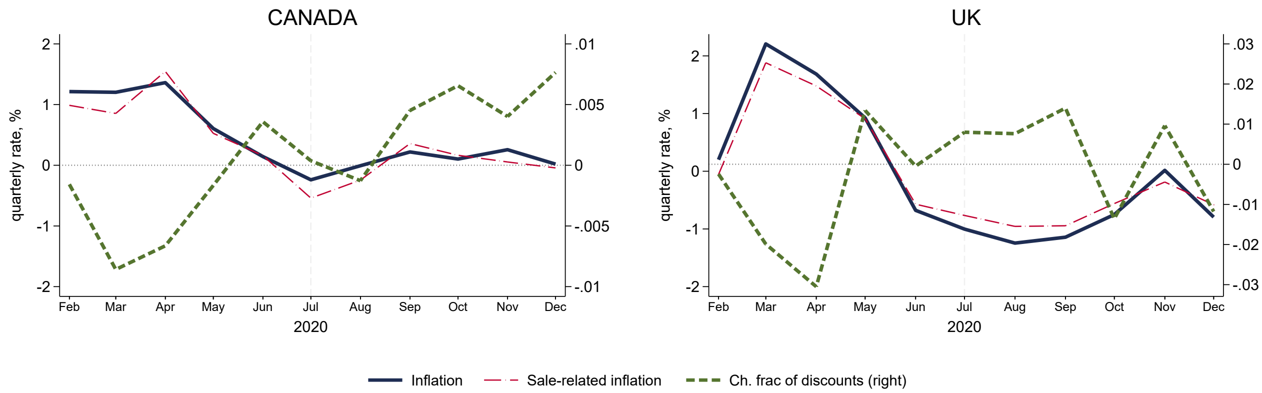


Figure E2: Inflation and discounts in 2020 in Canada and UK.

The results are not specific to the inflation surge. For countries that do not normally have many discounts (Group B countries), contribution of sales to inflation is low, both before and during the surge ($\beta_\pi = 0.03$ and $\beta_\pi = 0.02$). And for countries with high average inflation (Group C), contribution of discounts is also low over the sample period ($\beta_\pi = 0.02$). Hence, the fact that retailers rely on regular prices during high inflation does not appear to reflect specific circumstances around the post-pandemic inflation surge.

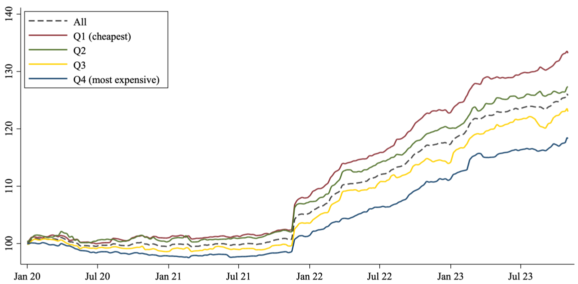
Our evidence suggests that retailers are more likely to use regular prices to accommodate persistent and/or volatile changes in economic environment. Indeed, fluctuations of sale-related inflation are more transient than regular price inflation, both before and during the inflation surge (Table E1). And although sale-related inflation became higher and more persistent during the surge, these changes were small relative to higher level and higher persistence of regular price inflation during the surge.

Figure E3 shows that in Group A countries the size of price discounts decreased (for Italy after 2021), but this decrease was modest relative to the size of discounts.

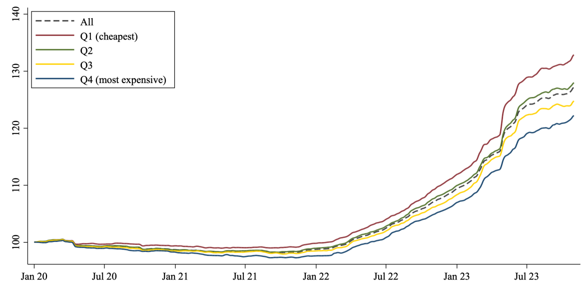
Figure E3: Size of price discounts.

Figures provides the average size of price discounts Δ_t. Averages are weighted means, with 3-digit COICOP weights. Discounts are identified by the sale flag. Series are smoothed by a 3-month backward looking moving average.

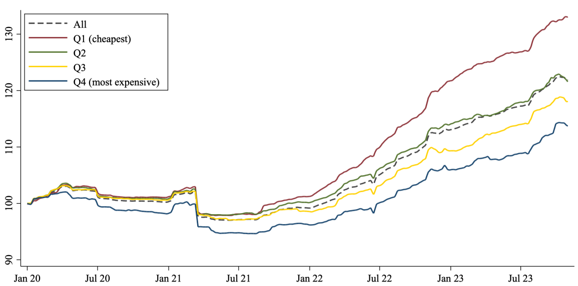
F Regular price indexes for unit price quartiles



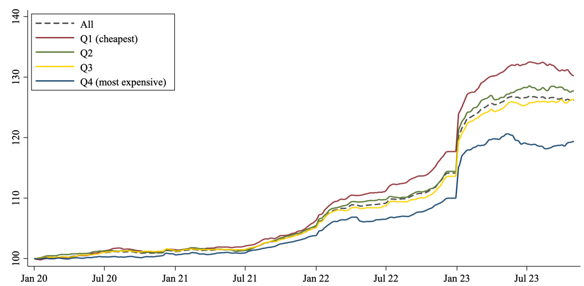
A. Canada



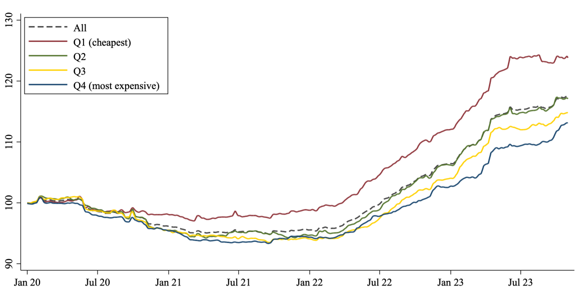
B. France



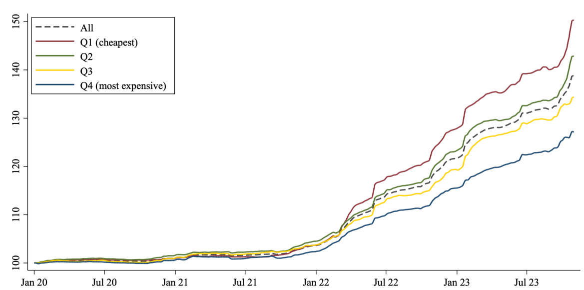
C. Germany



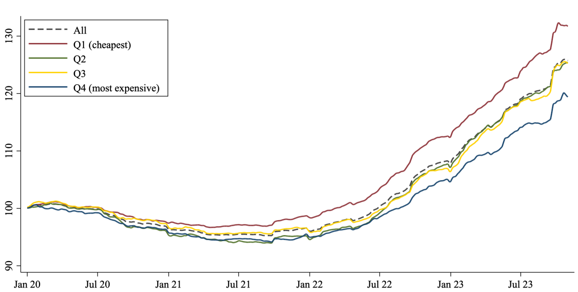
D. Netherlands



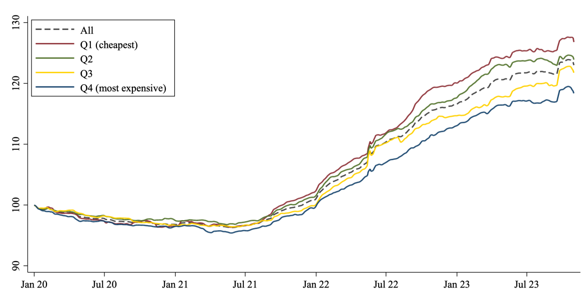
E. Italy



F. Spain



G. United Kingdom



H. United States

Figure F1: Regular price indexes for unit price quartiles.

G List of food products in Canadian Homescan Panel Data

#	Products	#	Products
1	BACON	58	PASTA SAUCES - WET PACKED
2	BAKED BEANS	59	PEANUT BUTTER
3	BEER PRODUCTS	60	PICKLES
4	BUTTER & DAIRY BLENDS/SPREADS	61	PRE-PACKAGED CHEDDAR CHEESE
5	CANNED ANCHOV & SARDINES	62	PREPACKAGED BAGGED SALAD
6	CARBONATED SOFT DRINKS	63	PREPACKAGED BREAD PRODUCTS
7	CARBONATED WATER	64	PREPACKAGED PRODUCE& FRUIT
8	CHIP/VEGETABLE DIP	65	PREPARED MUSTARD
9	CHOC CANDY PIECES LG SIZE	66	PREPARED PIZZA PIES FROZ.&RFG.
10	CHOCOLATE CNDY PIECES-REM BRND	67	PREPARED SALADS
11	CHOCOLATE TYPE CANDY BARS	68	PREPCKGD FRESH BAKED DELICACIES
12	COCONUT	69	PROCESSED CHEESE SLICES
13	COFFEE CREAMERS & FLAVOURNGS	70	R.T.E.DESSERTS-CND SNK T D.H.1
14	COFFEE-PACKAGED	71	RANDOM WEIGHT FRESH FISH-LACS
15	COOKING SPICES	72	READY TO EAT CEREALS
16	COTTAGE CHEESE	73	READY-TO-DRINK TEA
17	CREAM	74	REF YOGURT
18	CREAM CHEESE	75	REFRIGERATED ENTREES
19	DRINKABLE YOGURT	76	REMAINING BAGGED SALAD
20	DRY PACKAGED DINNERS	77	REMAINING PRE-PACKAGED CHEESE
21	DRY PASTA	78	REMAINING SNACK FOODS
22	DRY SAUCE GRAVY MIXES-ENVELOPE	79	RICE&NON-DAIRY ALTERNATIVE BEV
23	EGGS (CHICKEN EGGS ONLY)	80	RICE-REGULAR
24	FLAT WATER	81	SALAD & COOKING OILS
25	FLOUR-ALL-PURPOSE	82	SALAD DRESSING - READY TO USE
26	FRESH BREAD PRODUCTS-LAC	83	SAUSAGES-FRESH REFRIG.& FROZEN
27	FRESH MEAT-UPC	84	SEASONAL CHOCOLATE CONFECTIONS
28	FRESH POULTRY - LACS	85	SEASONINGS
29	FRESH TORTILLA SHELLS	86	SGRLESS BUBBLE GUM&CHEWING GUM
30	FRESH TRACK FRESH MEATS-LACS	87	SHELLED NUTS
31	FROZEN CONFECTIONS	88	SNACK & GRANOLA BARS
32	FROZEN ENTREES	89	SNACK CRACKERS
33	FROZEN FRNCH.FRIES/& VARIETY	90	SNACK FOODS-CORN
34	FROZEN FRUIT	91	SNACK FOODS-POTATO
35	FROZEN SEAFOOD	92	SOUR CREAM
36	FROZEN VEG.-REGULAR	93	SUGAR
37	FROZN.MEAT PATTS.&STEAKETTES	94	SWEET GOODS
38	FRUIT DRINKS	95	TACO TYPE RELISH AND SAUCE
39	FRUIT JUICES	96	TOFU & MEAT DAIRY ALTERNATIVE PRODUCTS
40	HOT CEREALS-OAT BASE	97	VINEGAR
41	ICE CREAM TYPE PRODUCTS	98	WET PACKED SOUP
42	INFANT FEEDING PRODUCTS CLD.GP	99	WET PACKED TUNA
43	JMS JLLES&FRT BSD SWT SPRDS FD	100	WET-PACKED CORN
44	KETCHUP - BOTTLED	101	WET-PACKED TOMATOES
45	LIQUOR	102	WHIPPING CREAM
46	LOW ALCOHOL BEVERAGES	103	WIENERS
47	LOW ALCOHOL MALT BEVERAGES	104	WINE PRODUCTS
48	LUNCHEON MEATS		
49	MARGARINE		
50	MAYONNAISE & SPOONABLE SLD.DR.		
51	MEAT AND SEAFOOD SAUCES		
52	MEAT SNACK STICKS		
53	MILK		
54	NON-CHOCOLATE CONFECTIONS		
55	ORIENTAL NOODLES		
56	ORIENTAL SAUCES		
57	PACKAGED CHOCOLATE CONFECTIONS		

Table G1: Food products.