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Staff Working Paper/Document de travail du personnel—2024-31

Last updated: August 16, 2024

Price Discounts and Cheapflation During the Post-Pandemic Inflation Surge

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DOI: https://doi.org/10.34989/swp-2024-31 | **ISSN** 1701-9397

Acknowledgements

Alberto Cavallo is a shareholder of PriceStats LLC, the private company that provided proprietary data used in this paper without any requirements to review the findings. We thank the editors, Laurence Ball and Yuriy Gorodnichenko, and the discussant Joe Vavra for their guidance and feedback on the paper. We thank Klaus Adam, Boragan Aruoba, Carola Binder, Luigi Palumbo and participants at the NBER conference "Inflation in the COVID Era and Beyond, Spring 2024" and Bank of Canada Brown Bag Lunch seminar for helpful comments and suggestions. Carly MacDonald, Tomas Pacheco and Gastón García Zavaleta provided excellent research assistance. The views expressed here are ours, and they do not necessarily reflect the views of the Bank of Canada.

Abstract

We study how within-store price variation changes with inflation, and whether households exploit it to attenuate the inflation burden. We use micro price data for food products sold by 91 large multi-channel retailers in 10 countries between 2018 and 2024. Measuring unit prices within narrowly defined product categories, we analyze two key sources of variation in prices within a store: temporary price discounts and differences across 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 goods relative to prices of more expensive varieties of the same good—exacerbated it. Using Canadian Homescan Panel data, we estimate that spending on discounts reduced the change in the average unit price by 4.1 percentage points, but expenditure switching to cheaper brands raised it by 2.8 percentage points.

Topics: Inflation and prices; Inflation: costs and benefits; Market structure and pricing
JEL codes: E21, E30, E31, L81

Résumé

Nous examinons comment les variations des prix dans un même magasin changent avec l'inflation, et voyons si les ménages en tirent parti pour alléger le fardeau causé par les hausses de prix. Nous utilisons des microdonnées sur les prix de produits alimentaires vendus entre 2018 et 2024 par 91 grands détaillants multicanaux provenant de 10 pays différents. En mesurant les prix unitaires de produits compris dans des catégories précises, nous analysons deux grandes sources de variation des prix au sein d'un magasin : les rabais temporaires et les différences de prix entre des produits similaires. Les prix des produits mis à rabais ont augmenté à un rythme beaucoup plus lent en moyenne que les prix réguliers, ce qui a contribué à alléger le fardeau de l'inflation. En revanche, les prix des produits bon marché ont augmenté plus rapidement que ceux de produits similaires plus chers (phénomène que nous appelons « cheapflation »), ce qui a alourdi ce fardeau. En utilisant des données obtenues de panels Homescan composés de participants canadiens, nous estimons que les dépenses en produits au rabais ont fait baisser la croissance du prix unitaire moyen de 4,1 points de pourcentage. Les dépenses liées à l'adoption de marques bon marché aux dépens de produits similaires plus chers ont quant à elles fait augmenter la croissance du prix unitaire moyen de 2,8 points de pourcentage.

Sujets : Inflation : coûts et avantages ; Inflation et prix ; Structure de marché et établissement des prix
Codes JEL : E21, E30, E31, L81

1 Introduction

The historic surge in inflation following the COVID-19 pandemic has intensified the need to understand the impact of high inflation on household welfare.[1] The variation in prices for similar products can directly influence the burden of inflation, which depends on the price disparities among items in a household's consumption basket. Although the macro literature shows that higher inflation is often accompanied by greater price dispersion across different stores,[2] much of the observed price disparities occur *within* narrow categories in a 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). Due to data limitations, the impact of high inflation on within-category price differences, as well as the extent to which households leverage this variation to mitigate the effects of rising prices, have not been studied before.

We address this question by analyzing micro price data from food products offered by 91 large multi-channel retailers across ten countries from January 1, 2018, to May 30, 2024, including Argentina, Brazil, Canada, France, Germany, Italy, Netherlands, Spain, the United Kingdom, and the United States. In all countries, prices during sales grew at low rates, even when inflation surged. By contrast, the prices of cheaper brands grew 1.3 to 1.9 times faster than the prices of more expensive brands—and only when inflation surged, not before or after. Using Canadian Homescan Panel data, we show that savings from purchasing products on sale and switching to cheaper brands were counteracted by higher inflation of cheaper varieties. These findings imply an important role of within-category price variation for the welfare cost of inflation.

We focus on the "Food and Beverages" category because it carries a significant weight in the household consumption baskets (usually between 10% and 20%), and it is one of the sectors that experienced the highest price growth during this period. More importantly for our purposes, food products come in many varieties and are relatively easy to classify and compare across different retailers and countries. We use these features of the data to construct *unit prices* by dividing the price of the product by its size.

Accurately measuring unit prices is crucial for assessing the degree of price dispersion across

[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.

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. Equipped with unit price data, we examine two primary sources of price variation within stores: temporary price discounts and differences across varieties of similar products. For temporary price discounts, or "sales," we break down inflation into components stemming from regular and sale-related price changes. The sale component includes variations in the frequency and size of discounts, as well as regular price fluctuations at the start or the end of sales. For the differences across varieties, we use unit prices to group products into quartiles, differentiating "cheap" and "premium" brands.

We first focus on the time series variation to show that regular price changes were the primary driver of inflation, mainly because retailers increased the proportion of price increases from about half to over two-thirds of all price changes. From January 2020 to January 2024, regular food prices in Europe and the U.S. increased by 15% to 23%, while in Brazil and Argentina, they rose by 39% and 228%, respectively. In contrast, sales had only a minor impact on inflation during this period. Month-to-month inflation during sales added up to only single-digit total price growth in all countries, except Argentina (17%). We use additional evidence from the U.K. CPI micro data to corroborate that sale-related price changes did not contribute to the inflation surge in either food or non-food sectors.

It may be surprising 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, the 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. Moreover, fluctuations in the number and size of discounts caused volatile inflation swings amid lockdowns in the early months of 2020 in the United States, Canada, and the United Kingdom (Jaravel and O'Connell, 2020b). However, we show that price discounts cannot support a *persistent* rise in prices. Retailers cannot consistently reduce their sales for prolonged periods when they need to raise their prices, and typical price increases at the end of sales are insufficient to make up for the absence of regular price adjustments during sales.

A second major source of variation in prices within a store is due to price differences across varieties of similar products within narrowly defined categories. We find that during the inflation surge, retailers systematically raised prices of cheaper 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 May 2024. Among developed countries in our sample, regular prices for the cheapest products (first quartile) grew by an additional 6 to 14 percentage points over prices of premium products (fourth quartile). As inflation and inflation inequality had all but returned to their pre-pandemic levels by May 2024, price *levels* of cheap products have increased by a factor between 1.3 and 1.9 relative to prices of expensive products.

This result, which we call "cheapflation," is robust to alternative quartile rankings, different definitions of regular prices, and for *transaction* prices obtained with scanner data in Canada. Furthermore, cheapflation was present only during the inflation surge, indicating it is not a pandemic effect but rather a high-inflation phenomenon. We discuss several supply- and demand-side mechanisms that could explain why cheapflation is associated with high inflation, including the possibility that relative demand for cheaper varieties increases with the aggregate inflation level. Indeed, given relatively low *posted* prices for discounted and cheaper varieties, households can generate much-needed savings by shifting their spending toward these products (Argente and Lee, 2021).

We analyze expenditure switching along both of these dimensions using data from the Canadian Nielsen Homescan Panel. We find that the shift of spending toward sale-related prices lowered the varying-weight price index by 4.1 percentage points, shaving off 24% of the price increase since January 2020 compared to 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 2.8 percentage points—a 16% increase relative to a fixed-basket index. Hence, as households switched to cheaper product varieties, their savings were 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 Canada, 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 flat or even decreasing, suggesting the cheapflation effect dominates.

The main contribution of this paper is to provide new evidence on the relationship between inflation and within-category unit price variation—the primary source of price options available to consumers who seek to reduce the inflation burden. The literature has largely been unable to examine price variation within categories due to data challenges, as it requires information on product size and packaging. The data employed in this paper meet this challenge. Moreover, the scale and scope of the data in the paper—across ten countries, countries with normally high and low inflation, countries with normally high and low use of discounts, observations for posted prices and transaction prices—support comprehensive analysis of the relationship between within-product price variation and inflation.

The literature on the welfare cost of inflation largely ignores within-category price variation. However, our evidence indicates that this variation imposes substantial costs on households during periods of high inflation. In fact, cheapflation imposes a dual burden from inflation. Households who substitute their favorite products with cheaper counterparts to save money 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 lower *real* consumption. And while sales present an opportunity for substantial savings, households willing to use them must invest significant time and effort to find the discounts.

Our paper also contributes to a related literature that studies inflation inequality and expenditure switching, both in normal times and in the context of the Great Recession. For example, Jaimovich, Rebelo, and Wong (2019) and Argente and Lee (2021) found that high-income U.S. households were more effective at reducing their prices by substituting toward cheaper brands or by finding discounts than low-income households; Ampudia, Ehrmann, and Strasser (2024) document similar results for euro area. In contrast to high-income households, low-income households tend to not exploit relative price differences and switch to cheaper varieties (Kaplan and Schulhofer-Wohl, 2017). Our paper studies how expenditure switching, price dispersion, and inflation inequality arise in the context of high inflation. Our evidence for both posted and transaction prices will allow future research to account for joint behavior of retailers and households amid surging inflation.

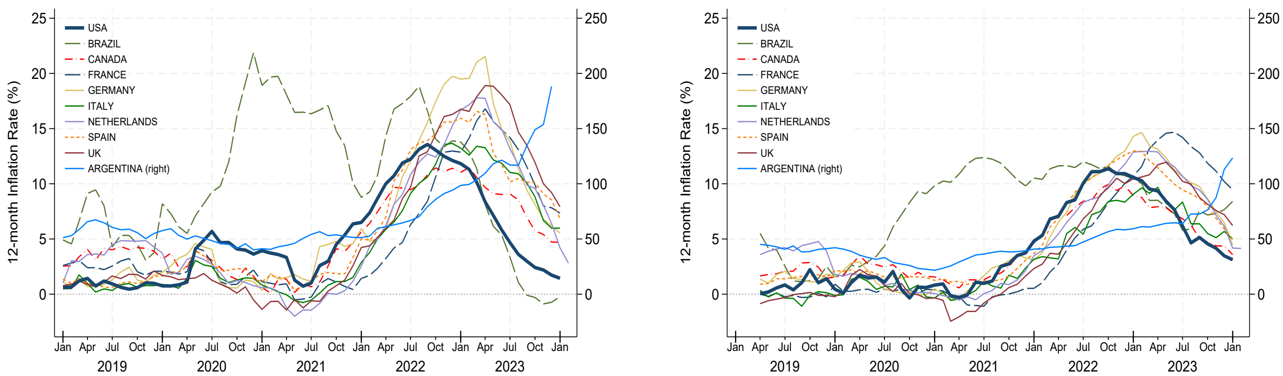
The paper is structured as follows. Section 2 introduces international micro price data, Section 3 documents changes in price indexes for regular and discounted prices, Section 4 analyzes inflation segmented by unit price quartiles, Section 5 discusses the Canadian Homescan Panel dataset and examines the impact of expenditure switching on effective prices, and Section 6 presents evidence of within-category 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 2,122,892 products sold by 91 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. The dataset spans January 1, 2018, to May 30, 2024.

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 errors resulting from the time aggregation of average revenue (Cavallo, 2018). Furthermore, 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 to 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 visualizes recent food inflation for countries in our sample. In Europe and North America, inflation surged in late 2021–early 2022 and took a little 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 the 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: 188% in Argentina in December 2023, and 21.8% and 18.8% in Brazil in December 2020 and August 2022, respectively.



(a) CPI - Annual Inflation

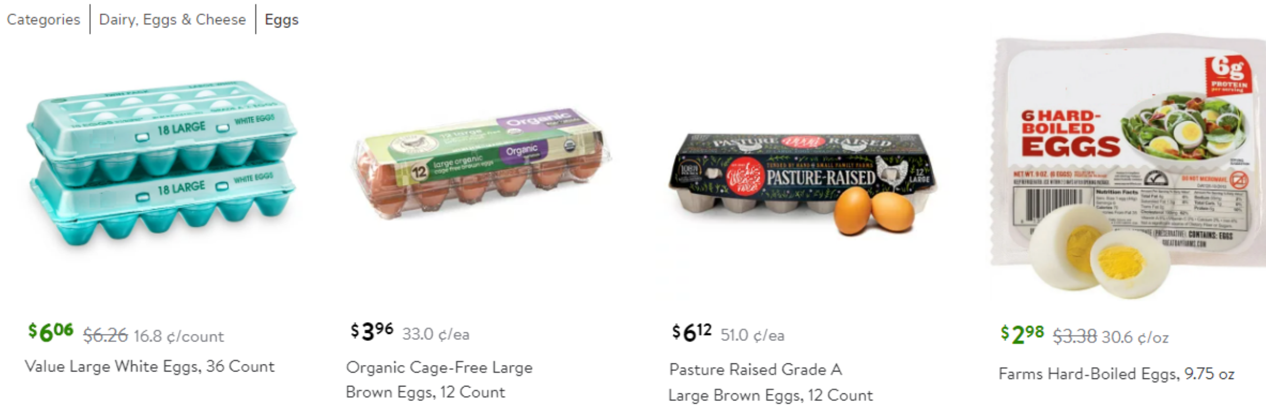
(b) Multi-channel retailers - Annual Inflation

Figure 1: Inflation rates for food products.

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

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(a). 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 description. Similarly, if a sale flag is not available, we can use a price algorithm to identify them.



(a) Example of a sale flag and unit price on a retailer's website

(b) Flag discounts

(c) V-shape discounts

Figure 2: Unit prices and price discounts.

Notes: Panel (a) provides an example of a sale flag and unit price on a retailer's website. Bottom charts show hypothetical price paths during a flag sale (Panel b) and V-shaped sale (Panel c). Sale-related price changes are regular or discounted price changes occurring 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").

Unit prices allow us to control for package sizes and distinguish between "cheap" and "premium" varieties of narrowly defined categories, such as "fresh eggs." Unit prices are available for about half of the products in our data, with significant variation across countries (see Appendix Table A1 for details). To construct the narrowest possible 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 the 3-digit level, which is commonly used by statistical agencies to construct price indices. In the example above, this 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 different varieties of similar products, such as "eggs." For example, a typical URL showing the products in Figure 2(a) would be structured like: https://www.retailer.com/browse/food/eggs. Third, we further distinguish products using the units of the package in which they are sold, such as count, weight, or volume. In the example above, fresh eggs are sold by unit (count), while hard-boiled eggs in the same URL are sold by weight (ounces). This extreme degree of differentiation is possible under the assumption that highly similar products are sold in the same unit. In the end, we are left with 127,130 COICOP-URL-unit categories, 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 this 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(a)), 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). Figures 2(b) and (c) illustrate hypothetical price observations corresponding to two definitions of sales. Sale advertisements typically include the discounted price next to the regular (undiscounted) price. 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 begins. 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.

Sale-related price changes are those occurring over the duration of the sale (shaded areas in bottom Figure 2). They include regular price changes at the beginning and the end of sales. These figures exemplify 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 1 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	0.05	27.9	0.08	22.6
BRAZIL	0.07	26.2	0.11	25.2
CANADA	0.18	28.8	0.16	31.0
FRANCE	0.03	25.3	0.06	15.1
GERMANY	0.03	33.1	0.03	32.5
ITALY	0.08	31.2	0.07	31.2
NETHERLANDS	0.02	30.5	0.06	24.2
SPAIN	0.06	18.0	0.07	16.4
UK	0.13	35.1	0.11	35.1
USA	0.13	28.9	0.12	28.3

Table 1: Fraction and size of discounts in 2018–2019.

Notes: For each country, columns "Share" provide the weighted mean monthly share of discounted prices in all price observations between May 2018 and December 2019, and columns "Size" give the weighted mean size of discounts (the difference between regular and discounted prices during sale). The 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.[3] 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 the products within the 3-digit COICOP categories.

The daily inflation is the weighted mean of 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 the regular price on day $t-1$ to the 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 all

[3] We use all available price change observations, even those for which unit prices are not available.

other price changes:

$$
\begin{aligned}
\pi_t &\equiv \pi_t^{RR} + \pi_t^{Sales}, \qquad (2)\\
\pi_t^{RR} &= \sum_{i=1}^{N_t} \omega_i I_{it}(1-I_{it}^S)(1-I_{it-1}^S)dp_{it}^{RR},\\
\pi_t^{Sales} &= \sum_{i=1}^{N_t} \omega_i I_{it}\left[I_{it}^S(1-I_{it-1}^S)(dp_{it}^{RS}-\Delta_{it}) + I_{it}^S I_{it-1}^S dp_{it}^{SS} + (1-I_{it}^S)I_{it-1}^S(dp_{it}^{SR}+\Delta_{it-1})\right],
\end{aligned}
$$

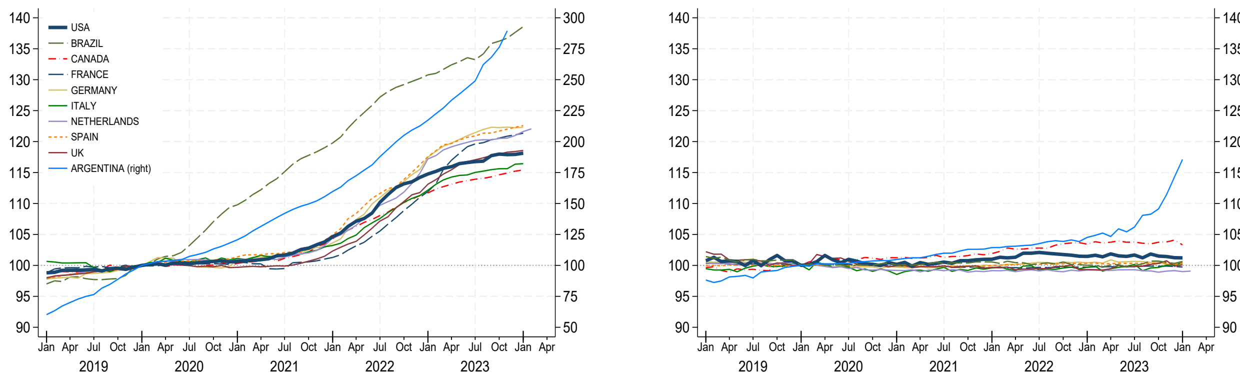
where the $dp_{it}^X = (p_{it}^R - p_{it-1}^R)$, $X = \{RR, RS, SR\}$, denotes the *regular* price change of type X, $dp_{it}^{SS} = p_{it} - p_{it-1}$ is the SS price change, and $\Delta_{it} = p_{it}^R - p_{it}$ is the absolute size of discount. Note that RS and SR changes combine discounts and start- or end-of-sale regular price changes. The total RS price change (the beginning of the 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 B provides details of the decomposition.

We time aggregate the daily time series to monthly frequency to facilitate visualization of the results. The monthly inflation rate is the sum of the 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.[4] The monthly average size of price changes is the ratio of corresponding monthly inflation rate and monthly fraction of adjustments.[5]

Figure 3 summarizes the cumulative month-to-month inflation rates for regular and sale-related price changes over the period between January 2019 and January 2024. In all countries, the price growth during this period reflected mainly regular price adjustments. Figure 3(a) shows that since 2020, regular food prices have increased by 15% to 23% in low-inflation countries, and by 39% and 228% in Brazil and Argentina.

[4]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 $1 - \prod_d(1 - F_d)$.

[5]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).



(a) Regular price changes

(b) Sale-related price changes

Figure 3: Cumulative monthly inflation rates for regular and sale-related price changes.

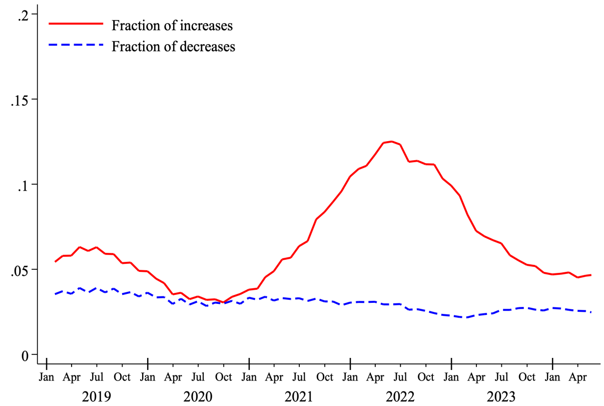
Notes: Figure provides cumulative monthly inflation rates, normalized to 100 in January 2020. Panel A shows the cumulative rates for monthly regular price changes. Panel B provides synthetic cumulative inflation rates for sale-related price changes, defined as the difference between the rates for all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

In contrast to regular prices, Figure 3(b) shows that month-to-month price changes during sales accrue to below single digits for all countries, except Argentina (17%).

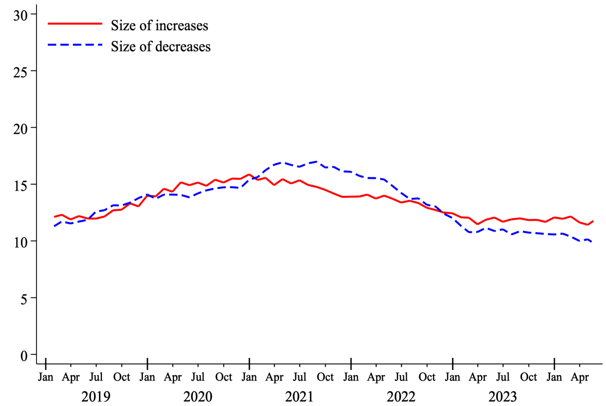
To determine whether these results also apply for non-food sectors, we compute this decomposition for food and non-food goods in the U.K. CPI micro data (Appendix B). Although CPI inflation in the food sector was the highest among goods sectors in the United Kingdom, increasing by 27.7% since January 2020, it also increased in other sectors (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 (mainly clothing and footwear), where discounts almost entirely offset regular price growth. This is not very surprising, given frequent occurrence of sales, especially clearance sales, in the Semi-durables sector (Kryvtsov and Vincent, 2020).

3.1 Drivers of regular price inflation

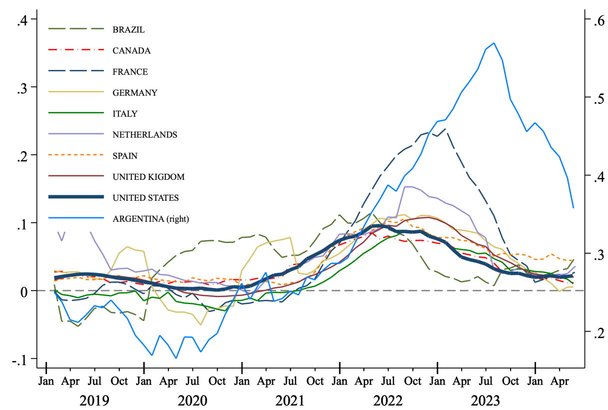
How do retailers attain high regular price growth during the inflation surge? Before the pandemic, about 55% of all regular price changes in low-inflation countries were price increases, and 45% of changes were decreases, i.e., increases and decreases were roughly balanced. This composition of regular price inflation components is representative of price adjustments in low-inflation environments well documented in previous studies.[6]



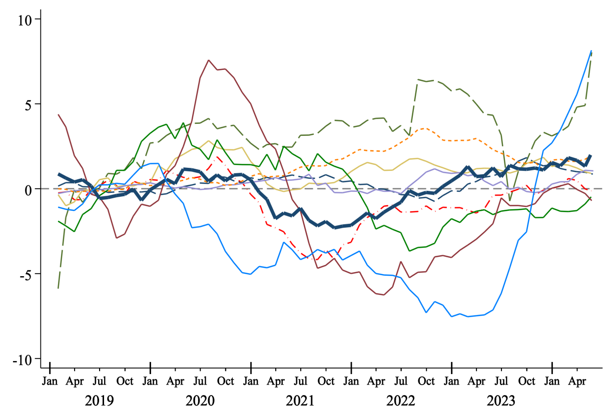
(a) Fraction of reg price changes (USA)



(b) Size of reg price changes (USA)



(c) FR+ v FR– (All countries)



(d) Size+ v Size– (All countries)

Figure 4: Fraction and size of regular price increases and decreases.

Notes: Top panels provide the average monthly fraction of RR increases and decreases, FR+ and FR– (Panel a), and the average absolute size of RR increases and decreases, Size+ and Size–, in percentage points relative to 2019 means (Panel b) for the United States. Bottom panels provide the differences between average monthly fraction of RR increases and decreases (Panel c), and the difference between average absolute size of RR increases and decreases (Panel d). Discounts are identified by a sale flag. Monthly averages are weighted means, with 3-digit COICOP weights. All monthly series are smoothed by (5,1,5) moving average.

During the inflation surge, retailers raised the proportion of price increases to decreases to about 2 to 1 (Appendix B). Figure 4(c) shows that in all countries in our data, the monthly fraction of upward adjustments increased relative to the fraction of downward changes. At the same time, the magnitude of price changes was fairly stable (Figure 4(d)). We find similar

[6]Studies of pricing behavior 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). Montag and Villar (2022) and Bilyk, Khan, and Kostyshyna (2024) provide more recent evidence for the United States and Canada, respectively.

patterns for non-food sectors in the UK CPI micro data. 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).

3.2 Why did sale-related price changes grow so little?

The fact that retailers did not directly use discounts to raise their prices may seem surprising. In countries with relatively frequent use of discounts (United States, United Kingdom, Canada, Italy), sale-related inflation accounted for half of the quarterly inflation variance before the inflation surge, and even higher share for monthly inflation rates (Appendix B). This includes the 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 in the first month of the lockdown in the United Kingdom at the end of March 2020.[7]

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 the definitions in (2) and Appendix B, inflation from sales π_t^{Sales} can be decomposed as follows:

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

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.

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

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

where F_t^{SR} (F_t^{RS}) is the fraction of SR (RS) price changes, $\Delta_t \equiv \frac{F_t^{SR}\Delta_t^{+} + F_t^{RS}\Delta_t^{-}}{F_t^{SR} + F_t^{RS}}$ is the average size of discounts in period t, and the change in the fraction of discounts, $H_t - H_{t-1}$, reflects the

[7] 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).

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, 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.

Appendix B provides 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)). Although such swings in discounts can cause volatile month-to-month inflation fluctuations, they cannot create a sustained rise in prices.[8] For example, even if U.S. retailers completely removed all discounts (Table 1), the cumulative rise in the price level would be only 3.8% (= $0.13 \cdot 28.9$). Retailers cannot keep shrinking their sales for long stretches of time when they need to raise prices in high-inflation environments.

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

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

The 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

[8]This evidence aligns with the literature, which suggests retailers use discounts to respond to unexpected but transient shocks (Kryvtsov and Vincent, 2020) or to 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.

zero regular price growth *during* sales. For example, Appendix B shows that 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 the unit prices for products that went through a sale diverge from the 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.

4 Cheapflation

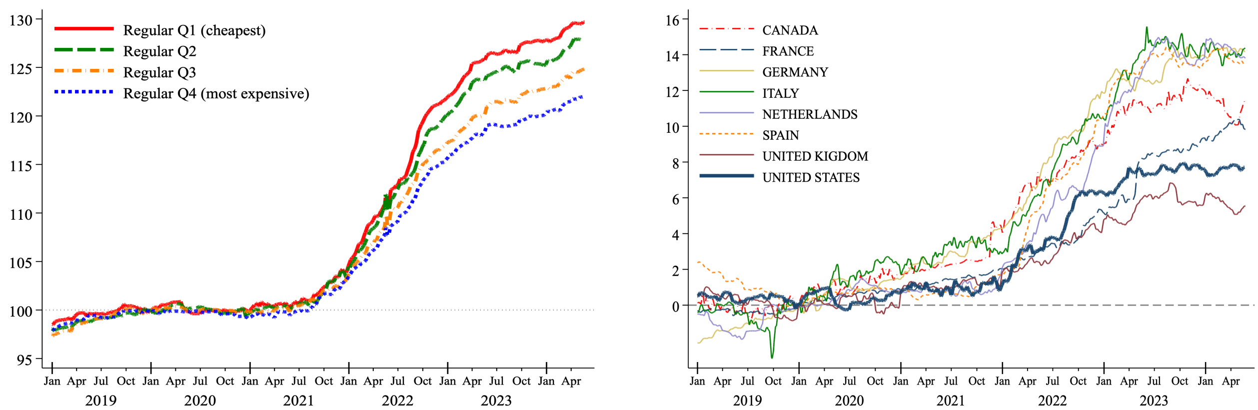
The second source of variation in prices within a store comes from price differences in narrow categories, defined by a COICOP-URL-unit combination. Within these categories, we group products into quartiles based on their average unit prices in 2019. Products falling into the first quartile are categorized 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 group and country, except Brazil, where unit prices are not available.

Figure 5(a) visualizes the quartile price indexes for the United States. There is a significant disparity in inflation rates between the first and last quartiles over the period from January 2020 to May 2024. The difference starts to increase in early 2021 and stabilizes by early 2023, suggesting that cheapflation is most prominent during the inflation surge. Since January 2020, cheaper products have experienced an inflation rate of 30%, while premium product prices increased by 22%. In other words, inflation for cheaper products was 1.4 times higher, leading to an additional 8 percentage points cumulative price growth relative to premium varieties. The differences in price growth represent convergence of prices within narrowly defined product categories.

We find cheapflation for all countries in our sample.[9] Table 2 provides the cumulative inflation rates for the cheapest and most expensive products. The differences in price growth among developed countries—visualized for low-inflation countries in Figure 5(b)— range between 6

[9]Benedetti et al. (2024) use web-scraped prices for milk and olive oil products in Italy between July 2021 and February 2023 and find that prices of the least expensive individual products increased faster than prices of the most expensive products in the same category and region. Štaermanis and Siliverstovs (2023) provide evidence from grocery stores in Latvia.

percentage points in the United Kingdom and 14 percentage points in Germany, Italy, and the Netherlands. Compared to the most expensive varieties, inflation for cheaper products was 1.3 to 1.9 times higher.



(a) Regular price index, by quartile

(b) Q1 - Q4 cumulative inflation since Jan 2020

Figure 5: Cheapflation.

Panel (a) provides the matched-model regular price indexes for products in quartiles of average unit price in 2019 for the United States. Discounts are identified by a flag. 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. Argentina is omitted for visual clarity.

	Cumulative Inflation Jan 2020 – May 2024 (%)			
	All Products	Cheapest Q1	Most Exp. Q4	Q1–Q4 ppt
CANADA	29	34	22	11
FRANCE	25	30	20	10
GERMANY	22	29	15	14
ITALY	21	29	15	14
NETHERLANDS	31	36	23	14
SPAIN	31	37	23	13
UNITED KINGDOM	21	24	18	6
UNITED STATES	26	30	22	8
ARGENTINA	3,513	3,740	3,371	369

Table 2: Cumulative inflation by unit regular price quartile.

Notes: Table shows the cumulative inflation rate from January 2020 to May 2024. The Q1 (cheapest) and Q4 (most expensive) products are selected based on their average unit regular price in 2019 (flag discounts).

Since we ranked products according to their 2019 prices, it is possible that subsequent relative price movements (stemming from the product life cycle or different price durations) or changes in the composition of products (due to product exits or because entering products are not included) may have mechanically influenced the cheapflation result. To rule out this possibility, we reconstruct matched-model regular price indexes using "dynamic" quartiles. Specifically, we classify the products into unit regular price quartiles quarter-by-quarter. We then construct matched-model regular price indexes using price changes by quartile *and* quarter. The difference now is that the set of products within the same quartile varies over time. This treatment is conservative, since some products that were in Q1 (Q4) in 2019 move to higher (lower) quartiles later, reducing the gap between Q1 and Q4 inflation. Nonetheless, the results provided in Appendix C show that cheapflation is robust to this treatment of the data, ruling out product cohort effects as the key driver of cheapflation. Furthermore, Adam, Alexandrov, and Weber (2023) estimate that relative price deviations due to sticky prices account for at most 1% of the observed price dispersion in the U.K. CPI micro data.

The results are also robust to the alternative definition of regular prices (using V-shape sales) and for *transaction* prices, as we show in Section 5 for food products in Canada. Finally, in the United States in Figure 5(a)—and in each country in our sample—price growth across quartiles is similar before and after the inflation surge. This suggests that cheapflation manifests itself largely during high inflation and is not driven by other factors introduced by the pandemic.

4.1 Discussion of the mechanisms of cheapflation

There are several mechanisms that could explain why cheapflation occurs during times of high inflation. We broadly classify them as supply- and demand-side mechanisms.

On the supply side, cost structures and supply chains can differ between cheap and expensive products. The supply of cheaper products often relies on basic raw materials or transportation, making supply costs more exposed to fluctuations in commodity prices such as sugar, plastics, or crude oil (Bambridge-Sutton, 2024). Cheaper products depend more on global supply chains, making them susceptible to disruptions that cause price pressures such as those during the Covid-19 pandemic and Russia's invasion of Ukraine (Cavallo and Kryvtsov, 2023). In contrast, premium products rely more on R&D and branding costs and are often produced in smaller quantities by larger and more productive firms (Faber and Fally, 2021), better insulating them from the supply disruptions that affected mass-produced cheap products.[10] Hence, post-pandemic rebalancing of supply chains may have raised the costs of supplying cheaper products

[10] Jaravel (2019) provides evidence that in normal times, innovation in products consumed by richer households can also dampen their inflation rate in the long run.

relative to high-end products (Kopytov et al., 2021). Additionally, cheaper brands include many private-label store brands: during this time, retailers invested in raising the quality of their store brands, bringing their unit prices closer to national brands (Newman and Stamm, 2024).

Furthermore, differences in margins can affect cost pass-through for cheap and expensive goods. Cheaper varieties typically have lower profit margins due to competitive pricing that aims to attract price-sensitive customers. As a result, retailers lack the "buffer" to absorb additional costs and are therefore more likely to quickly pass on cost increases into consumer prices. Moreover, if manufacturers or retailers try to maintain similar *dollar* price changes across varieties, it would imply higher inflation for cheaper products due to their lower base price. Evidence of such behaviors can be found in Sangani (2023) and Alvarez et al. (2024).

On the demand side, cheapflation may reflect an increase in relative demand for cheaper products during high-inflation periods. A shift in spending from high- to low-priced varieties within narrow sectors is expected amid rising inflation and falling real income (Jaimovich, Rebelo, and Wong, 2019). In particular, low-income consumers, who primarily purchase cheaper goods, might experience more significant shifts in purchasing power. In fact, during this time, fiscal stimulus targeted at low-income families would have indirectly contributed to an increase in relative demand for cheaper products. In the next section, we provide evidence that consumers in Canada indeed switched their spending toward cheaper brands during the pandemic. In addition, the prices of goods sold to poorer households increase more quickly because poor households become relatively less elastic faster than the rich do (Mongey and Waugh, 2024). Our results are consistent with Argente and Lee (2021), who used scanner data to show that during the Great Recession, expenditure switching led low-income households to experience higher inflation than high-income households. They found that almost half of the difference was due to changes in product prices. In our case, the real income shock is driven by high inflation, and the magnitude of the expenditure and price responses appears to be significantly larger.

In the end, even if households were able to save money by purchasing cheaper brands during this period, our results suggest that some of these savings were offset by faster price increases of those brands. Moreover, when overall inflation returned to pre-pandemic levels, the relative prices of cheaper options remained *permanently* higher, even though the inflation inequality abated. This may help explain why some consumers may think that prices are "too high": not just relative to the past, but also relative to more expensive varieties. Finally, we note that by switching from their favorite products to cheaper alternatives, households also incur the utility cost of consuming less preferred items. A full welfare calculation would have to take all these costs into account.

5 Expenditure switching

While most of the increase in measured inflation stemmed from regular price increases, the ultimate inflationary burden depends on the reallocation of expenditures along the product spectrum. Consumers can save money by shifting their spending toward cheaper goods. For each product in the consumption basket, such an adjustment occurs along both dimensions: a lower price for the same-quality product or lower-quality product. For example, as the price of Mel's favorite milk brand "Nature's Best 1% Milk Carton 2LT" becomes more expensive, she can wait until it is on sale or look for a lower price in another store. This option usually comes with the cost of searching or waiting. Alternatively, she may want to buy a different package of the same brand, "Nature's 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 for an average consumer 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 the evidence in Sections 3 and 4, we focus on expenditure switching *within* narrow product categories. Appendix D presents additional evidence on expenditures switching across retailers.

5.1 Canadian Nielsen Homescan Panel data

The data collected by NielsenIQ contain information on the expenditures of Canadian households on food and household goods. Individual transactions have been recorded from 2013 by households from a participating panel of approximately 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 D 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).[11] The unit price is measured as dollars spent on each transaction (after discounts) per number of standardized units. The unit *regular* price is defined similarly, but without the discounts.

We 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. The *Full sample* basket refers to all retailer-UPC pairs for which the average unit price is observed in both months t and $t-1$. The *Constant basket* contains only retailer-UPC pairs for which the 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 six times smaller than the full sample basket.

We are primarily interested in the effect of expenditure switching across groups of 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.[12]

[11]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.

[12]A more comprehensive treatment of expenditure switching would require construction of superlative chained

First, we 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, we 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.

Following Section 3, the 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 the dollars spent on discounted transactions for retailer-UPC i in month t, and let s_{it} denote total dollars spent in month t. The expenditure switching from regular to discounted prices is summarized by the share of expenditures on discounted transactions in all expenditures:

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

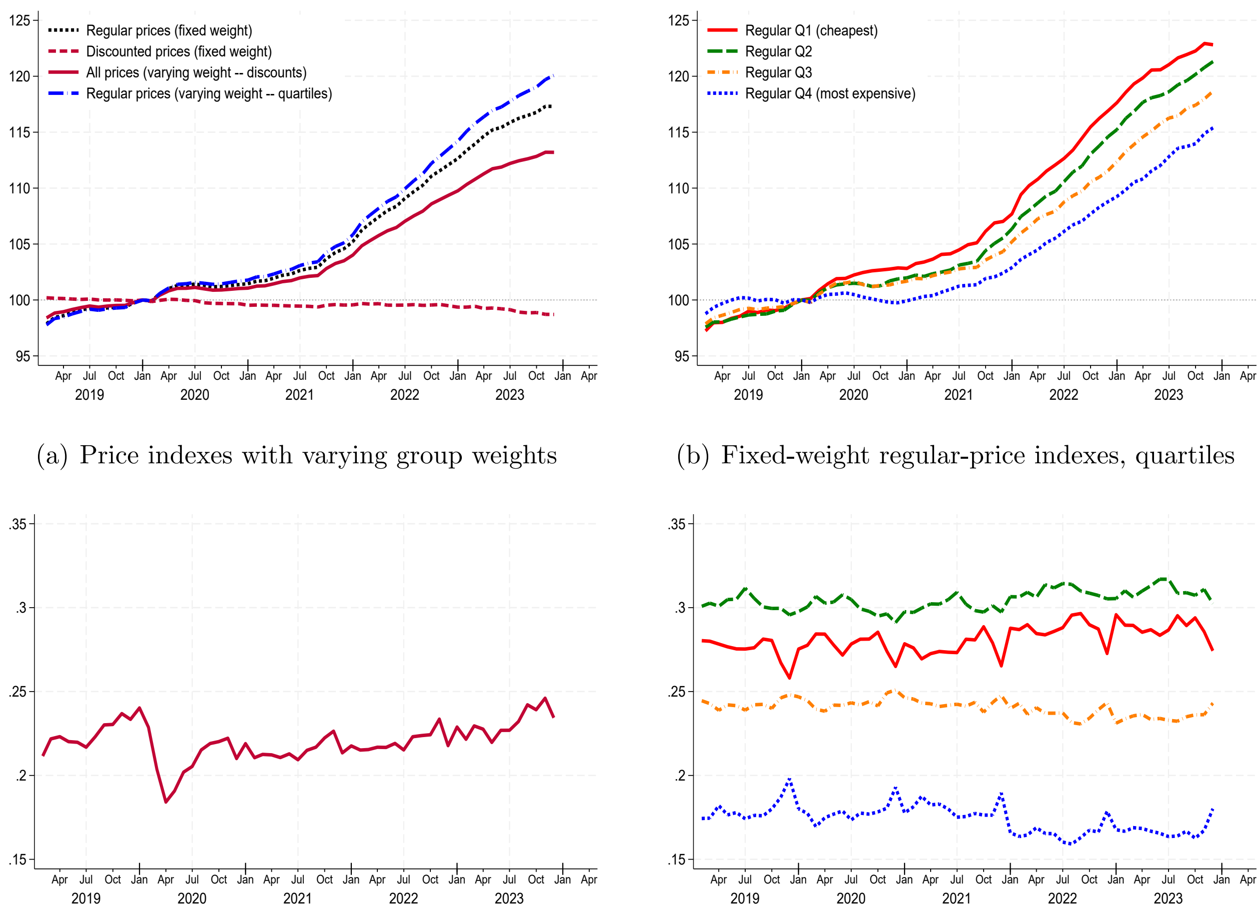
To visualize the impact of expenditure switching from regular to discounted prices, we construct the varying-weight inflation rate as the weighted average of fixed-weight inflation rates with weight equal to the respective expenditure shares:

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

As before, we visualize the cumulative inflation rates for regular and sale-related changes, which we now call "price indexes" in short. Figure 6(a) provides fixed-weight price indexes for regular and discounted transactions for all products (full-sample), π_t^{RR} and π_t^{Sales}. While regular prices grew by 17.3% from January 2020 to December 2023, the cumulative rate of sale-related price changes was –1.3%. Figure 6(c) shows that after the initial sharp fall to 0.18 at the

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.

beginning 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 4.1 percentage points (column 2 in Table 3). Hence, expenditure switching to discounts shaved off roughly 24% of the price increase since January 2020 relative to the increase for regular-price transactions. The results are similar for food and non-food product groups and when using a 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 6: Prices and expenditure switching for all products.

Notes: Panel (a) shows price indexes for the full UPC sample: 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 full sample basket 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 product varieties, 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 6(b) shows that cheaper brands experienced faster growth of transaction prices, corroborating the facts from multi-channel retailers in Section 4. Figure 6(d) shows that in late 2021, when Canadian inflation started to surge, expenditures gradually shifted from more expensive to cheaper brands.[13] 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 2.8 percentage points (row 3 in Table 3). Hence, while households switched to cheaper (lower-quality) brands, their savings were offset by the higher relative price growth for those brands. This finding is strongest for non-food products, suggesting greater expenditure switching in these categories. The effect is smaller for the constant basket due to the limited number of brands available for substitution in this sample (Appendix D).

	All	**Food**	**Non-food**
Regular prices (fixed weight), %	**17.3**	**18.8**	**12.5**
Varying weight – discounts, %	**13.2**	**14.4**	**9.6**
(2) – (1)	-4.1	-4.4	-2.9
Varying weight – quartiles, %	**20.1**	**20.4**	**19.2**
(3) – (1)	2.8	1.6	6.7
Varying weight – retailers, %	**17.3**	**18.9**	**12.5**
(4) – (1)	0.0	0.1	-0.1
# products	163	104	59
# UPC	185,069	113,623	72,427
# observations	9,504,389	8,218,723	1,285,666

Table 3: Unit price changes between January 2020 and December 2023.

Notes: Table provides cumulative monthly inflation rates (in %) from January 2020 to December 2023 (full sample). 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 product groups (all products, food, non-food).

Finally, we analyze expenditure switching *across* retailers. We do not find evidence that

[13] Argente and Lee (2021) use U.S. Nielsen scanner data to show that the difference in inflation rates experienced by low- and high-income households widened during the Great Recession. They show that 46% of the difference is due to changes in product prices (keeping consumption baskets fixed), and the remaining 54% reflected differences in consumer responses to prices, reflecting differences in within-category substitution (29%), differences in shopping behavior (12%), and adoption of product varieties (13%).

this had much impact on the inflation rate experience by consumers during this time period.[14] We split retailers into three groups: high- and low-value brick-and-mortar (BMO) retailers, and online retailers. In Appendix D, we document 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 has remained 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 0.42 in April 2020 to 0.51 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 3).

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.

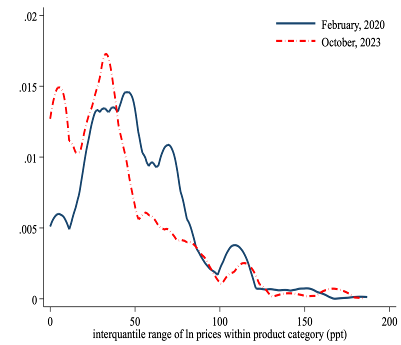
We measure price dispersion by the interquartile range of unit prices within retailer and narrow product category in each month. Figure 7 shows a substantial variation in unit price dispersion across products in a given month, for both posted prices (in the United States and Canada, Panels (a)–(b)) and transaction prices (in Canada, Panel (c)).

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

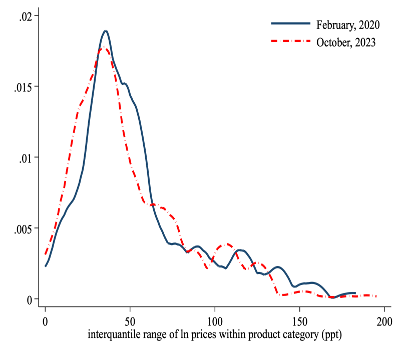
Figure 7 shows the evolution of the median within-product price dispersion in our sample. In all six cases—unit posted prices in the United States and Canada, and unit transaction prices in Canada, using full sample and constant basket—median within-product price dispersion appears

[14] Kaplan and Menzio (2015) use the U.S. Homescan Panel data to estimate that half of the variation in prices that household pay is due to differences in expensiveness of retail stores they choose to shop in. Coibion, Gorodnichenko, and Hong (2015) employ a different scanner dataset for U.S. grocery store transactions 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.

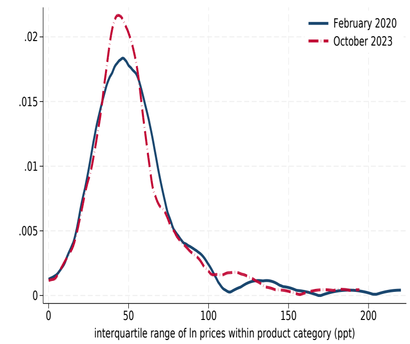
to be fairly stable after the onset of the pandemic (early 2020) or decreasing (in 2022 and 2023).



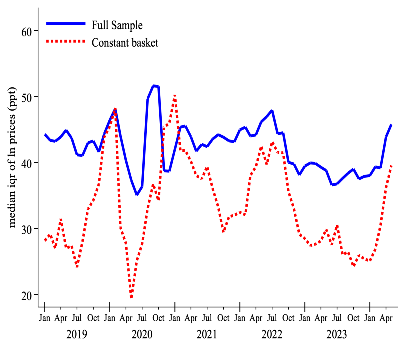
(a) IQR, posted prices (USA)



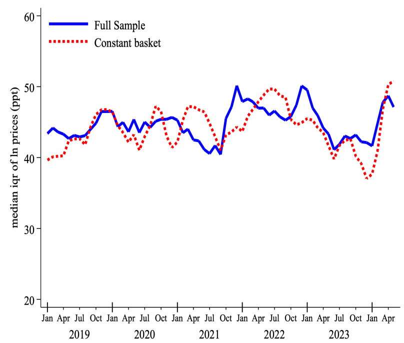
(b) IQR, posted price (CAN)



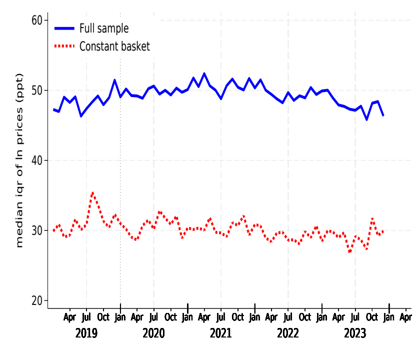
(c) IQR, transaction prices (CAN)



(d) Med IQR, posted prices (USA)



(e) Med IQR, posted prices (CAN)



(f) Med IQR, trans prices (CAN)

Figure 7: Within-product unit price dispersion for food.

Notes: Panels (a)–(c) provide kernel densities of the interquartile range (IQR) for ln unit prices within retailer-product in a given month. Panels (d)–(f) provide the time series for the median of interquartile ranges for ln unit prices within retailer-product in a given month. Panels (a) and (d) use unit posted prices for food sold by multi-channel retailers in PriceStats data for the United States. Constant basket comprises 15,363 unique products that enter before March 2020 and never exit. For Canada, it comprises 17,951 unique products. Panels (b) and (e) provide PriceStats series for Canada. Panels (c) and (f) use unit transaction prices for food products in the Canadian Homescan Panel dataset.

This finding contrasts the positive relationship between inflation and price dispersion documented in previous studies.[15] The key focus—and difference—in these studies is on price dispersion *across* firms. A positive correlation of across-firm price dispersion and inflation is in line with models of sticky prices, either due to costly price adjustments by firms (Sheremirov,

[15] 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), Adam, Alexandrov, and Weber (2023) for the United Kingdom (1996–2016). Sheremirov (2020) examines U.S. retail scanner data for 2001–2011 and finds a positive correlation between regular price dispersion and inflation but a negative correlation when price discounts are included. Reinsdorf (1994) finds that the dispersion for 65 products in 9 U.S. cities in 1980–1982 decreases with inflation but increases with expected inflation.

2020) or to the consumers' costs of acquiring price information (Drenik and Perez, 2020). Also in standard Calvo sticky price models, the prices of adjusting firms drift farther away from prices of non-adjusting firms when inflation is higher.

What these models miss, however, is the effect that expenditure switching across different product varieties can have on pricing behaviors within categories. Documenting this type of price dispersion requires micro data for prices within stores-categories and for product parameters that allow controlling for variation in product size and packaging. The data used in this paper address this challenge. Moreover, the scale and scope of the data in the paper support a comprehensive analysis of the relationship between within-product price dispersion and inflation by including countries with high and low inflation, countries with high and low use of discounts, and observations for posted prices and transaction prices.

7 Conclusions

We analyze the effects of inflation on within-store price variations and examine how households used these variations to alleviate the inflation burden. Adjusting for product sizes, we calculated unit prices for food products sold by 91 large multi-channel retailers in ten countries between 2018 and 2024 and explored two primary sources of price variation: temporary price discounts and differences across similar products within narrowly defined categories.

Our findings reveal that discounts grew at a lower average rate than regular prices, helping mitigate the inflation burden for consumers. On the other hand, we found ample evidence for a phenomenon we termed "cheapflation," where the prices of cheaper goods increased at a faster rate than those of more expensive varieties of the same product. This exacerbated the inflation burden, as consumers who switched to cheaper brands to save money faced higher relative price increases for these goods. Using Canadian Homescan Panel data, we further estimated that the use of discounts reduced the growth in the average unit price by 4.1 percentage points, accounting for 24% of the total change since January 2020. Conversely, switching to cheaper brands increased average unit price growth by 2.8 percentage points, which represents a 16% increase relative to a fixed-weighted index.

These results underscore the significant role of within-category price variation in shaping the welfare cost of inflation. While discounts provided a cushion against rising prices, the rapid increase in prices for cheaper brands placed additional financial strain on households. Moreover, switching to less preferred, lower-quality products introduces an additional utility cost, further complicating the real impact of inflation on consumer welfare.

Overall, our study highlights the dual nature of within-store price dynamics during periods of high inflation, offering insights into how different pricing strategies and consumer behaviors interact to influence the overall inflation experience. Understanding these mechanisms is crucial for policy makers aiming to address the broader impacts of inflation on household welfare.

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— ONLINE APPENDIX —

Price Discounts and Cheapflation During the Post-Pandemic Inflation Surge[1]

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[1]Alberto Cavallo is a shareholder of PriceStats LLC, the private company that provided proprietary data used in this paper without any requirements to review the findings. We thank Carly MacDonald, Tomas Pacheco, and Gastón García Zavaleta for excellent research assistance. The views expressed here are ours, and they do not necessarily reflect the views of the Bank of Canada.

A Summary statistics for food products

	# Retailers	# Categories	# Products	# Unit Prices	% Unit Prices
ARGENTINA	9	6,945	170,923	71,324	41.7
BRAZIL	12	8,891	228,497	1,622	.7
CANADA	12	11,349	271,890	55,818	20.5
FRANCE	12	17,442	364,920	268,403	73.6
GERMANY	7	8,766	178,152	91,007	51.1
ITALY	5	3,627	80,711	68,521	84.9
NETHERLANDS	7	22,486	161,145	55,531	34.5
SPAIN	9	12,443	177,025	96,517	54.5
UK	10	21,748	193,521	145,662	75.3
USA	8	13,433	296,108	155,168	52.4

Table A1: Multi-channel retail data by country.

	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 A2: 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.

B Regular and sale-related prices: additional results

B.1 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_{it}^S be the discount indicator (flag or V-shape), and p_{it}^R 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

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

Denote the absolute size of discount by $\Delta_{it} = p_{it}^R - p_{it}$, the regular price change by $dp_{it}^X = (p_{it}^R - p_{it-1}^R)$, $X = RR, SR, RS$, and the SS price change by $dp_{it}^{SS} = (p_{it} - p_{it-1})$. Note that since we define an unobserved regular price as the last observed regular price, $dp_t^{SR} = 0$, this gives

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

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

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

$$
\begin{aligned}
F_t^{RR+} &= \sum_{i=1}^{N_t} \omega_i I_{it}^+ (1 - I_{it}^S)(1 - I_{it-1}^S), & F_t^{RR-} &= \sum_{i=1}^{N_t} \omega_i I_{it}^- (1 - I_{it}^S)(1 - I_{it-1}^S), \\
F_t^{SR} &= \sum_{i=1}^{N_t} \omega_i I_{it} (1 - I_{it}^S) I_{it-1}^S, \\
F_t^{SR,reg+} &= \sum_{i=1}^{N_t} \omega_i I_{it}^{SR+} (1 - I_{it}^S) I_{it-1}^S, & F_t^{SR,reg-} &= \sum_{i=1}^{N_t} \omega_i I_{it}^{SR-} (1 - I_{it}^S) I_{it-1}^S, \\
F_t^{RS} &= \sum_{i=1}^{N_t} \omega_i I_{it} I_{it}^S (1 - I_{it-1}^S), \\
F_t^{RS,reg+} &= \sum_{i=1}^{N_t} \omega_i I_{it}^{RS+} I_{it}^S (1 - I_{it-1}^S), & F_t^{RS,reg-} &= \sum_{i=1}^{N_t} \omega_i I_{it}^{RS-} I_{it}^S (1 - I_{it-1}^S), \\
F_t^{SS+} &= \sum_{i=1}^{N_t} \omega_i I_{it}^+ I_{it}^S I_{it-1}^S, & F_t^{SS-} &= \sum_{i=1}^{N_t} \omega_i I_{it}^- I_{it}^S I_{it-1}^S.
\end{aligned}
$$

The average sizes of those changes are

$$
\begin{aligned}
D_t^{RR+} &= \frac{1}{F_t^{RR+}} \sum_{i=1}^{N_t} \omega_i I_{it}^{+} (1 - I_{it}^S)(1 - I_{it-1}^S) dp_{it}^{RR}, \\
D_t^{RR-} &= -\frac{1}{F_t^{RR-}} \sum_{i=1}^{N_t} \omega_i I_{it}^{-} (1 - I_{it}^S)(1 - I_{it-1}^S) dp_{it}^{RR}, \\
D_t^{SR+} &= \frac{1}{F_t^{SR,reg+}} \sum_{i=1}^{N_t} \omega_i I_{it}^{SR+} (1 - I_{it}^S) I_{it-1}^S dp_{it}^{SR}, \\
D_t^{SR-} &= -\frac{1}{F_t^{SR,reg-}} \sum_{i=1}^{N_t} \omega_i I_{it}^{SR-} (1 - I_{it}^S) I_{it-1}^S dp_{it}^{SR}, \\
D_t^{RS+} &= \frac{1}{F_t^{RS,reg+}} \sum_{i=1}^{N_t} \omega_i I_{it}^{RS+} I_{it}^S (1 - I_{it-1}^S) dp_{it}^{RS}, \\
D_t^{RS-} &= -\frac{1}{F_t^{RS,reg-}} \sum_{i=1}^{N_t} \omega_i I_{it}^{RS-} I_{it}^S (1 - I_{it-1}^S) dp_{it}^{RS}, \\
D_t^{SS+} &= \frac{1}{F_t^{SS+}} \sum_{i=1}^{N_t} \omega_i I_{it}^{+} I_{it}^S I_{it-1}^S dp_{it}^{SS}, \\
D_t^{SS-} &= -\frac{1}{F_t^{SS-}} \sum_{i=1}^{N_t} \omega_i I_{it}^{-} I_{it}^S I_{it-1}^S dp_{it}^{SS}, \\
\Delta_t^{+} &= \frac{1}{F_t^{SR}} \sum_{i=1}^{N_t} \omega_i I_{it} (1 - I_{it}^S) I_{it-1}^S \Delta_{it-1}, \\
\Delta_t^{-} &= \frac{1}{F_t^{RS}} \sum_{i=1}^{N_t} \omega_i I_{it} I_{it}^S (1 - I_{it-1}^S) \Delta_{it}.
\end{aligned}
$$

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 (B.1), inflation from sales π_t^{Sales} can be decomposed as follows:

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

The first term on the right-hand side of (B.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 (B.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.2 Regular price inflation components

	Before surge				During surge			
	FR+	***FR−***	***Size+***	***Size−***	***FR+***	***FR−***	***Size+***	***Size−***
CANADA	0.14	0.13	21.5	22.8	0.11	0.07	15.4	19.0
FRANCE	0.11	0.10	10.8	11.4	0.23	0.11	10.1	11.8
GERMANY	0.08	0.06	13.5	15.8	0.13	0.06	11.1	11.8
ITALY	0.07	0.07	21.4	23.3	0.11	0.06	14.8	19.8
NETHERLANDS	0.11	0.08	8.7	9.5	0.17	0.08	7.9	8.1
SPAIN	0.10	0.08	11.3	12.5	0.16	0.09	12.3	12.9
UK	0.04	0.02	20.3	26.1	0.09	0.02	12.8	19.7
USA	0.08	0.06	14.7	16.4	0.10	0.05	13.5	16.4
	Full sample							
ARGENTINA	0.40	0.11	14.6	15.1				
BRAZIL	0.23	0.17	13.9	14.7				

Table B1: Frequency and size of RR increases and decreases.

Notes: For each country, table provides the monthly fraction of price increases and decreases in all observations ($FR+$ and $FR-$) and average absolute size of those changes ($Size+$ and $Size-$). Discounts are identified by a sale flag. Sample period is between May 2018 and January 2024. Statistics are computed for the sample prior to ("Before surge") or after the start of the country-specific surge ("During surge"). Country surge dates are given in Table A2. All statistics are weighted by corresponding country's 3-digit COICOP weights.

B.3 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 β_π of regressing π_t^{Sales} on π_t. Table B2 provides β_π for each country and for the pooled sample (excluding country fixed effects) over the entire sample. Figure B1 provides scatterplots for observations across low inflation countries. Contribution of sale-related inflation decreases with time aggregation, reflecting lack of persistence of sale-related inflation.

	monthly rates	quarterly rates	annual rates
ARGENTINA	0.09	0.08	0.06
BRAZIL	0.10	0.01	-0.01
CANADA	0.39	0.25	0.19
FRANCE	0.01	0.01	0.01
GERMANY	0.07	0.04	0.03
ITALY	0.44	0.12	0.03
NETHERLANDS	0.07	0.02	0.00
SPAIN	0.05	0.03	0.02
UK	0.37	0.14	0.02
USA	0.48	0.18	0.08
Pooled (ex. ARG, BRA)	**0.31**	**0.14**	**0.09**
Pooled	**0.11**	**0.08**	**0.06**

Table B2: Summary of discounted price changes.

Notes: Table provides the fraction of inflation variance due to sale-related inflation (β_π) from May 2018 to January 2024. Quarterly (annual) rates are 3-(12-)month backward moving averages.

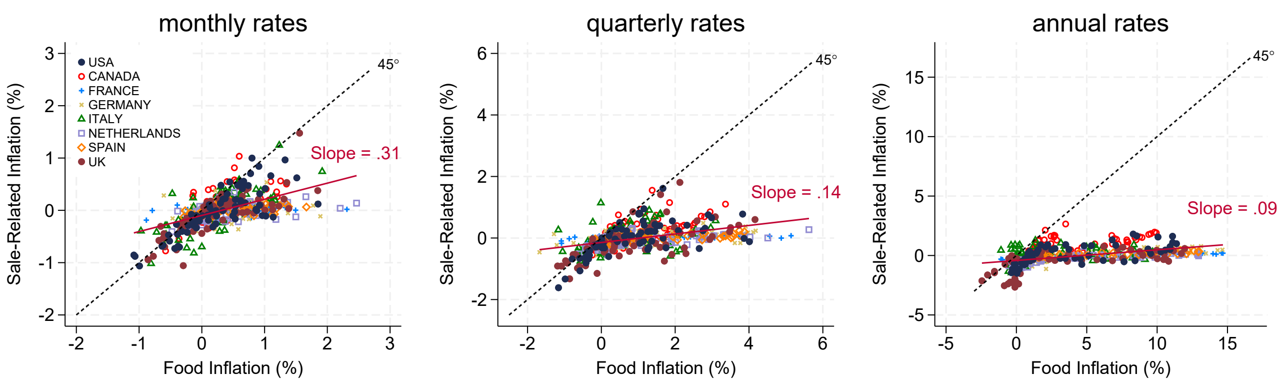


Figure B1: Co-movement of sale-related and overall inflation in food.

Notes: Figure summarizes contribution of sale-related inflation to overall food inflation from May 2018 to January 2024 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).

B.4 Contributions of inflation components

Table B3 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).[2]

Based on inflation behavior prior to the surge, countries are clearly divided into three groups. For countries in **Group A** (CAN, UK, USA, ITA),[3] sale-related inflation accounts for a significant

[2]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 $\frac{cov(\pi_t^{Sales},\pi_t)}{var(\pi_t)}$.

[3]Karadi et al. (2023) provide evidence that supermarket prices in Italy were more responsive to the first wave of

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 B3). The co-movement of sale-related inflation with inflation is even higher at monthly rates (Figure B2). 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 B3). And although sale-related inflation became higher and more persistent during the surge, these changes were small relative to the higher level and higher persistence of regular price inflation during the surge.

Table B3 shows that 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 ($\beta_\pi = 0.02$).

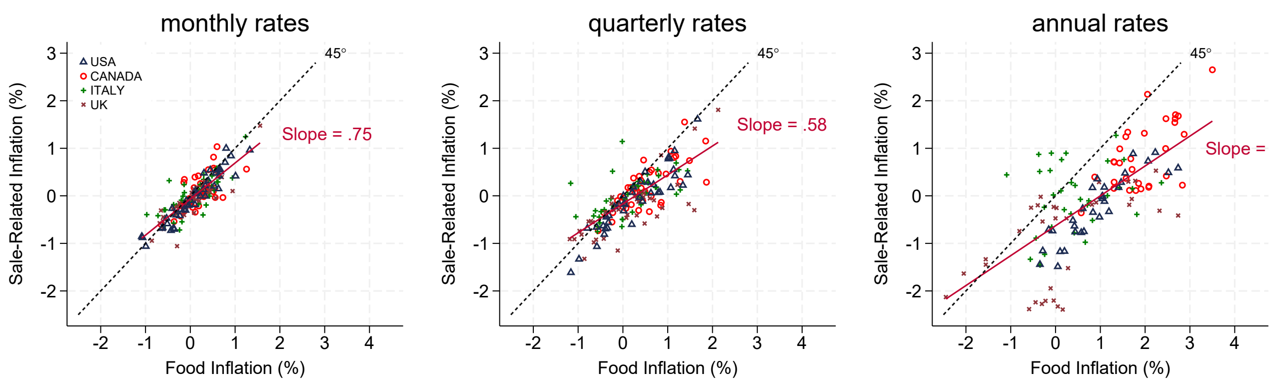


Figure B2: π_t and π_t^{Sales} rates before surge, pooled across USA, UK, CANADA, ITALY.

Notes: Figure summarizes contribution of sale-related inflation to overall food inflation from May 2018 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.

COVID-19 lockdowns than prices in Germany.

	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	0.27	0.67	0.51	1.00	1.86	0.95	0.78	1.00
Regular price inflation, π^{RR}	0.30	0.43	0.71	0.49	1.74	0.81	0.93	0.90
Sale-related inflation, π^{sales}	-0.03	0.53	0.36	0.51	0.12	0.41	0.40	0.10
GROUP B (FRA, GER, NED, ESP)								
Inflation, π	0.32	0.61	0.74	1.00	2.36	1.31	0.93	1.00
Regular price inflation, π^{RR}	0.39	0.56	0.75	0.97	2.33	1.25	0.92	0.98
Sale-related inflation, π^{sales}	-0.06	0.15	0.25	0.03	0.03	0.13	0.35	0.02
	Full sample							
GROUP C (ARG, BRA)								
Inflation, π	7.67	5.36	1.02	1.00				
Regular price inflation, π^{RR}	7.30	4.71	1.02	0.95				
Sale-related inflation, π^{sales}	0.36	0.81	0.82	0.05				

Table B3: 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 (A2). Sample period is from May 2018 to January 2024. 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 B3(a) shows that 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)). The size of price discounts decreased (for Italy after 2021), but this decrease was modest relative to the size of discounts (Figure B3(b)). Figure B4 shows how the dips in discount rates during lockdowns in Canada and the U.K. contributed to spikes in inflation rates. By contrast, once inflation surged, the share of inflation variance due to discounts in these countries fell to a mere 0.09 (last column in Table B3). Figure B3(c) shows the ratio of average size of end-of-sale regular price increases and the average size of RR price increases for Group A countries. Almost always, regular price increases at the end of sales are smaller than RR price increases.

(a) Monthly share of discounts

(b) Discount size

(c) Ratio: SR to RR regular price increase

Figure B3: 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 average size of price discounts Δ_t. Panel (c) 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.

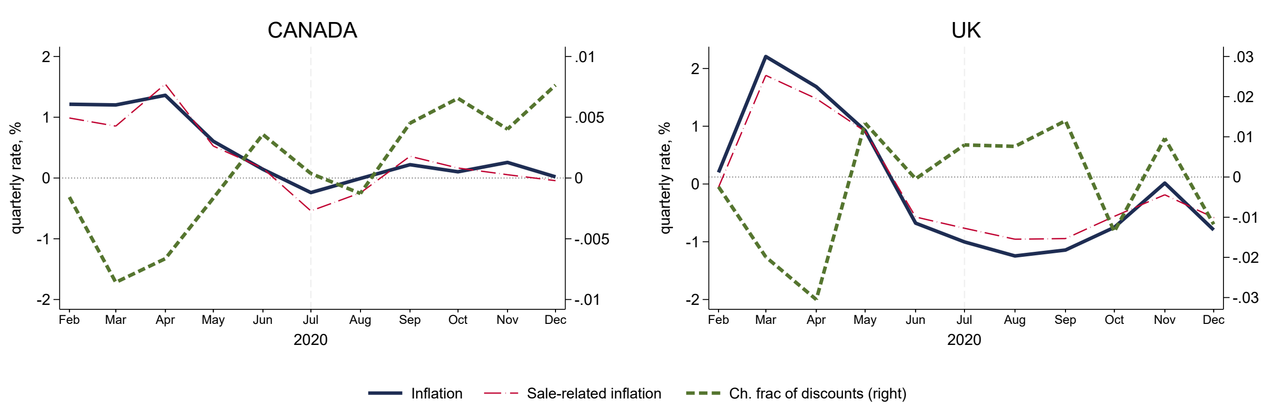


Figure B4: Inflation and discounts in 2020 in Canada and the U.K.

Finally, Figure B4 breaks down the cumulative price increase for each country into regular and sale-related price increases, and the latter if further broken down into components due to discounts and regular price changes at the beginning/end of sales.

	Flag				V-shapes			
	Regular	Sales			Regular	Sales		
		Total	Discounts	Regular		Total	Discounts	Regular
ARGENTINA	228.2	17.1	3.5	13.6	235.4	9.9	1.6	8.3
BRAZIL	38.6	0.6	-0.1	0.7	36.4	2.8	0.5	2.3
CANADA	15.4	3.3	-0.6	3.9	15.9	2.8	1.5	1.3
FRANCE	21.4	-0.3	-0.1	-0.2	21.6	-0.5	0.1	-0.7
GERMANY	22.3	0.1	-0.7	0.8	21.0	1.4	0.2	1.1
ITALY	16.4	0.4	-1.0	1.4	14.7	2.1	0.4	1.7
NETHERLANDS	22.1	-0.9	-1.3	0.4	19.9	1.3	0.7	0.5
SPAIN	22.6	0.3	0.0	0.4	21.7	1.2	0.1	1.2
UK	18.6	0.1	0.0	0.1	14.3	4.4	2.6	1.8
USA	18.1	1.2	-0.4	1.6	16.7	2.7	0.9	1.8

Table B4: Cumulative monthly inflation rates between January 2020 and January 2024, % change.

Notes: The table provides cumulative inflation rates (in %) for regular and sale-related price changes between January 2020 and January 2024. 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 $\pi_t^{reg,end} + \pi_t^{reg,start}$).

B.5 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.[4] 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 five 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 B5 and Table B5 below.

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

While food CPI inflation was 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 B5 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. This stems from the omission of short-lasting sales in the monthly ONS data: the shift toward longer sale durations implies that during sales, prices are faster to fall behind undiscounted prices.

Unlike in other sectors, in the 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.

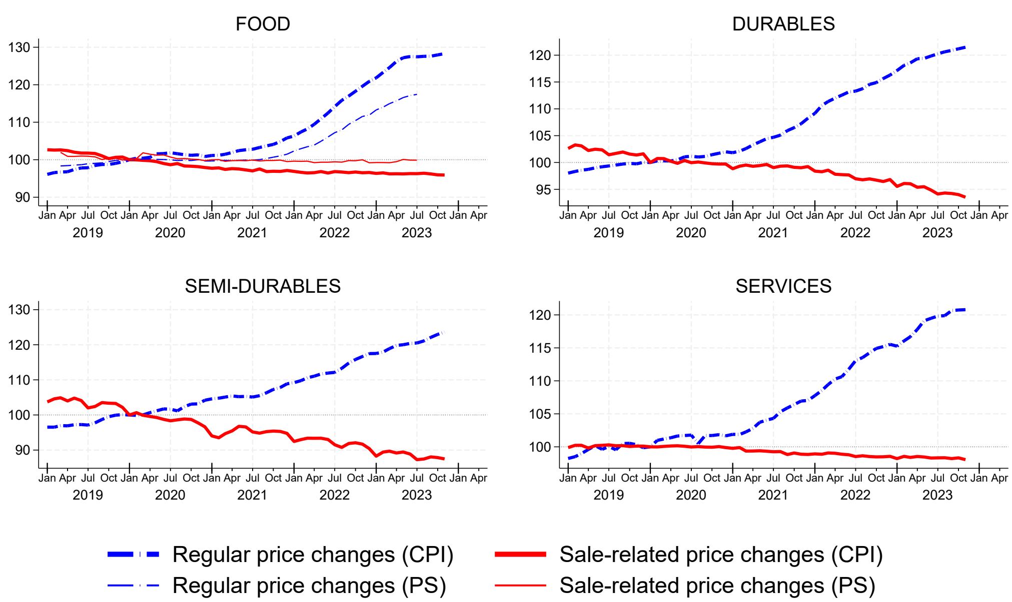


Figure B5: Regular and sale-related inflation across U.K. sectors.

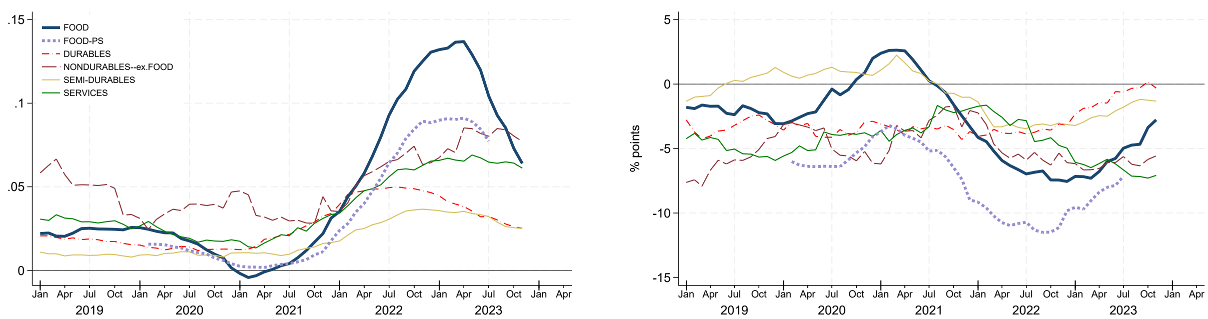
Notes: Figures provides cumulative month-to-month inflation rates for regular and sale-related price changes between January 2019 and July 2023 by sector in the United Kingdom. Discounts are identified by a sale flag. Indexes are normalized to 100 in January 2020. For food and beverages, thin lines provide components computed from PriceStats multichannel retail data for the United Kingdom, plotted in Figure 3.

	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 B5: 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 B6 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–

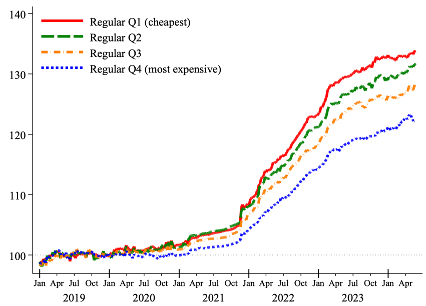
(b) Size+ v Size–

Figure B6: Monthly fraction of RR increases relative to decreases in UK CPI data.

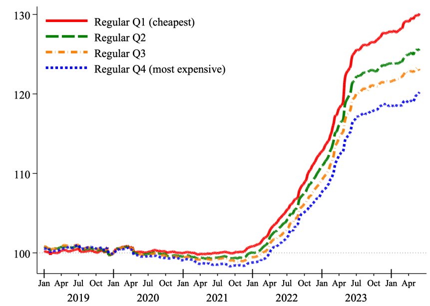
Notes: Figures provide the difference between average monthly fraction of RR increases and decreases (Panel a) and the difference between average absolute size of RR increases and decreases (Panel b). Discounts are identified by a sale flag. Time series are 12-month backward moving averages. Monthly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

C Cheapflation: additional results

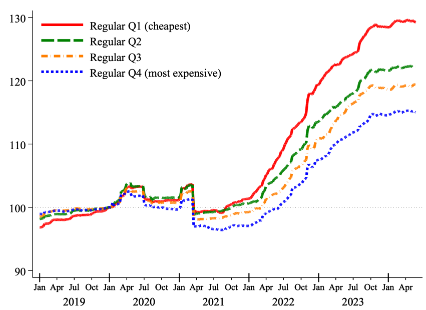
C.1 Breakdown by country



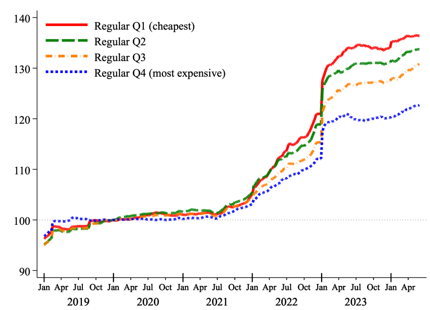
A. Canada



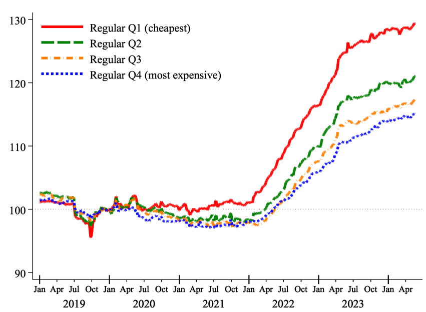
B. France



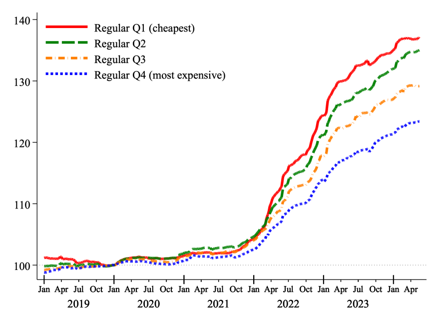
C. Germany



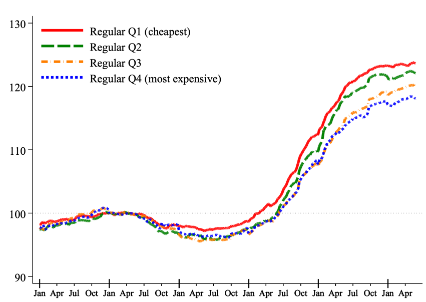
D. Netherlands



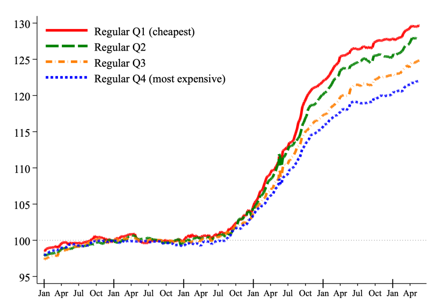
E. Italy



F. Spain



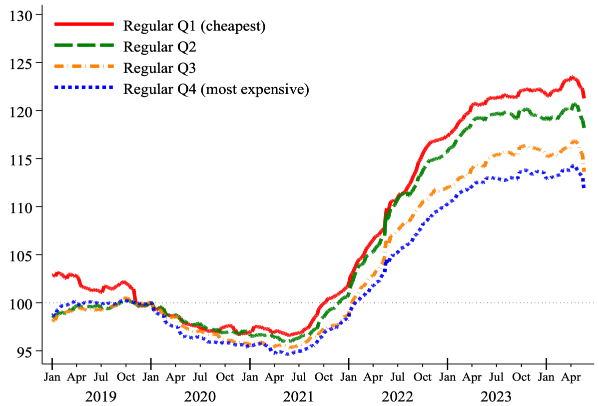
G. United Kingdom



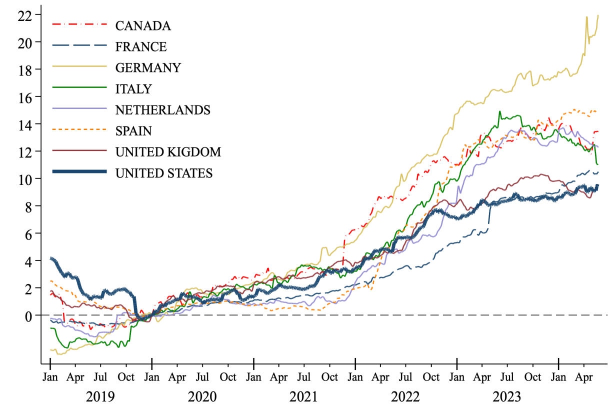
H. United States

Figure C1: Regular price indexes for unit price quartiles.

C.2 Cheapflation (V-shape discounts)



(a) Regular price index, by quartile



(b) Q1 vs Q4 cumulative inflation since Jan 2020

Figure C2: Cheapflation (V-shape discounts).

Panel (a) provides the matched-model regular price indexes for products in quartiles of average unit price in 2019 for the United States. Discounts are identified by V-shape filter. 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.

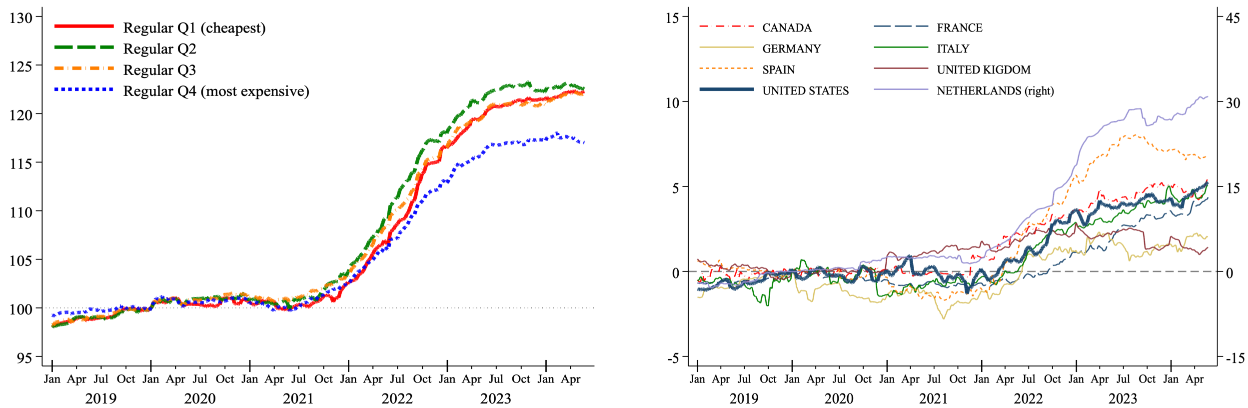
	Cumulative Inflation Jan 2020 – May 2024 (%)			
	All Products	Cheapest Q1	Most Exp. Q4	Q1–Q4 ppt
CANADA	19	25	11	13
FRANCE	23	28	18	11
GERMANY	3	14	-8	22
ITALY	12	20	9	11
NETHERLANDS	27	31	19	12
SPAIN	29	36	21	15
UNITED KINGDOM	16	21	11	9
UNITED STATES	17	21	12	10
ARGENTINA	3,224	3,405	3,139	266

Table C1: Cumulative inflation by unit regular price quartile (V-shape discounts).

Notes: Table shows the cumulative inflation rate from January 2020 to May 2024. The Q1 (cheapest) and Q4 (most expensive) products are selected based on their average unit regular price in 2019 (V-shape discounts).

C.3 Dynamic unit price quartiles

In the main text, products are ranked according to average unit regular price in 2019. This section provides the results where instead products are ranked in each quarter. Price indexes now are constructed using regular price changes by quartile *and* quarter. This implies that products sets for Q1, Q2, Q3, and Q4 vary from quarter to quarter due to relative price movements or product entry and exit.



(a) Regular price index, by quartile

(b) Q1 vs Q4 cumulative inflation since Jan 2020

Figure C3: Cheapflation, dynamic quartiles.

Panel (a) provides the matched-model regular price indexes based on regular price changes corresponding to quartiles of average unit price levels defined in each quarter for the United States. Discounts are identified by a sales flag. 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.

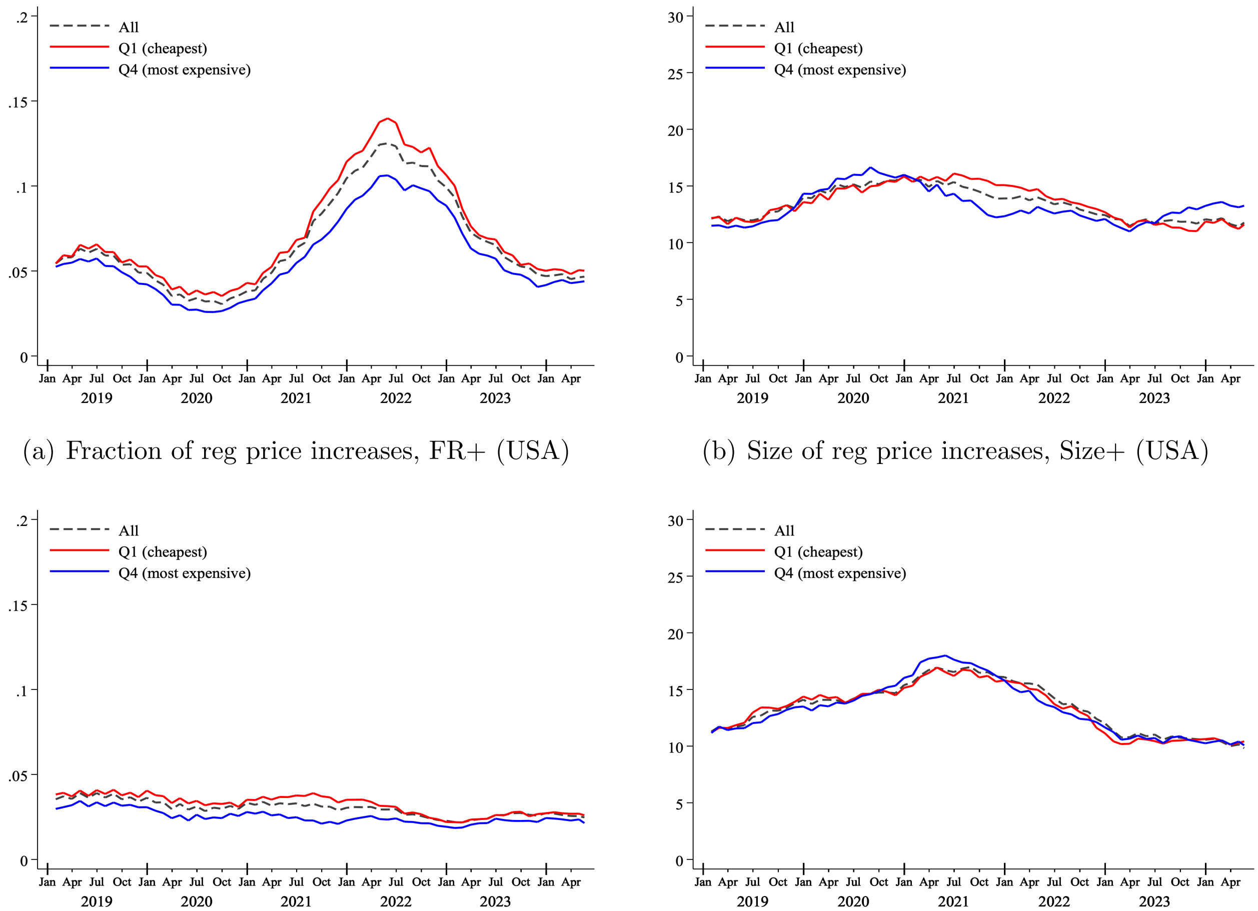
	Cumulative Inflation Jan 2020 – May 2024 (%)			
	All Products	Cheapest Q1	Most Exp. Q4	Q1–Q4 ppt
CANADA	25	27	21	5
FRANCE	25	27	23	5
GERMANY	28	29	27	2
ITALY	17	20	15	5
NETHERLANDS	34	35	4	31
SPAIN	28	31	24	7
UNITED KINGDOM	22	22	20	1
UNITED STATES	21	22	17	5

Table C2: Cumulative inflation, dynamic unit regular price quartiles (flag discounts).

Notes: Table shows the cumulative inflation rate from January 2020 to May 2024. Rates are based on regular price changes corresponding to quartiles of average unit price levels defined in each quarter.

C.4 Price adjustments, by unit price quartiles

Figure C4 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.



(a) Fraction of reg price increases, FR+ (USA)

(b) Size of reg price increases, Size+ (USA)

(c) Fraction of reg price decreases, FR– (USA)

(d) Abs Size of reg price decreases, Size– (USA)

Figure C4: Fraction and size of regular price increases and decreases.

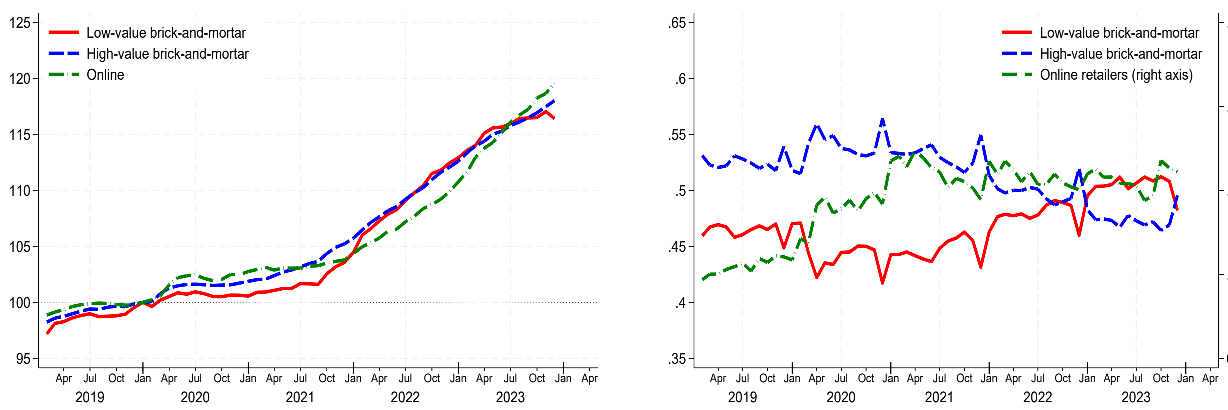
Notes: Figures provide the average monthly fraction of RR increases and decreases (Panels a and c), and the average absolute size of RR increases and decreases (Panels b and d) for the United States. Quartiles correspond to ranking by average regular unit price in 2019: Q1 are the cheapest varieties, Q4 are the most expensive. Discounts are identified by a sale flag. Monthly averages are weighted means, with 3-digit COICOP weights. All monthly series are smoothed by (5,1,5) moving average.

D Nielsen data: additional results

D.1 Expenditure switching across stores

While the main text focused on prices and expenditures within retailer and product category, Canadian Homescan Panel data allow analysis of expenditure switching *across* retailers. 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. 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 1(a) shows fixed-weight price indexes constructed for UPCs in each group using full sample 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 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 D1: Transaction prices and expenditures for all products, by retailer group (full sample).

Notes: Panel A shows fixed-weight price indexes for full UPC sample 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 1(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.[5] Substitution toward premium stores in 2020 may reflect households' switching from food away from home due to widespread restaurant closures during lockdowns early in the pandemic. But the bulk of spending in high-value BMO stores switched back to low-value retailers, raising their share in regular price expenditures from 0.42 in April 2020 to 0.51 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 3 in the main text).

D.2 Summary table, constant basket

		All	Food	Non-food
(1)	**Regular prices (fixed weight), %**	**20.3**	**20.4**	**19.0**
(2)	**Varying weight – discounts, %**	**16.1**	**16.2**	**16.3**
	(2) – (1)	-4.1	-4.3	-2.7
(3)	**Varying weight – quartiles, %**	**20.5**	**20.6**	**20.1**
	(3) – (1)	0.2	0.2	1.1
(4)	**Varying weight – retailers, %**	**20.3**	**20.5**	**19.1**
	(4) – (1)	0.1	0.1	0.1
	# products	104	56	160
	# UPC	17,997	3,170	21,167
	# observations	2,327,994	205,098	2,533,092

Table D1: Unit price changes between January 2020 and December 2023 (constant basket).

Notes: Table provides cumulative monthly inflation rates (in %) from between January 2020 to December 2023. Sample includes only UPCs with observations in all 60 months (constant basket case). 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 product groups (all products, food, non-food).

[5] According to Statistics Canada (https://www150.statcan.gc.ca/n1/pub/11-621-m/11-621-m2023002-eng.htm), the share of e-commerce annual retail sales in total retail sales for food and beverages was 0.7% in 2020, 1.7% in 2020, and 2.1% in 2021.

D.3 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 & FLAVOURINGS	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 FRENCH 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	FROZEN 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 D2: Food products.