Journal of Monetary Economics 148 (2024) 103644

Contents lists available at ScienceDirect

Journal of Monetary Economics

journal homepage: www.elsevier.com/locate/jme

Price discounts and cheapflation during the post-pandemic inflation surge☆

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ARTICLE INFO

Replication package: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FNY7IP4

JEL classification:
E21
E30
E31
L81

Keywords:
Inflation
Prices
Price dispersion
Expenditure switching
COVID-19 pandemic

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 ten 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.

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

☆ 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.

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[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) and Drenik and Perez (2020) for Argentina; Reinsdorf (1994), Nakamura et al. (2018) and Sheremirov (2020) for the United States.

https://doi.org/10.1016/j.jmoneco.2024.103644
Received 21 June 2024; Received in revised form 18 July 2024; Accepted 19 July 2024
Available online 24 July 2024

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 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 et al. (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 et al. (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.

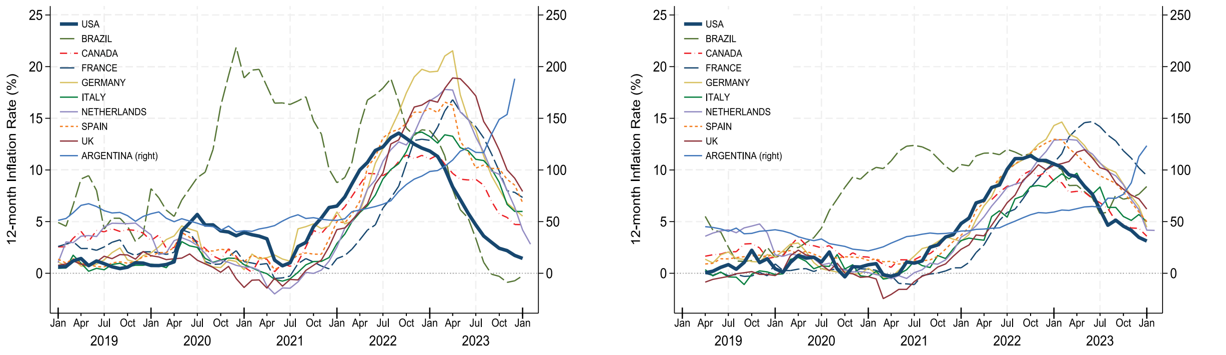
The data are collected using consistent methodologies across various countries, ensuring high comparability for similar categories of goods over identical time periods. The frequent updates and detailed nature of the data help mitigate measurement errors commonly associated with other sources, particularly 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. Fig. 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.

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 Fig. 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.

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



(a) CPI - Annual Inflation

(b) Multi-channel retailers - Annual Inflation

Fig. 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.

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

	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

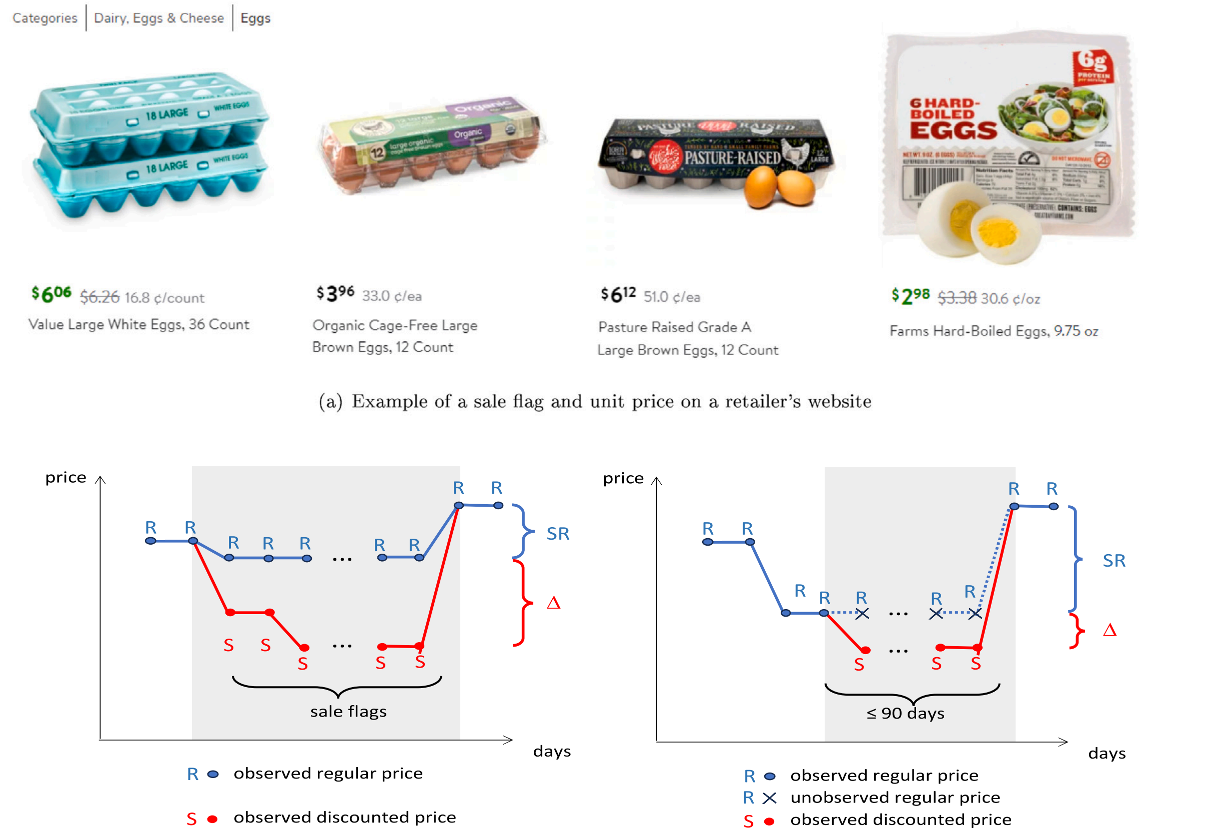
Notes: For each country, columns “Share” provide the weighted mean monthly share of discounted prices in all price observations between May 2018 and December 2019, and columns “Size” give the weighted mean size of discounts (the difference between regular and discounted prices during sale). The weights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

(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 Fig. 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 Fig. 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). Fig. 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 Fig. 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.



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

(b) Flag discounts

(c) V-shape discounts

Fig. 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").

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^S_{it} be the discount indicator (flag or V-shape), and p^R_{it} 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.

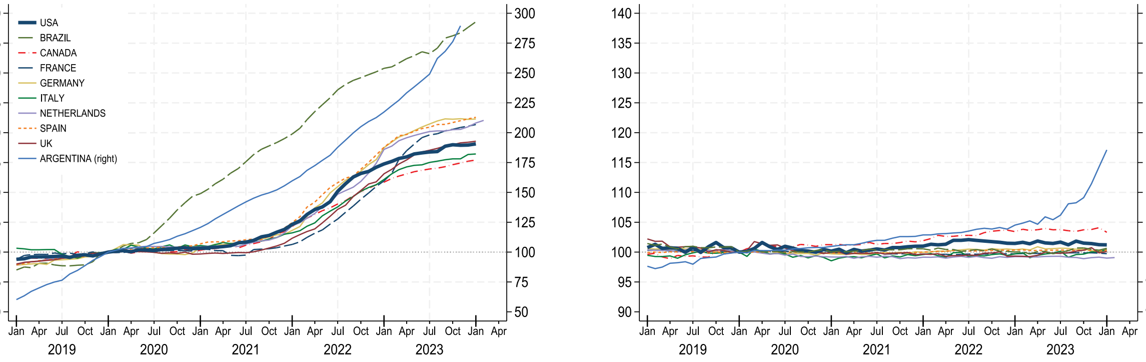
The daily inflation is the weighted mean of log price changes

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

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^{RR}_t sums up RR changes, and *sale-related inflation* sums up all other price changes:

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

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



(a) Regular price changes

(b) Sale-related price changes

Fig. 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.

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]

Fig. 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. Fig. 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.

In contrast to regular prices, Fig. 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

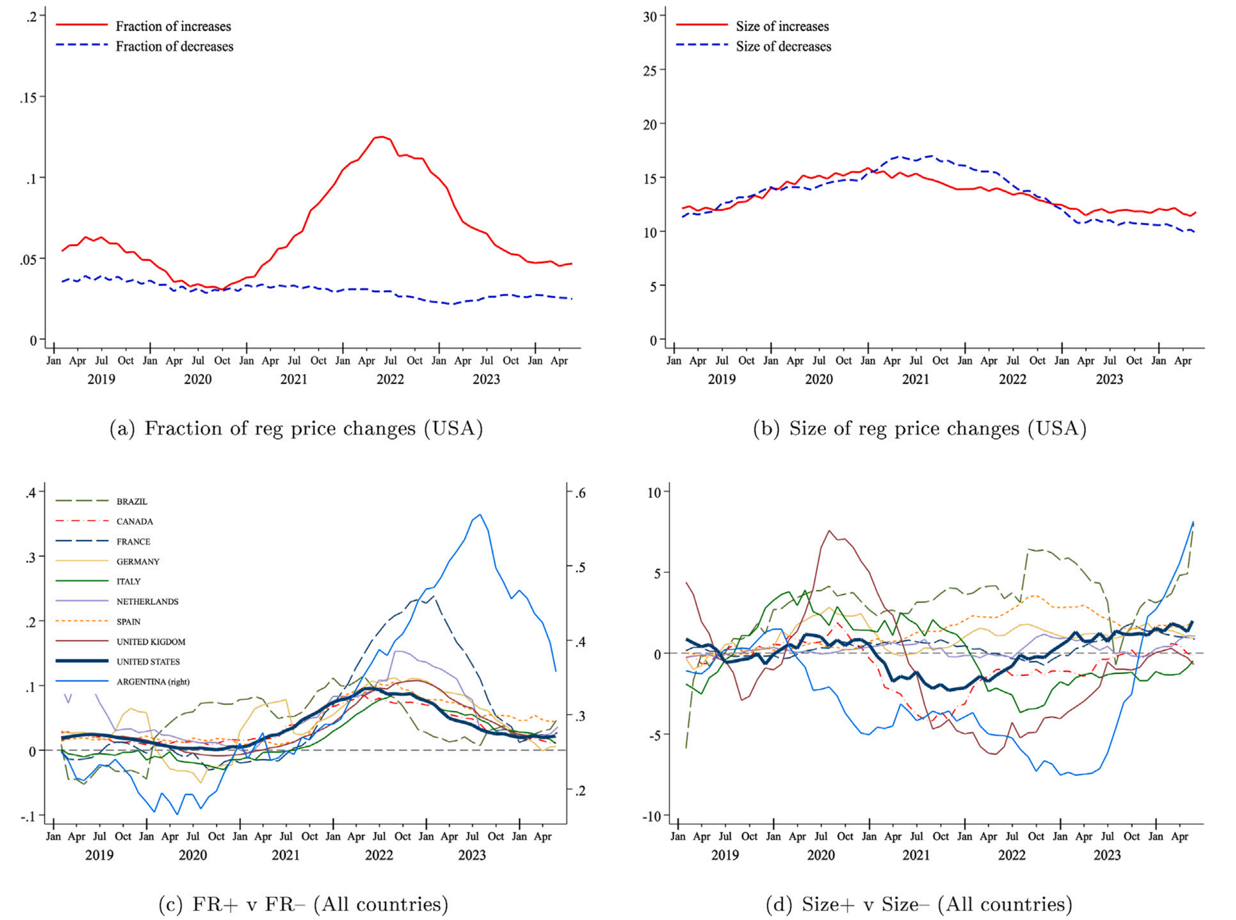
How do retailers attain high regular price growth during the inflation surge? Before the pandemic, about 55% of all regular price changes in low-inflation countries were price increases, and 45% of changes were decreases, i.e., increases and decreases were roughly balanced. This composition of regular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

During the inflation surge, retailers raised the proportion of price increases to decreases to about 2 to 1 (Appendix B). Fig. 4(c) shows that in all countries in our data, the monthly fraction of upward adjustments increased relative to the fraction of downward

[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).

[6] Studies of pricing behavior include, for the United States: Klenow and Kryvtsov (2008), Nakamura and Steinsson (2008) and Klenow and Malin (2010); Argentina: Alvarez et al. (2018); Brazil: Barros et al. (2009); Euro area: Álvarez et al. (2006) and Gautier et al. (2024); Canada: Kryvtsov (2016); United Kingdom: Dixon and Tian (2017). Montag and Villar (2022) and Bilyk et al. (2024) provide more recent evidence for the United States and Canada, respectively.



(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)

Fig. 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.

changes. At the same time, the magnitude of price changes was fairly stable (Fig. 4(d)). We find similar 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 et al., 2024).

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

[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).

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 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 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.

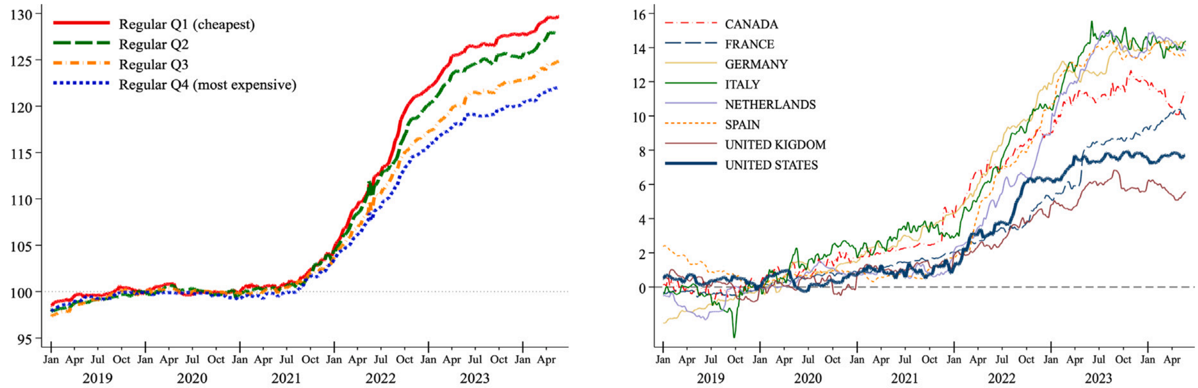
The remaining two components of sale-related price inflation – beginning-of-sale regular price changes and SS price changes – are quantitatively small for flag sales, and they are zero by definition for V-shape sales.

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.

Fig. 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.

[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.



(a) Regular price index, by quartile (b) Q1 - Q4 cumulative inflation since Jan 2020

Fig. 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.

Table 2
Cumulative inflation by unit regular price quartile.

	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	3513	3740	3371	369

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).

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 Fig. 5(b) – range between 6 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.

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 et al. (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 Fig. 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.

[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.

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 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 et al., 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.

[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.

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]

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:

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

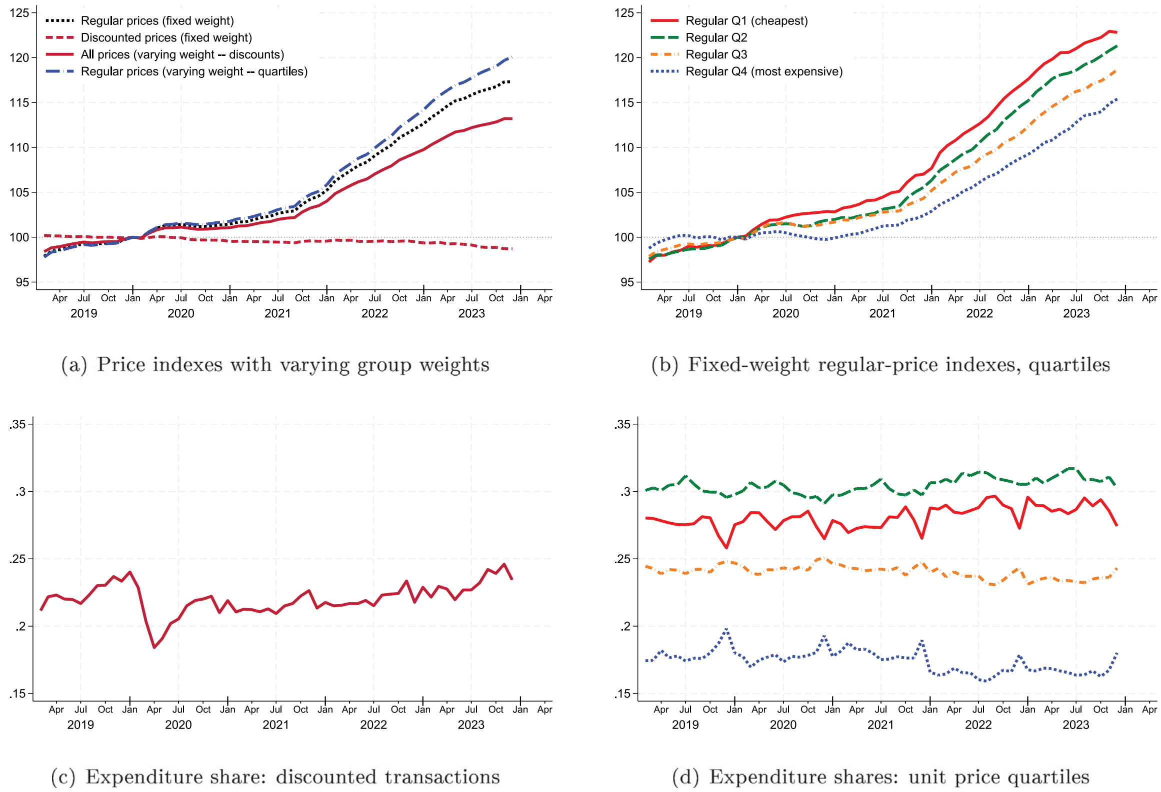
To visualize the impact of expenditure switching from regular to discounted prices, we construct the varying-weight inflation rate as the weighted average of fixed-weight inflation rates with weight equal to the respective expenditure shares:

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

As before, we visualize the cumulative inflation rates for regular and sale-related changes, which we now call "price indexes" in short. Fig. 6(a) provides fixed-weight price indexes for regular and discounted transactions for all products (full-sample), π_t^{RR} and

[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 g as equivalent to 1 ml. 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 indexes (Ivancic et al., 2011). Analysis of chained indexes would entail two additional challenges: distinguishing expenditure switching within versus across groups of transactions and the chain drift (Nakamura et al., 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.



(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

Fig. 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.

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%. Fig. 6(c) shows that after the initial sharp fall to 0.18 at the 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.

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.

Fig. 6(b) shows that cheaper brands experienced faster growth of transaction prices, corroborating the facts from multi-channel retailers in Section 4. Fig. 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).

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

[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%).

[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 et al. (2015) employ a different scanner dataset for U.S. grocery store transactions to find that

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

	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

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).

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. Fig. 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.

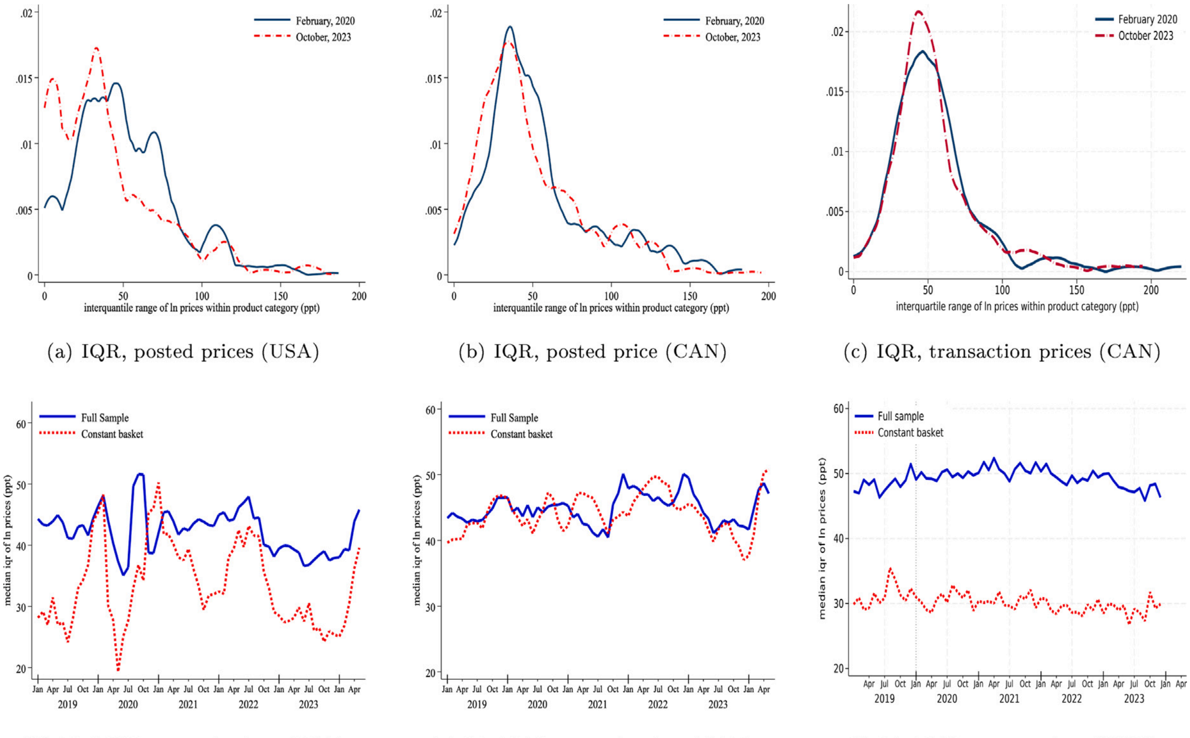
Fig. 7 shows the evolution of the median within-product price dispersion in our sample. In all six cases – unit posted prices in the United States and Canada, and unit transaction prices in Canada, using full sample and constant basket – median within-product price dispersion appears to be fairly stable after the onset of the pandemic (early 2020) or decreasing (in 2022 and 2023).

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, 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.

during economic slumps, consumers move their spending from high- to low-value retailers. Gorodnichenko and Talavera (2017) and Gorodnichenko et al. (2018) document differences in pricing behavior by online retailers vis-à-vis brick-and-mortar stores.

[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 et al. (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.



(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)

Fig. 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.

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.

Transparency declaration

The National Bureau of Economic Research has provided financial sponsorship to make this article open access and had no influence or involvement over the review or approval of any content.

Data availability

Replication package: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FNY7IP4

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jmoneco.2024.103644.

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