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Retail pricing format and rigidity of regular prices

Sourav Ray[1] | **Avichai Snir**[2] | **Daniel Levy**[3]

[1]University of Guelph
[2]Bar-Ilan University
[3]Bar-Ilan University, Emory University, ISET at Tbilisi State University, ICEA, and RCEA

Correspondence
Daniel Levy, Department of Economics, Bar-Ilan University, Ramat Gan, 5290002, Israel.
Email: daniel.levy@biu.ac.il

Abstract
We study the rigidity of regular and sale prices, and how it is affected by pricing formats (i.e. pricing strategies). We use data from three large Canadian stores with different pricing formats (Every-Day-Low-Price, Hi-Lo and Hybrid) that are located within a 1 km radius of each other. Our data contain both the actual transaction prices and actual regular prices as displayed on the store shelves. We combine these data with two 'generated' regular price series (filtered prices and reference prices) and study their rigidity. Regular price rigidity varies with store formats because different format stores treat sale prices differently, and consequently define regular prices differently. Correspondingly, the meanings of price cuts and sale prices vary across store formats. To interpret the findings, we consider the store pricing format distribution across the USA and Canada.

1 | INTRODUCTION

'A central question in macroeconomics is whether nominal rigidities are important' (Eichenbaum *et al.* 2011, p. 234). A large literature, starting with Barro (1972), Mankiw (1985), Kashyap (1995), Carlton (1986), Cecchetti (1986), Lach and Tsiddon (1992, 1996), Levy *et al.* (1997, 1998), Dutta *et al.* (1999, 2002), Bils and Klenow (2004), and Konieczny and Skrzypacz (2005), assesses the importance of nominal rigidities by measuring how often prices change.[1]

An important distinction in this literature is between regular and sale prices. As Nakamura and Steinsson (2008) note, price changes associated with sale prices might have different macroeconomic effects than regular price changes. That is because sale prices are transient and, consequently, they do not generate as much cumulative effect on the aggregate price level as regular price changes. In addition, sale prices are less correlated with economic shocks than regular prices, suggesting that the adjustment to aggregate shocks takes place, mostly, via regular price changes.[2] Recent studies of price-setting models, therefore, distinguish between regular and transaction prices.[3]

In this paper, we argue that the distinction between regular and sale prices does not depend only on whether the price change is temporary or not. It also depends on the store pricing format (i.e. pricing strategy): stores that follow different pricing formats have different notions of temporary price changes, which can potentially lead to different patterns of regular price rigidity. This aspect of retail pricing practice, however, has not received much attention in the context of price rigidity, although it might affect the transmission of supply shocks to consumer prices (He *et al.* 2023). Our goal is to fill this gap in the literature.

The existing retail pricing formats (or strategies) can broadly be grouped into three main types: (1) Hi-Lo, (2) Every-Day-Low-Price (EDLP), and (3) Hybrid (HYB). Whereas Hi-Lo stores run frequent sales, which they promote using sale signs, leaflets, and so on, EDLP stores run fewer temporary price cuts, and when they do, the price cuts are rarely promoted. HYB stores combine some features of the Hi-Lo and EDLP formats. For example, we find that the number of temporary price cuts at the HYB store in our data is similar to the number of temporary price cuts at the EDLP store. Most of the temporary price cuts at the HYB stores, however, are promoted, as in the Hi-Lo store.

We use a unique dataset from three large Canadian food stores. The dataset has three features that are particularly important for the questions that we ask. First, it includes *both* the actual regular and the actual transaction prices as posted on the stores' shelves.[4] Second, the stores differ in their pricing format: one follows Hi-Lo, the second follows EDLP, and the third is an HYB. Third, the stores are located within a 1 km radius, serving the same pool of clientele.

To assess how the treatment of sale prices affects price rigidity, we study the rigidity of four price series at each store. One is the *transaction price* series, which includes the sale prices as defined by the store, and three are regular price series: *regular prices* as defined by the stores; *filtered prices*, which we generate from the transaction price series by filtering out temporary price cuts using the Nakamura and Steinsson (2008) Sales Filter A; and *reference prices*, which we generate from the transaction prices by removing all short-lived prices using the Chahrour (2011) algorithm, building on Eichenbaum *et al.* (2011).

We find that the pricing format has a large effect on regular price rigidity. If we follow the stores' notion of regular prices, then regular prices at the EDLP store are more flexible than at the Hi-Lo or HYB stores: the likelihood that the EDLP store changes a regular price on a given week is 13.38%, in contrast to 5.34% at the HYB store, and 4.06% at the Hi-Lo store. If we treat filtered prices as regular prices, then regular prices at the HYB and EDLP stores are more flexible than at the Hi-Lo store: the likelihood that the HYB store changes a regular price on a given week is 4.50%, similar to 4.25% at the EDLP store, while the likelihood at the Hi-Lo store is 3.55%. If we treat reference prices as regular prices, then regular prices at the HYB store are more flexible than at the EDLP or Hi-Lo stores: the likelihood that an HYB store changes a regular price on a given week is 3.95%, with 2.70% at the EDLP store, and 2.23% at the Hi-Lo store.

We recognize that the empirical studies in this literature usually report their results for filtered (or reference) price series because they are interested primarily in identifying specific patterns of price changes to match and/or replicate data parameters for fitting structural models. For that purpose, knowing how retailers label their regular prices is less consequential.

However, recognizing that stores that follow different pricing formats treat temporary price cuts differently is likely to matter for macro-level price rigidity for several reasons.

First, the macroeconomic literature often treats temporary price cuts as pre-planned events, designed to maintain a brand's image and/or market share (Anderson *et al.* 2017; Warner and Barsky 1995). Our finding that stores that follow different pricing formats (or strategies) treat temporary price cuts differently, suggests that they might be driven by different incentives and motivations when they make decisions on temporary price cuts.

Second, as Chevalier and Kashyap (2019) note, sales have a large effect on sales volumes. Indeed, the effective price level at Hi-Lo and HYB stores is strongly affected by temporary price cuts (Glandon 2018). However, the effect of temporary price cuts might be different at an EDLP store, where the price cuts are not promoted as sales. Therefore the role that temporary price cuts play in the transmission of monetary shocks likely depends on the distribution of store pricing formats.

Third, although the stores are located within 1 km of each other and serve the same clientele, we find that the stores' regular prices exhibit different degrees of rigidity, depending on the definition of regular prices. If we consider regular prices as defined by the store, then the most flexible prices are 3.6 times as flexible as the least flexible prices. If we consider the filtered prices, then the most flexible prices are only 1.3 times as flexible as the least flexible prices. If we consider the reference prices, then the most flexible prices are 1.7 times as flexible as the least flexible prices. Thus the choice of a definition of regular prices can have a large effect on the differences found in the measured price rigidity across stores.[5]

Fourth, Carvalho (2006), Konieczny and Rumler (2006), Nakamura and Steinsson (2008), Álvarez *et al.* (2016) and Baley and Blanco (2021) emphasize the role that heterogeneity in price rigidity plays in determining the market responsiveness to monetary shocks. We find that regardless of the definition of 'regular' prices, there is a significant heterogeneity of price rigidity across stores that follow different pricing formats. This suggests that the heterogeneity of pricing formats might play a role in determining the macro-level price rigidity.

Fifth, Ellickson and Misra (2008) find regional differences in the geographical distribution of Hi-Lo, EDLP, and HYB stores across the USA. This, along with our finding that stores with different pricing formats have different regular price rigidities, suggests that the heterogeneity in the distribution of pricing formats across the USA might play a role in the variability of the effects of monetary policy by regions or states, as reported by Angeloni and Ehrmann (2007) and Francis *et al.* (2012).

In addition to discussing the frequency of price changes, we study the size of price changes. Firms can respond to shocks by either changing the frequency of price changes or changing the size of price changes (Sheshinski and Weiss 1977). Álvarez *et al.* (2016) show that when all firms respond to a common shock, the variance of the shock equals the number of price changes times the average size of price changes. They also show that for a large class of sticky price models that assume zero inflation and symmetric menu costs, the responsiveness of a market to shocks is captured by a sufficient statistic, which is proportional to the kurtosis of the size of price changes divided by the number of price changes. We find that if we look at the transaction prices, or at the regular prices as defined by the stores, then there are significant differences across stores between the product of the number of price changes and the average size of price changes, and between the sufficient statistics of the three stores. If we look at the filtered or reference price, there are still differences across stores in the product of the number of price changes and the average size of price changes, but the differences in the sufficient statistics are no longer statistically significant.

Further, it is possible that the differences that we find in the product of the number of price changes and the average size of price changes are an artifact of the short time series that we have. Therefore it seems that the filtered and reference price series are capturing the stores' responsiveness to shocks better than the transaction prices or the regular prices as defined by the stores. However, the differences in the price rigidity across stores likely affect the aggregate price rigidity, especially because we find evidence of synchronization across stores. As Carvalho (2006) shows, strategic complementarities across stores with different levels of price rigidity tend to slow down the market responsiveness to aggregate shocks.

An important limitation of our data is its shortness—we have data for only 52 weeks. This might lead to two types of errors. First, for many goods, the filtered and reference price series have no price changes, which may bias downwards our estimates of the duration of prices. Second, sales filters are inherently less accurate near the endpoints (Nakamura and Steinsson 2008), and this might also affect the accuracy of our estimates. To overcome this limitation, we obtained data for a supermarket in Israel that belongs to a chain that follows an HYB strategy. The data, which cover 171 weeks for 447 products, include both the regular and transaction prices as posted by the store. We augment these price series with filtered and reference price series. We find that the frequency of price changes at the Israeli supermarket is similar to that of the Canadian HYB store. We conclude that short time series leads to underestimation of the price duration. The effect of the imprecision due to endpoints, however, is small.

The paper is organized as follows. In Section 2, we discuss the pricing format landscape in the USA and Canada. In Section 3, we describe the data. In Section 4, we highlight key characteristics of the data. In Section 5, we discuss temporary price cuts and generated regular prices. In Section 6, we assess the rigidity of the transaction, regular, filtered, and reference prices. In Section 7, we discuss the role that the size of the price changes plays in the adjustment process. In Section 8, we discuss the synchronization of price changes across stores. In Section 9, we describe the various robustness checks that we have run and discuss the results of the analyses that we have conducted using Israeli data. In Section 10, we address data representativeness and limitations. We end the paper in Section 11 with a summary of key findings, possible macroeconomic implications of our findings, and avenues for future research.

2 | PRICING FORMAT LANDSCAPE IN THE USA AND CANADA

Studying price rigidity at stores with EDLP, Hi-Lo, and HYB pricing formats is important because these are the most common pricing formats in the USA, Canada, and other countries. Indeed, according to Ellickson and Misra (2008, p. 813): 'The majority of both marketers and practitioners frame a store's pricing decision as a choice between offering everyday low prices [EDLP] or deep but temporary discounts [Hi-Lo].'

EDLP retailers guarantee 'every-day-low-price', and thus they rarely offer discounts (He *et al.* 2023). Hi-Lo (or PROMO) retailers charge higher prices but offer frequent promotions by temporarily cutting prices below the EDLP prices (Hoch *et al.* 1994; Lal and Rao 1997; Gauri *et al.* 2008).

As Ellickson and Misra (2008) note, however, the EDLP/Hi-Lo dichotomy is too narrow because firms can choose a hybrid (HYB) format by adopting a mixture of EDLP and Hi-Lo, for example, by varying the product categories on sale, or by changing the frequency of sales across the categories (Bolton and Shankar 2003). Thus the HYB format can take various forms, combining some features of the EDLP and Hi-Lo formats, while adapting the particulars to the relevant settings, depending on the overall market positioning, local market structure, and so on. The specific features of an HYB format can therefore vary by area, competitive landscape, and so on.

In other words, the pricing format space in practice is a continuum along the entire spectrum between EDLP and Hi-Lo. For example, Walmart, Costco, and Food Lion are EDLP retailers, Target follows a Hi-Lo format, while Publix is in between, following mostly an HYB format.[6]

Table 1 shows the distribution of food store pricing formats by store type in the USA. According to the table, the share of the three pricing formats among large stores is about 33% EDLP, 30% Hi-Lo, and 37% HYB, and among small stores, it is about 22% EDLP, 50% Hi-Lo and 28% HYB.

Figure 1 shows the distribution of food store pricing formats across the USA. Although all three formats are present in all parts of the USA, Ellickson and Misra (2008) find regional variations as follows: EDLP format stores are particularly popular in the south, south-east, southern central, and south-west; Hi-Lo format stores are particularly popular in the Great Lakes, southern central, north-east and west coast; and HYB format stores are particularly popular in the north-west, south-west, west coast, north-east, and south-east.[7]

Unfortunately, we know less about the pricing format landscape of the Canadian retail food market. In particular, we do not have information on the pricing format of Canadian supermarket chains, or their geographical distribution. We can offer several observations, nevertheless.

First, based on the population size difference between the USA and Canada, the Canadian market size is about one-tenth of the US market. Second, four Canadian provinces populate

TABLE 1 Distribution of Store Pricing Formats by Store Type in the USA: All Food Retailers.

Type of chain/store	EDLP stores (%)	Hi-Lo stores (%)	HYB stores (%)
Large chains/stores			
Chain	33	30	37
Vertically integrated	35	29	36
Large store size	32	30	38
Many checkouts	31	30	39
Small chains/stores			
Independent	22	50	28
Not vertically integrated	21	47	32
Small store size	23	52	26
Few checkouts	22	52	26

Notes: The distinction between large versus small stores/chains is based on four criteria: chain/independent, vertically/not-vertically integrated, large/small store, and many/few checkouts. A 'chain' has 11 or more stores, while 'independent' has 10 or fewer. Vertically integrated firms operate their own distribution centers. 'Large' versus 'small' store sizes and 'many' versus 'few' checkouts are defined by the upper and lower quartiles of the full store-level census. The figures are the averages for 17,388 stores in the USA, with annual revenues of at least $2 million.
Source: Ellickson and Misra (2008).

FIGURE 1 Distribution of food stores by pricing format across the USA. Source: Ellickson and Misra (2008).

most of Canada's large retail food stores. Ontario, the most populous province of Canada, currently has 5583 supermarket stores; Quebec has 4405 stores, British Columbia 1681, and Alberta 1645. Yukon has just 16 supermarket stores.[8] Third, unlike the USA, where the stores are spread across the entire country, in Canada, the majority of the retail supermarket stores are located in the southern part of the country along the US border, which is a populated part of Canada.

Perhaps most importantly, however, the pricing practices of Canadian retailers are similar to the pricing practices of US retailers. Indeed, some of the US-based large retail food chains operate stores in Canada as well. These include Shop 'n Save, SuperValu, Safeway, Lucky, Costco, Walmart, Whole Foods, A&P, and Price Chopper.[9]

A retail food chain might operate stores with different pricing formats.[10] Pricing format, however, is one of the key components of the stores' strategic positioning. A decision about the pricing format, therefore, has long-term consequences, because the cost of changing a pricing format is likely to be prohibitively expensive. Indeed, there are many examples, including J. C. Penny, Sears, and Montgomery World, that tried to reposition themselves by changing their pricing format, but failed, often dramatically, many of them going bankrupt.[11] Consequently, stores do not change pricing formats in response to small or temporary shocks but change only as part of long-term strategic decisions.

3 | DATA: TRANSACTION PRICES AND REGULAR PRICES

Our data come from three large Canadian supermarket stores that belong to three large chains: Loblaw's, Provigo, and Super-C. The stores are located in Montreal's Notre-Dame-de-Grâce neighborhood, a middle-class residential district.[12] Loblaw's is the largest Canadian retailer, operating 400 stores.[13] Super-C operates 97 stores, and Provigo 300 stores.[14]

Table 2 reports the stores' size, parking area, annual sales, number of products, and number of employees. Based on sales (equivalent to $16–23 million) and the number of products, these are large superstores, comparable to some of the largest US chain stores, such as those studied by Levy *et al.* (1997) for measuring menu costs.

The three stores differ in their pricing format: Provigo is a Hi-Lo store, Loblaw's is an EDLP store, and Super-C is an HYB store.[15] Figure 2 shows the stores' locations.

In each store, we hand-collected weekly price data from 30 July 2003 to 23 July 2004. Every week, for each good, we manually recorded either one price or two prices, shown on the shelf price tags. If a good was not on sale, then we recorded the regular price, which was also the transaction price. If a good was on sale, then the retailer posted *the regular price next to the transaction price*, and we recorded both. Figure 3 shows actual price tag examples from the three stores.

We thus have two weekly price series for each good at each store: *transaction prices* and *regular prices*. Both are classified as such by the store managers. That is, our regular and transaction prices are *regular prices* and *transaction prices* as viewed by the store management, and as communicated to the shoppers through shelf price tags. In any week, the two prices of a good differ from each other if the good is on sale that week. Otherwise, the two prices coincide.

From each store, we have observations for 89 national brand goods in 11 product categories. In addition, we have price data for 39 private-label goods (10 at the EDLP store, 10 at the Hi-Lo store, and 19 at the HYB store).[16] For each good, we have 52 weekly price observations. In other words, we have no missing observations, giving us a total of 15,912 weekly observations.[17] In addition to the prices, we recorded the products' locations: back/middle/front aisle and bottom/eye-level/top shelf.[18] These serve as controls in the regression equations that we estimate.

Our dataset is small because it was hand-collected, but it has three unique features. First, we have *both* the actual regular prices and the actual transaction prices of each product, each week, as posted on store shelves. Thus we can match the regular prices with the corresponding transaction prices (if they differ), as viewed by the stores' management and the shoppers. Second, the stores in our sample represent three pricing strategies (EDLP, Hi-Lo, and HYB). Third, the stores are located close to each other (see Figure 2), catering to consumers from the same geographical area.

Table 3 gives the average regular and transaction prices at each of the stores, along with the results of Wilcoxon rank-sum tests for pairwise comparisons. We find that all pairwise comparisons are statistically significant for both the regular and transaction prices. The Hi-Lo store has the highest average regular (transaction) price, C$4.58 (C$4.47); the HYB store has the lowest

TABLE 2 General Information on the Stores Sampled.

	EDLP (Loblaw's)	Hi-Lo (Provigo)	HYB (Super-C)
Total floor area (m^2)	7695	2969	7133
Total parking area (m^2)	19,204	3021	10,700
Annual sales (in Canadian $)	30 million	24 million	21 million
Total number of products	39,000	28,000	33,000
Total number of employees	235	175	180

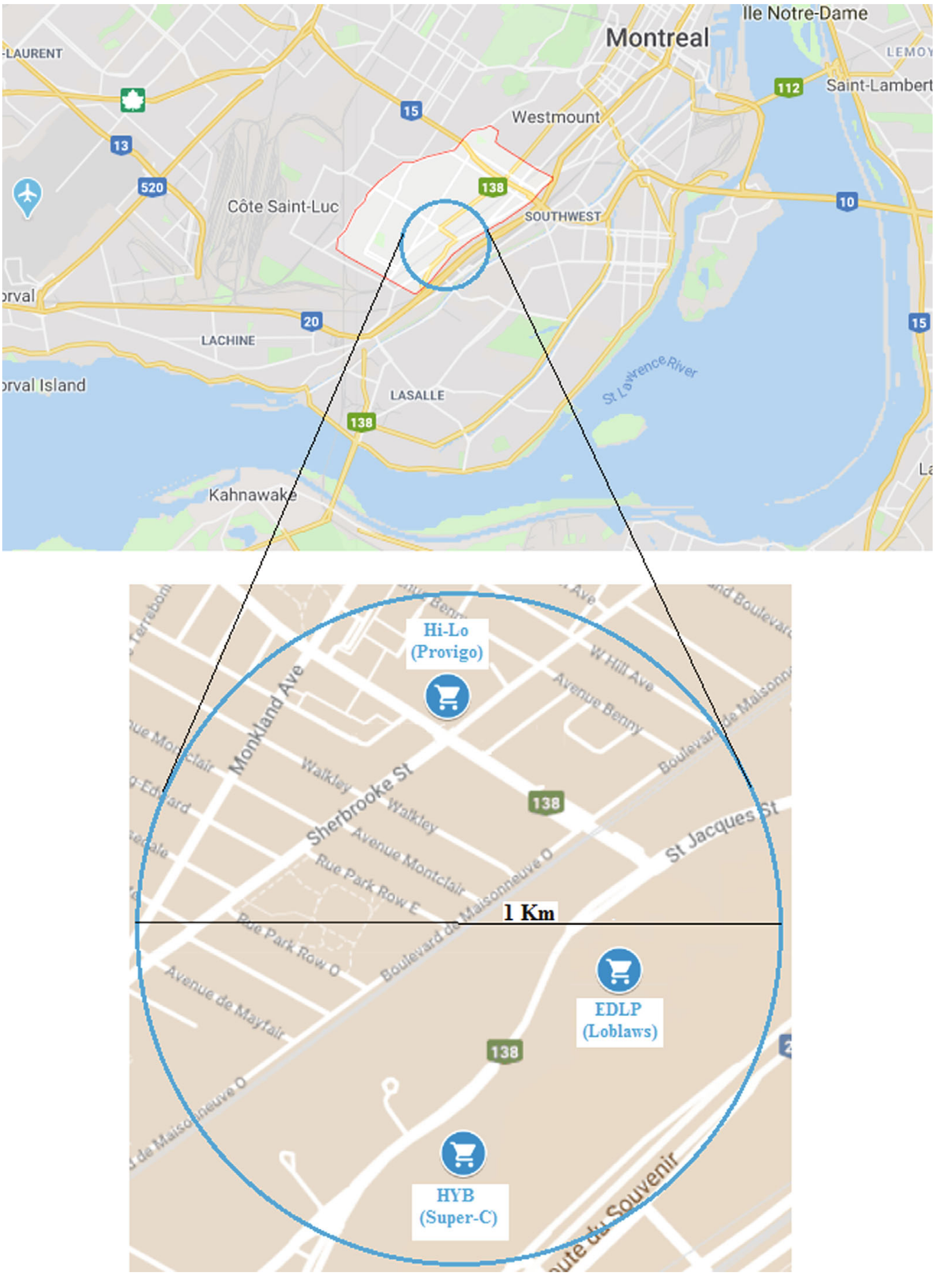

FIGURE 2 Notre-Dame-de-Grâce District in Montreal, Canada (polygon marked in the middle of the top map), and the locations of the three stores in the district (magnified circle in the lower map). *Notes*: The exact addresses of the stores are: Provigo (Hi-Lo), 6485 Sherbrooke Street, W., Montreal; Loblaw's (EDLP), 6600 St Jacques Street, Montreal; and Super-C (HYB), 6900 St Jacques Street, Montreal.

FIGURE 3 Price tag examples with the transaction and regular prices. *Notes*: The top image shows the transaction price (C$1.49), which is also the regular price, of Biscuit Soda at Super-C (HYB). The middle image shows the transaction price (C$1.69) and the regular price (C$1.99) of Grains Croquant at Loblaw's (EDLP). The bottom image shows the transaction price (C$1.99) and the regular price (C$2.49) of Pores en Dés at Provigo (Hi-Lo).

TABLE 3 Statistical Significance of the Average Price Differences Between the Stores, for Regular and Transaction Prices.

	EDLP (Loblaw's)	Hi-Lo (Provigo)	HYB (Super-C)	EDLP vs. Hi-Lo	EDLP vs. HYB	Hi-Lo vs. HYB
Regular price	C$4.12	C$4.58	C$3.98	$z = 8.66$ ***	$z = 3.16$ ***	$z = 11.42$ ***
Transaction price	C$4.11	C$4.47	C$3.94	$z = 6.60$ ***	$z = 3.99$ ***	$z = 10.18$ ***

Notes: The table reports the average regular and transaction prices at each store, together with the results of their pairwise comparison across the three stores. The EDLP vs. Hi-Lo column reports the results of Wilcoxon rank-sum tests for the equality of the average price at the EDLP store and the average price at the Hi-Lo store. The EDLP vs. HYB column reports the results of Wilcoxon rank-sum tests for the equality of the average price at the EDLP store and the average price at the HYB store. The Hi-Lo vs. HYB column reports the z-values of Wilcoxon rank-sum tests for the equality of the average price at the Hi-Lo store and the average price at the EDLP store. ***indicates $p < 0.01$.

average regular price (transaction price), C$3.98 (C$3.94); and the EDLP store has average regular (transaction) price in between, C$4.12 (C$4.11).

4 | SAMPLE PRICE SERIES: A GENERAL PICTURE AND SOME CHARACTERISTICS

To illustrate price behaviour and its effects on price rigidity/flexibility, we depict in Figure 4 the regular and transaction price series at the three stores for five products: dishwashing liquid, Perrier, frozen dessert, eggs, and Cheerios. A visual examination of the plots leads to the following general observations.

- Average prices at the Hi-Lo store are higher than at the EDLP and HYB stores.
- The Hi-Lo store offers frequent and deep temporary price cuts, where its price falls below the EDLP and HYB prices.
- The price gaps between the EDLP and HYB stores are small. For three products (dishwashing liquid, frozen dessert, and Cheerios), the average EDLP store prices are below the HYB store prices, and for two products (Perrier and eggs) it is the other way around.
- The transaction prices at the Hi-Lo store change more often than at the other stores.
- The regular prices at the EDLP store change more frequently than at the other stores.
- The total numbers of price changes at the EDLP and HYB stores are similar. But there is an important difference between them: at the EDLP store, the vast majority of these price changes are presented as changes in *regular prices*, whereas at the HYB store, most price changes are classified as *sale prices*.[19]
- The EDLP store rarely presents temporary price cuts as sales. In our entire dataset, we find only 12 price cuts that the EDLP store classifies as 'sales'. Figure 4 shows one such case—the sale of eggs at the start of the sample period. This 'sale' is characteristic of sales at the EDLP store: when the EDLP store defines a price cut as a 'sale', it is usually an exceptionally deep price cut.
- Temporary price cuts that are not sales occur also at the Hi-Lo and HYB stores. For example, in the price of Perrier at the Hi-Lo store, we see price cuts in the 8th and 35th weeks, which the store classifies and presents as cuts in the regular price. Such temporary regular price changes are rare in the Hi-Lo and HYB stores.

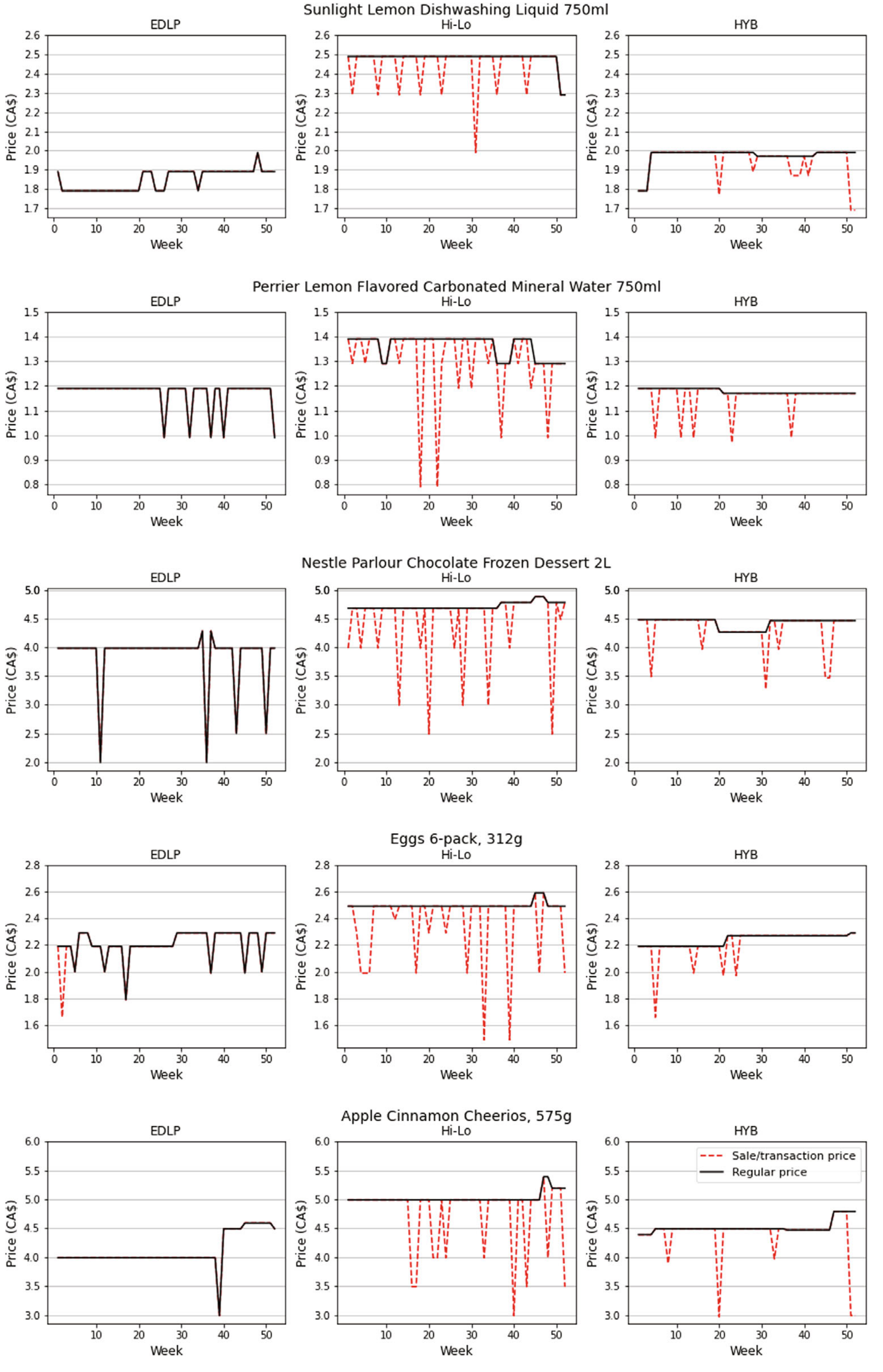

FIGURE 4 Examples of weekly regular prices (solid line) and weekly transaction prices (dashed line) for five national brand goods at the three stores (EDLP, Hi-Lo, and HYB). *Notes*: From 30 July 2003 to 23 July 2004.

- Sales do not always end with the pre-sale price. Sometimes the post-sale price is lower than the pre-sale price. For example, at the Hi-Lo store, in the 43rd week, there is a sale of Perrier, but when the price returns to the regular price after the sale ends, the new regular price is below the previous regular price.
- Consistent with Anderson *et al.* (2017), the post-sale price may exceed the pre-sale price as well. For example, the transaction price of frozen dessert at the HYB store drops in the 31st week because of a sale, and then it goes back up, but to a higher level than before the sale. We see a similar event in the case of eggs at the HYB store in the 21st week.
- Prices sometimes go up for very short periods, consistent with Chahrour (2011) and Syed (2015). For example, the price of dishwashing liquid at the EDLP store in the 47th week, or the price of frozen dessert at the EDLP store in the 33rd week.

To summarize, the Hi-Lo store offers far more temporary price cuts than the other two stores. In addition, at the Hi-Lo and HYB stores, when the transaction prices are reduced temporarily, the regular prices usually remain unchanged. At the EDLP store, in contrast, the temporary price cuts are treated by the store as cuts in regular prices.

Thus at the Hi-Lo and HYB stores, when a price is cut temporarily, buyers observe the reduced price along with the unchanged regular price, allowing them to assess the gains from buying at the reduced price. This also alerts them that if they do not buy now, they will likely face higher prices next time. Consumers facing such situations are likely to buy more than they would normally do, especially if the good is storable (Hendel and Nevo 2013; Fox and Syed 2016; Glandon 2018).

When an EDLP store reduces the price temporarily, however, the consumers likely treat the reduced price as a regular price because that is how the store presents it. In such situations, they have no incentive to buy more than they would normally do, as they do not see any sign that hints at the possibility of higher prices in the weeks ahead.

5 | TEMPORARY PRICE CUTS AND GENERATED REGULAR PRICES

To assess the effect of the store-pricing format on price rigidity/flexibility, we consider the behaviour of four price series for each good, at each store. The first two price series are the transaction and regular price series as defined by the store. These are the actual prices that we hand-collected from the store shelves. The third is a filtered price series that we generated by employing the Nakamura and Steinsson (2008) sales filter A. The filter identifies temporary V-shaped (not necessarily symmetric) price cut patterns as sale prices. Following Chahrour (2011), we assume that sales last 6 weeks or less. The fourth price series is a *reference* price series that we generate based on Eichenbaum *et al.* (2011), using the Chahrour (2011) algorithm, which employs a 13-week rolling window.[20] The Chahrour (2011) algorithm is designed to remove temporary price changes, regardless of their direction. It sets the reference price equal to the modal price in a rolling window, then makes some modifications to smooth the resulting reference price series.

Figure 5 demonstrates the properties of the four price series. The figure shows the transaction, regular, filtered, and reference prices of a dishwashing liquid at the EDLP, Hi-Lo, and HYB stores.[21] At the EDLP store, there is a small number of V-shaped price cuts that look like sale prices, but the EDLP store views them as regular price changes, thus the transaction and regular prices at the EDLP store coincide. The filtered prices are smoother because the filter removes all V-shaped price cuts. The reference prices are similar to the filtered prices, with the exception that the Chahrour (2011) filter also removes the one-week price hike that occurs in the 48th week.

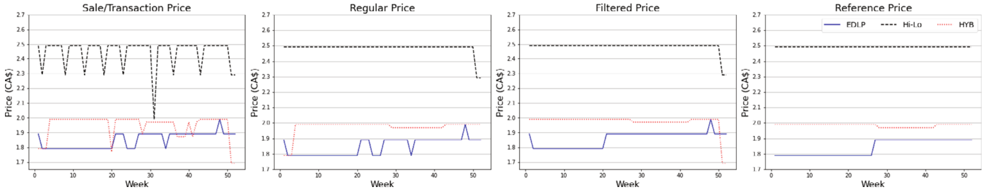

FIGURE 5 Four weekly price series (transaction price, regular price, filtered price, and reference price) of Sunlight Lemon Dishwashing Liquid 750 mL at the three stores sampled. *Notes*: EDLP (solid line), Hi-Lo (dashed line), and HYB (dotted line), from 30 July 2003 to 23 July 2004.

TABLE 4 Generated Regular Prices: Promoted Sale Events Versus Filtered Sale Events.

	EDLP (Loblaw's)	Hi-Lo (Provigo)	HYB (Super-C)	EDLP vs. Hi-Lo	EDLP vs. HYB	Hi-Lo vs. HYB
Promoted sale events	12	508	265	$\chi^2 = 498.27$ ***	$\chi^2 = 215.55$ ***	$\chi^2 = 106.84$ ***
Filtered sale events	265	509	280	$\chi^2 = 83.17$ ***	$\chi^2 = 0.15$	$\chi^2 = 95.00$ ***
Reference sale events	261	497	262	$\chi^2 = 79.32$ ***	$\chi^2 = 0.95$	$\chi^2 = 102.00$ ***

Notes: The Promoted sale events are the number of promoted sales, i.e. the cases where the sale price displayed on the shelf price tag was lower than the regular price posted next to it. The Filtered sale events are the number of sale events identified as sales by the Nakamura and Steinsson (2008) sales filter A. The Reference sale events are sale events identified as sales by the Chahrour (2011) algorithm. The EDLP vs. Hi-Lo column reports the Pearson χ^2 test statistics for the differences in the proportion of sale events between the EDLP store and the Hi-Lo store. The EDLP vs. HYB column reports the Pearson χ^2 test statistics for the differences in the proportion of sale events between the EDLP store and the HYB store. The Hi-Lo vs. HYB column reports the Pearson χ^2 test statistics for the differences in the proportion of sale events between the Hi-Lo store and the HYB store.
***indicates $p < 0.01$.

At the Hi-Lo store, regular prices last long periods, with frequent V-shaped price cuts. Consequently, transaction prices are more volatile than regular prices. The filtered series resemble the regular series, demonstrating that the filter performs well with the Hi-Lo store data. The reference price series is a smoothed transaction price series, thus in this case, it remains unchanged during the sample period.

The HYB store offers few V-shaped transaction price cuts, thus its regular prices are smoother than the transaction prices. The filtered prices are similar to regular prices, suggesting that the sales filter performs well also at the HYB store. The only place where it misses a sale is at the end of the sample period, where the price cut is treated by the filter as a regular price change because it 'cannot find' a price increase that must follow the price cut.

Figure 5 illustrates well the general pattern found in our data. We summarize the findings on temporary price cuts in Table 4, which shows the number of sale events according to the various price series. Row 1 reports the number of promoted sales, defined as periods when a store's transaction price was below the store's regular price, thus informing the consumers that a product is on sale. Row 2 reports the number of filtered sale events, defined as periods when the filtered price is above the transaction price. Row 3 reports the number of reference sale events, defined as periods when the reference price is above the transaction price. Columns 4–6 give the results of Pearson χ^2 tests for comparing the shares of price changes between each pair of stores.

The results underscore the differences in the way the stores use and treat temporary price cuts. According to all definitions, the Hi-Lo store uses more temporary price cuts than the other stores. In our sample, it had 508 promoted sale events, 509 price cuts that the Nakamura and Steinsson (2008) sales filter A defined as filtered sale events, and 497 price cuts that the Chahrour (2011) algorithm defined as reference sale events. All these numbers are significantly larger than at either of the other stores.

The EDLP store offers 12 promoted sales, significantly less than at either the Hi-Lo store (508 promoted sales) or the HYB store (265 promoted sales). However, the numbers of temporary price cuts at the EDLP and HYB stores are similar. According to the sales filter, there are 265 filtered sale events at the EDLP store and 280 at the HYB store. According to the reference prices, there are 261 sale events at the EDLP store and 262 at the HYB store. In both cases, the differences are not statistically significant.

Thus according to all price series, the Hi-Lo store has significantly more temporary price cuts than any of the other stores. The EDLP and HYB stores have a similar number of temporary price cuts, but the HYB store promotes them as sales, while the EDLP store does not. Instead, the EDLP store treats most of these price cuts as regular price changes.

6 | VARIATION IN PRICE RIGIDITY: PRICE CHANGE FREQUENCY AND PRICE SPELL DURATION

6.1 | Summary statistics

Given the emphasis in the literature on the different effects that regular and sale prices have on the aggregate price level, it is of interest to study how the stores' treatment of temporary price cuts affects their price rigidity. In panel A of Table 5, we present category-level average weekly price change frequencies at each store for the 11 product categories, for each of the four price series (transaction, regular, filtered, and reference). The averages are computed over all goods in each category.

The figures in Table 5 indicate substantial heterogeneity in the average frequency of weekly transaction price changes across categories, consistent with Bils and Klenow (2004) and Nakamura and Steinsson (2008). Except for the EDLP store, which treats temporary price cuts as regular price changes, the price variability is smaller for regular prices than for transaction prices. In all stores, the variance is even smaller for the filtered and reference prices.

Despite the heterogeneity that we find across categories, however, when we compare across stores, we find a consistent pattern. We, therefore, compare the overall average frequencies across stores rather than across categories. Table 6 presents the results of Pearson χ^2 tests of proportions of price changes for pairwise comparisons.

The Hi-Lo store has the highest frequency of weekly transaction price changes, 23.29%, compared to 13.83% and 13.76% at the EDLP and HYB stores, respectively. The differences between the Hi-Lo and the EDLP stores, and between the Hi-Lo and the HYB stores, are significant ($\chi^2 = 152.39$ and $\chi^2 = 162.89$, respectively, with $p < 0.01$ in both cases). There is no statistically significant difference between the EDLP and HYB stores ($\chi^2 = 0.01$, $p > 0.92$).

If we look at the regular prices as defined by the stores, then the EDLP store has the highest frequency of weekly price changes with 13.38%, compared to 4.06% and 5.34% at the Hi-Lo and HYB stores, respectively. All pairwise differences are statistically significant, with χ^2 statistics 281.09 and 208.19 for comparing the EDLP store with the Hi-Lo and HYB stores, respectively, and 9.80 for comparing the Hi-Lo store with the HYB store ($p < 0.01$ in all cases).

The results are somewhat different for the filtered series. The average frequencies of filtered price changes at the EDLP and HYB stores, 4.25% and 4.50%, respectively, are about the same ($\chi^2 = 0.40$, $p > 0.52$), and both exceed the corresponding figure at the Hi-Lo store, 3.55%. The χ^2 statistics for comparing the Hi-Lo store with the EDLP and HYB stores are 3.35 ($p < 0.07$) and 6.24 ($p < 0.02$), respectively.

TABLE 5 Frequency of Price Changes and Implied Price Duration.

	EDLP (Loblaw's)				Hi-Lo (Provigo)				HYB (Super-C)			
Product category	Transaction	Regular	Filtered	Reference	Transaction	Regular	Filtered	Reference	Transaction	Regular	Filtered	Reference
Panel A: Average weekly frequency of price changes												
Baby products & foods	5.77%	5.77%	1.92%	0.77%	5.77%	0.38%	0.38%	0.00%	6.54%	5.38%	2.69%	3.08%
Beverages	23.08%	22.69%	6.92%	2.88%	35.58%	4.42%	5.77%	1.92%	17.83%	5.59%	3.50%	2.97%
Breakfast/cereals	14.50%	14.20%	2.96%	2.07%	24.26%	2.81%	2.81%	1.48%	17.47%	4.81%	4.65%	4.33%
Condiments, sauces & spread	19.58%	19.58%	4.37%	2.27%	29.37%	4.72%	4.02%	2.97%	14.96%	5.13%	4.06%	4.49%
Dairy products	14.81%	14.42%	5.77%	4.42%	15.58%	5.38%	4.04%	3.46%	15.38%	6.25%	4.97%	3.85%
Frozen food	15.11%	14.56%	3.85%	2.75%	21.15%	3.57%	3.85%	1.92%	14.74%	6.20%	5.34%	4.06%
Health & beauty aid	12.31%	9.81%	5.58%	4.23%	15.00%	7.50%	5.77%	4.42%	10.96%	5.19%	4.42%	4.42%
Households	9.48%	9.48%	3.71%	2.75%	20.33%	2.20%	2.06%	1.24%	12.14%	5.41%	5.29%	3.73%
Juices	15.38%	14.90%	3.13%	1.68%	34.38%	4.57%	4.09%	2.16%	15.87%	6.25%	5.29%	5.29%
Paper towel, tissue & pet supplies	3.85%	3.85%	2.75%	1.65%	18.68%	3.02%	2.47%	2.47%	7.69%	3.21%	3.42%	2.56%
Soups/canned foods	11.54%	11.54%	4.81%	3.37%	34.62%	6.25%	1.92%	1.44%	13.74%	5.22%	4.67%	4.95%
Total	13.83%	13.38%	4.25%	2.70%	23.29%	4.06%	3.55%	2.23%	13.76%	5.34%	4.50%	3.95%
Panel B: Implied average price duration in weeks												
Baby products & foods	16.83	16.83	51.50	129.50	16.83	259.50	259.50	N/A	14.79	18.07	36.64	32.00
Beverages	3.81	3.89	13.94	34.16	2.27	22.10	16.83	51.50	5.09	17.37	28.10	33.14
Breakfast/cereals	6.38	6.53	33.30	47.78	3.60	35.08	35.08	67.10	5.21	20.30	21.01	22.61
Condiments, sauces & spread	4.59	4.59	22.38	43.50	2.88	20.68	24.37	33.14	6.17	19.00	24.13	21.78
Dairy products	6.24	6.42	16.83	22.10	5.91	18.07	24.26	28.39	5.99	15.49	19.62	25.50
Frozen food	6.10	6.35	25.50	35.90	4.21	27.50	25.50	51.50	6.27	15.63	18.22	24.13
Health & beauty aid	7.61	9.69	17.43	23.13	6.15	12.83	16.83	22.10	8.61	18.75	22.10	22.10
Households	10.04	10.04	26.46	35.90	4.40	45.00	48.03	80.39	7.73	17.98	18.40	26.34
Juices	5.99	6.20	31.50	58.93	2.37	21.39	23.97	45.72	5.79	15.49	18.40	18.40
Paper towels, tissue & pet supplies	25.50	25.50	35.90	60.17	4.84	32.59	39.94	39.94	12.49	30.70	28.75	38.50
Soups/canned foods	8.16	8.16	20.30	29.21	2.35	15.49	51.50	68.83	6.77	18.65	20.91	19.72
Total	6.72	6.96	23.00	36.53	3.77	24.13	27.63	44.26	6.75	18.22	21.69	24.79

Notes: In panel A, we report the average weekly frequency of price changes $\bar{f}$ (in %), for each one of the 11 product categories included in our data, for the three stores. For each category, we computed $\bar{f}$ as the ratio of the total number of price changes per week in the category, to the number of products in the category (Levy *et al.* 1997, Table 1, p. 797; Gorodnichenko and Talavera 2017). The average weekly frequency of a price change at each store is calculated for the transaction price, the regular price (as classified and presented by the store), the filtered price (the prices after removing temporary price reductions as identified by Nakamura and Steinsson (2008) sales filter A) and the reference price. We use the Chahrour (2008) algorithm with a 13-week rolling window to derive the reference prices. The 'Total' row gives the average weekly frequency computed over all goods, in each store. In panel B, we report the implied average duration of the prices in weeks. The average duration is calculated as $-[\ln(1-\bar{f})]^{-1}$.

TABLE 6 Statistical Significance of the Pairwise Differences in the Mean Price Changes Frequency.

	EDLP (Loblaw's)		HYB (Super-C)	
Hi-Lo (Provigo)				
Transaction	(23.29%, 13.83%)	$\chi^2 = 152.39$***	(23.29%, 13.76%)	$\chi^2 = 162.89$***
Regular	(4.06%, 13.38%)	$\chi^2 = 281.09$***	(4.06%, 5.34%)	$\chi^2 = 9.80$***
Filtered	(3.55%, 4.25%)	$\chi^2 = 3.35$*	(3.55%, 4.50%)	$\chi^2 = 6.24$**
Reference	(2.23%, 2.70%)	$\chi^2 = 2.33$	(2.23%, 3.95%)	$\chi^2 = 26.17$***
EDLP (Loblaw's)				
Transaction			(13.83%, 13.76%)	$\chi^2 = 0.01$
Regular			(13.38%, 5.22%)	$\chi^2 = 208.19$***
Filtered			(4.25%, 4.58%)	$\chi^2 = 0.40$
Reference			(2.70%, 3.95%)	$\chi^2 = 13.01$***

Notes: The figures in parentheses, in the format '(row, column)', are the average weekly price change frequencies at the corresponding pairs of stores.
***, **, * indicate $p < 0.01$, $p < 0.05$, $p < 0.10$, respectively.

Focusing on the reference prices—that is, 'long-lived' prices—the HYB store has the highest frequency of weekly price changes with 3.95%, exceeding the frequency at the EDLP store, 2.70% ($\chi^2 = 13.01, p < 0.01$) and at the Hi-Lo store, 2.23% ($\chi^2 = 26.17, p < 0.01$). The gap between the EDLP and Hi-Lo stores is not statistically significant ($\chi^2 = 2.33, p > 0.12$).

Thus if we consider the filtered prices, then the EDLP and HYB stores have more flexible prices than the Hi-Lo store. If we look at the reference prices, then the HYB store has the most flexible prices.

In panel B of Table 5, we report the implied average price duration in weeks. To alleviate the effect of truncation on the measured duration, we calculate the duration as

$$-[\ln(1-\bar{f})]^{-1}, \tag{1}$$

where $\bar{f}$ is the average weekly price change frequency (Levy *et al.* 1997; Nakamura and Steinsson 2008). For the EDLP store, the average durations of price spells are 6.72, 6.96, 23.00, and 36.53 for the transaction, regular, filtered, and reference prices, respectively. For the Hi-Lo (HYB) store, the corresponding values are 3.77 (6.75), 24.13 (18.22), 27.63 (21.69), and 44.26 (24.79).

As Carvalho (2006) shows, however, calibrating sticky price models using information on average frequencies, may underestimate price stickiness because of Jensen's inequality. We, therefore, calculate an alternative measure of price durations,

$$-\frac{1}{N_C}\sum_{i\in C}\left[\ln(1-f_i)\right]^{-1}, \tag{2}$$

where f_i is the weekly price change frequency of product i in category C, and N_C is the number of products in category C. Using our data to calculate equation (2), however, has a drawback, because we have to drop products that have zero price changes, biasing our estimates downwards. The results are summarized in panel B of Table E1 in Online Appendix E.

For the EDLP store, the expected durations of price spells are 10.70, 10.94, 26.01, and 33.52 for the transaction, regular, filtered, and reference prices, respectively. For the Hi-Lo (HYB) store, the corresponding values are 8.94 (10.55), 27.66 (21.96), 29.53 (24.44), and 36.23 (28.30).

Comparing the duration figures based on equation (2) to those based on equation (1), we find that for the transaction prices, equation (1) underestimates the durations by 33.0%–137.1%. For the regular prices, as defined by the store, equation (1) underestimates the durations by 14.6%–57.2%. For the filtered prices, equation (1) underestimates the durations by 6.9%–13.1%. For the reference price, we find that for both the EDLP and Hi-Lo stores, the results based on equation (1) are larger than the results based on equation (2), implying that the bias due to the removal of products with zero price changes is quite significant. This also suggests that the results reported in panel B of Online Appendix Table E1 for the regular and the filtered price series might be biased downwards.

Therefore, to better compare the two measures of price stickiness, we use equation (1) again, but this time we apply it to the sample that we used to calculate equation (2). That is, we use information only on products that had at least one price change. The results are reported in Table E2 of Online Appendix E. We find that when we use the same samples, the price stickiness based on equation (2) is 19.5%–142.9% greater than when we use equation (1). We also find that the differences depend on both the price flexibility of the products and the variance in the flexibility across products. Using the average frequencies, therefore, leads to a particularly severe underestimation of the price stickiness for transaction prices at the Hi-Lo store (142.9%) and at the EDLP store (70.1%). The underestimation is least severe for the filtered and reference prices at the HYB store, 19.5% and 22.2%, respectively.

6.2 | Econometric estimation

The results above are suggestive, but they could be affected by heterogeneity across goods, categories, etc. To account for the effects of covariates, while controlling for cross-category heterogeneity in the average frequency of price changes and for truncation, we estimate a series of Cox semi-parametric hazard functions, one regression for each series of price changes:

$$h(t) = h_0(t) \times \exp\left(\beta_1\ EDLP + \beta_2\ HYB + X\gamma + Z\delta\right), \tag{3}$$

where $h(t)$ is the hazard of a price change at time t, and $h_0(t)$ is the baseline hazard when all covariates equal 0. The main covariates are dummies for the EDLP and HYB stores. The elements of X are further covariates, which include the price level of the good, defined for each store as the average transaction price over the sample period, a dummy for private label products, a dummy for price changes made in January, and a dummy for price changes made in Christmas week. Here, Z includes fixed effects for the product location in the stores—for the aisle (back/front/middle) and for the shelf (bottom/top/middle). We allow for recurrent price changes, and we stratify the data by categories to allow the hazard in different categories to be non-proportional.

Table 7 summarizes the estimation results. The values in the table are the proportional changes in the hazard in response to a one-unit change in each covariate. Robust standard errors, clustered at the good–store level, are reported in parentheses.

We find that prices are more likely to change in January, consistent with Nakamura and Steinsson (2008). We also find that except for the regular price series, prices are more likely to change in Christmas week than at other times.[22] More importantly, we find that the results of the hazard function estimation corroborate the findings that we discuss above. Consider first the hazard function estimate for transaction prices. According to column (1), the hazard that a price will change at the EDLP (HYB) store is 0.66 (0.64) times the hazard at the Hi-Lo store, and the differences are statistically significant ($p < 0.01$ in both cases). There

TABLE 7 The Hazard of a Price Change.

	Transaction prices (1)	Regular prices (2)	Filtered prices (3)	Reference prices (4)
EDLP store	0.66*** (0.063)	3.62*** (0.410)	1.26 (0.159)	1.20 (0.146)
HYB store	0.64*** (0.052)	1.41*** (0.144)	1.28*** (0.124)	1.70*** (0.162)
Price level	0.99 (0.011)	1.02* (0.009)	1.02 (0.014)	1.02 (0.136)
Private label	0.70*** (0.082)	0.85 (0.102)	0.84 (0.097)	1.13 (0.140)
January dummy	1.29** (0.129)	1.38** (0.176)	2.78*** (0.366)	2.61*** (0.306)
Christmas dummy	2.20*** (0.468)	1.53 (0.499)	6.85*** (3.821)	2.45*** (0.802)
χ^2	93.69***	259.7***	86.3***	117.7***
N	2951	1479	945	782

Notes: The results of estimating hazard function regressions of the hazard of a price change. The hazard functions allow the hazard for different categories to be non-proportional. Column (1) gives the results for transaction price changes. Column (2) gives the results for regular price changes. Column (3) gives the results for filtered price changes, using the Nakamura and Steinsson (2008) sales filter A, to remove temporary price reductions. Column (4) gives the results for reference price changes, using the Chahrour (2011) algorithm to identify the reference prices. The numbers in the table show the hazard ratios. EDLP store is a dummy for goods offered at the EDLP store. HYB store is a dummy for goods offered at the HYB store (base group: Hi-Lo store). Price level is the average transaction price over the 52-week sample period. Private label is a dummy for private label goods. January dummy is a dummy for price changes that occur in January. Christmas dummy is a dummy for price changes that occur in the week of 25 December. The regressions also include fixed effects for the product location in the store, for the aisle (back/front/middle), and for the shelf position (bottom/top/middle). Robust standard errors, clustered at the good–store level, are reported in parentheses.
***, **, * indicate $p < 0.01$, $p < 0.05$, $p < 0.10$, respectively.

are no statistically significant differences between the hazards at the EDLP and HYB stores ($\chi^2 = 0.09$, $p > 0.76$).

Next, consider the hazard function estimate for regular prices—here, we find the opposite. The hazard that a regular price will change at the EDLP store is 3.62 times the hazard at the Hi-Lo store ($p < 0.01$). The hazard that a regular price will change at the HYB store is 1.41 times the hazard at the Hi-Lo store ($p < 0.01$). The difference between the EDLP and HYB stores is also significant ($\chi^2 = 116.87$, $p < 0.01$).

When we look at the filtered prices, we find that the hazard that a filtered price will change at the EDLP store is 1.26 higher than at the Hi-Lo store. The difference is not statistically significant ($p > 0.24$). The hazard that a filtered price will change at the HYB store is 1.28 times the hazard at the Hi-Lo store ($p < 0.02$). There is no significant difference between the hazards of the EDLP and HYB stores ($\chi^2 = 1.10$, $p > 0.29$).

Finally, considering the reference prices, we find that the hazard that a reference price will change at the EDLP store is 1.20 times the hazard at the Hi-Lo store, but the difference is not statistically significant ($p > 0.14$). The hazard that a reference price will change at the HYB store is 1.70 times the hazard at the Hi-Lo store ($p < 0.01$). The difference between the EDLP and HYB stores is statistically significant too ($\chi^2 = 10.81$, $p < 0.01$).

In sum, there are significant differences in the price rigidity between the stores, regardless of which price series we consider. If we consider transaction prices, then the Hi-Lo store has the most flexible prices. If we consider regular prices, then the Hi-Lo store has the least flexible prices, whether as defined by the store, as defined by the sales filter A, or as defined by the Chahrour (2011) algorithm. The EDLP store has the most flexible prices if we consider regular prices as defined by the store. The HYB store has the most flexible prices if we consider reference prices. If we consider filtered price series, then the EDLP and HYB stores have similar levels of price rigidity.

7 | THE SIZE OF PRICE CHANGES

Retailers can respond to changes in economic conditions by varying either the frequency of price changes or the size of price changes (Sheshinski and Weiss 1977; Caballero and Engel 2007). Above, we studied the frequency of price changes. In this section, we focus on the size of price changes.

Álvarez *et al.* (2016) show that for a large class of sticky price models, the volatility of the underlying shocks in the steady state should equal $N\left(\Delta p_{i,s,t}\right) \times \text{var}\left(\Delta p_{i,s,t}\right)$, where $N\left(\Delta p_{i,s,t}\right)$ is the average number of price changes per year, and $\text{var}\left(\Delta p_{i,s,t}\right)$ is the variance of price changes (Baley and Blanco 2021). Following Álvarez *et al.* (2016), we calculate the size of price changes as $\Delta p_{i,s,t} = \ln\left(p_{i,s,t}\right) - \ln\left(p_{i,s,t-1}\right)$, where

$$p \in \{\text{transaction price, regular price, filtered price, reference price}\}$$

is the price of product i sold in store $s \in \{\text{EDLP, Hi} - \text{Lo, HYB}\}$ in week t, conditional on a price change.

Assuming that stores that are located in the same neighbourhood face similar shocks, we expect that they would have similar values of $N\left(\Delta p_{i,s,t}\right) \times \text{var}\left(\Delta p_{i,s,t}\right)$. Figure 6 depicts the values of $N\left(\Delta p_{i,s,t}\right) \times \text{var}\left(\Delta p_{i,s,t}\right)$ for each store, for each of the four price series. We calculate $N\left(\Delta p_{i,s,t}\right)$ using the values in panel B of Online Appendix Table E1. The vertical lines in the figure represent 95% confidence intervals, which we calculate by bootstrapping the calculation 1000 times.

For transaction prices, the results suggest that the Hi-Lo store responds to shocks more than the EDLP store, which responds more than the HYB store. This reflects the large number of sales at the Hi-Lo store, which are both common and large in percentage terms. Therefore the responsiveness of the transaction prices likely overestimates the response of the Hi-Lo store to shocks, as sales are often set in advance (Warner and Barsky 1995; Nakamura and Steinsson 2008; Anderson *et al.* 2017).

For regular prices as defined by the stores, we find that the EDLP store responds much more than the Hi-Lo and HYB stores. This reflects the EDLP store's practice of defining temporary price changes as regular price changes. It is therefore likely that focusing on regular prices as defined by the store would likely overestimate the responsiveness of the EDLP store to underlying shocks.

For filtered prices, we find that although the likelihoods of a filtered price change at the EDLP and HYB stores are about the same, the HYB store has a lower measure of responsiveness than either of the other two stores. This reflects the smaller size of price changes at the HYB store.

The HYB store has a lower measure of responsiveness than either of the other two stores also for the reference price, again reflecting the small price changes that it makes. However, it is important to note that our measures of the average number of price changes are lower bounds on the true values. Therefore it is possible that we underestimate the number of price changes that each of the stores makes in the steady state. If we had a longer time series, we might have found that the HYB store's response is not different from that of the other stores.

To explore this possibility further, we employ an alternative measure of the responsiveness of stores to shocks. Álvarez *et al.* (2016) show that if we assume symmetric menu costs and zero inflation, then for a large class of sticky price models, the real effects of a small monetary shock depend on the ratio of two statistics: the kurtosis of the size of price changes, and the frequency of price changes. The frequency is important because when firms adjust prices more often, they can respond quickly to a monetary shock, dampening the real effects of the shock. The kurtosis is equally important because a small kurtosis implies a selection (Golosov and Lucas 2007); that is, price changes are made by the firms whose prices are in the greatest need of adjustment, which also reduces the real effects of a monetary shock.

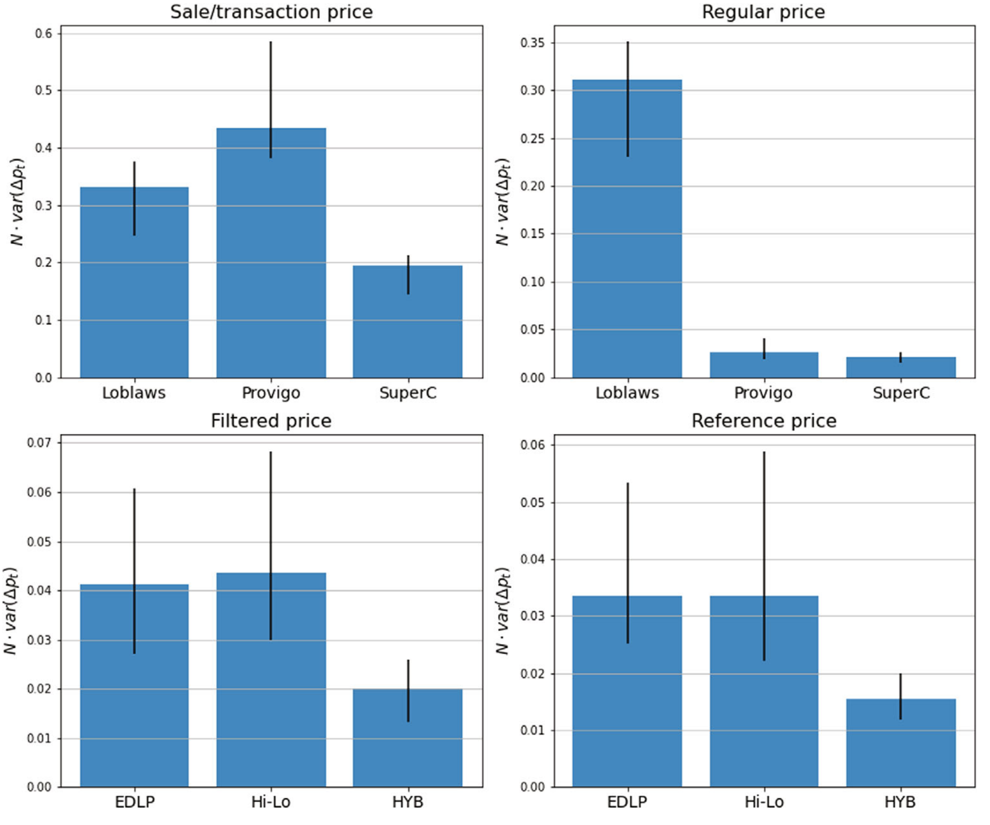

FIGURE 6 The product of the average number of price changes per year and the variance of the size of price changes. *Notes*: The vertical lines depict 95% confidence intervals. The y-axis scales vary across plots.

Figure F1 in Online Appendix F depicts histograms of the sizes of price changes. We find that there is a large variation in the kurtosis values, both across stores and across price measures. If we look at the transaction price, then we find that kurtosis is between 3.48 at the Hi-Lo store and 4.63 at the HYB store. When we focus on regular prices, the kurtosis of the EDLP store remains almost unchanged (4.29), but the removal of sales, which are usually large in percentage terms, leads to an increase in the kurtosis of the Hi-Lo (8.52) and HYB (5.78) stores. For filtered prices, the kurtosis values are more similar across the three stores: 8.64 at the EDLP store, 7.52 at the Hi-Lo store, and 7.48 at the HYB store. There is also a large variation in the kurtosis values of the reference prices: 5.17 at the EDLP store, 7.32 at the Hi-Lo store, and 4.24 at the HYB store.

The large variation of kurtosis across stores suggests that depending on the price series, variations in the size of price changes might play a different role in the transmission of monetary shocks. However, Álvarez *et al.* (2016) show that when we pool price changes of different products, we might bias the estimated kurtosis upwards (Midrigan 2011). Therefore, following Álvarez *et al.* (2016), we standardize the price changes by computing

$$Z_{\Delta p_{i,s,t}} = \frac{\Delta p_{i,s,t} - \overline{\Delta p_{i,s}}}{\sigma_{\Delta p_{i,s}}},$$

where $\overline{\Delta p_{i,s}}$ is the average size of price changes in the category of product i in store s, and $\sigma_{\Delta p_{i,s}}$ is the standard deviation of the size of price changes in the category of product i in store s. We then pool the standardized price changes and draw the histograms again.

Figure 7, which depicts the resulting histograms, suggests that once we standardize the data, the kurtosis values are more similar across stores and price measures. For the transaction prices, kurtosis is in the range 3.77–4.30, for the regular prices 4.02–5.29, for the filtered prices 3.74–5.05, and for the reference prices 3.76–4.03. These results are in the same range as in Midrigan (2011), Álvarez *et al.* (2016), and Cavallo (2018).

To offer an intuitive assessment of the significance of these results for the transmission of monetary shocks, we use the sufficient statistics of Álvarez *et al.* (2016). According to Álvarez *et al.* (2016), the real effects of a monetary shock are proportional to $\mathrm{kur}\left(\Delta p_{i,s,t}\right)/N\left(\Delta p_{i,s,t}\right)$, where $\mathrm{kur}\left(\Delta p_{i,s,t}\right)$ is the kurtosis of price changes in store s. Using information on kurtosis from Figure 7, we calculate $\mathrm{kur}\left(\Delta p_{i,s,t}\right)/N\left(\Delta p_{i,s,t}\right)$ for each of the four price series, in each of the three stores. To obtain 95% confidence intervals we bootstrap the calculations 1000 times.

Figure 8 depicts the values of $\mathrm{kur}\left(\Delta p_{i,s,t}\right)/N\left(\Delta p_{i,s,t}\right)$ for each of the four price measures and for each of the three stores. We find that for transaction prices, the Hi-Lo store has a significantly lower value of $\mathrm{kur}\left(\Delta p_{i,s,t}\right)/N\left(\Delta p_{i,s,t}\right)$ than the other two stores. For regular prices as defined by the stores, the EDLP store has a ratio that is significantly lower than at the other two stores. If we focus on the filtered or reference prices, however, the ratios are not statistically different across the three stores. Therefore if we believe that the regular prices, as defined by the filtered or reference prices, capture the responsiveness of the firms to shocks, then for the class of models studied by Álvarez *et al.* (2016), an economy populated by any of the three stores would have a similar response to a monetary shock.

8 | SYNCHRONIZATION OF PRICE CHANGES

Carvalho (2006) finds that when an economy is populated by firms with different degrees of price rigidity, then the macro-level price rigidity is exacerbated relative to an economy in which all firms have the same level of price rigidity. This is particularly true in the presence of strategic complementarities, because when stores keep their prices close to the average price of their competitors, stores with rigid prices slow down the market response to shocks.

To obtain an estimate for strategic complementarities, we study the synchronization of price changes across stores by calculating for each product the Fisher–Konieczny index of synchronization (Fisher and Konieczny 2000). The index attains values between 0 and 1, where 0 indicates perfect staggering (firms change prices at constant intervals), and 1 indicates perfect synchronization (prices change simultaneously in all stores). We focus on the 89 national brand products that are sold in all three stores.

Figure 9 depicts the histogram of the Fisher–Konieczny indices of the 89 products. Focusing on the transaction prices, the indices are in the range of 0–0.61, with an average of 0.26. This value is higher, indicating more synchronization, than reported by Fisher and Konieczny (2000), and similar to that of Lach and Tsiddon (1996).

In other words, the stores in our sample do not synchronize price changes perfectly, but they are also far from perfect staggering. It, therefore, seems that the stores in our sample respond to price changes made by other stores, which seems reasonable since they are located in the same neighbourhood.

Looking at regular prices, as defined by the store, by the Nakamura and Steinsson (2008) sales filter, and by the Chahrour (2011) reference price series, we find that they are less synchronized than changes in the transaction prices. For regular prices, the average Fisher–Konieczny index is 0.11, for the filtered prices 0.09, and for the reference prices 0.10. In other words, the stores in our sample seem to change their transaction prices in response to changes in the transaction prices of the other stores. Changes in the regular prices, however, are less synchronized. A possible explanation is that when a store changes a price, the other stores might not be certain whether the

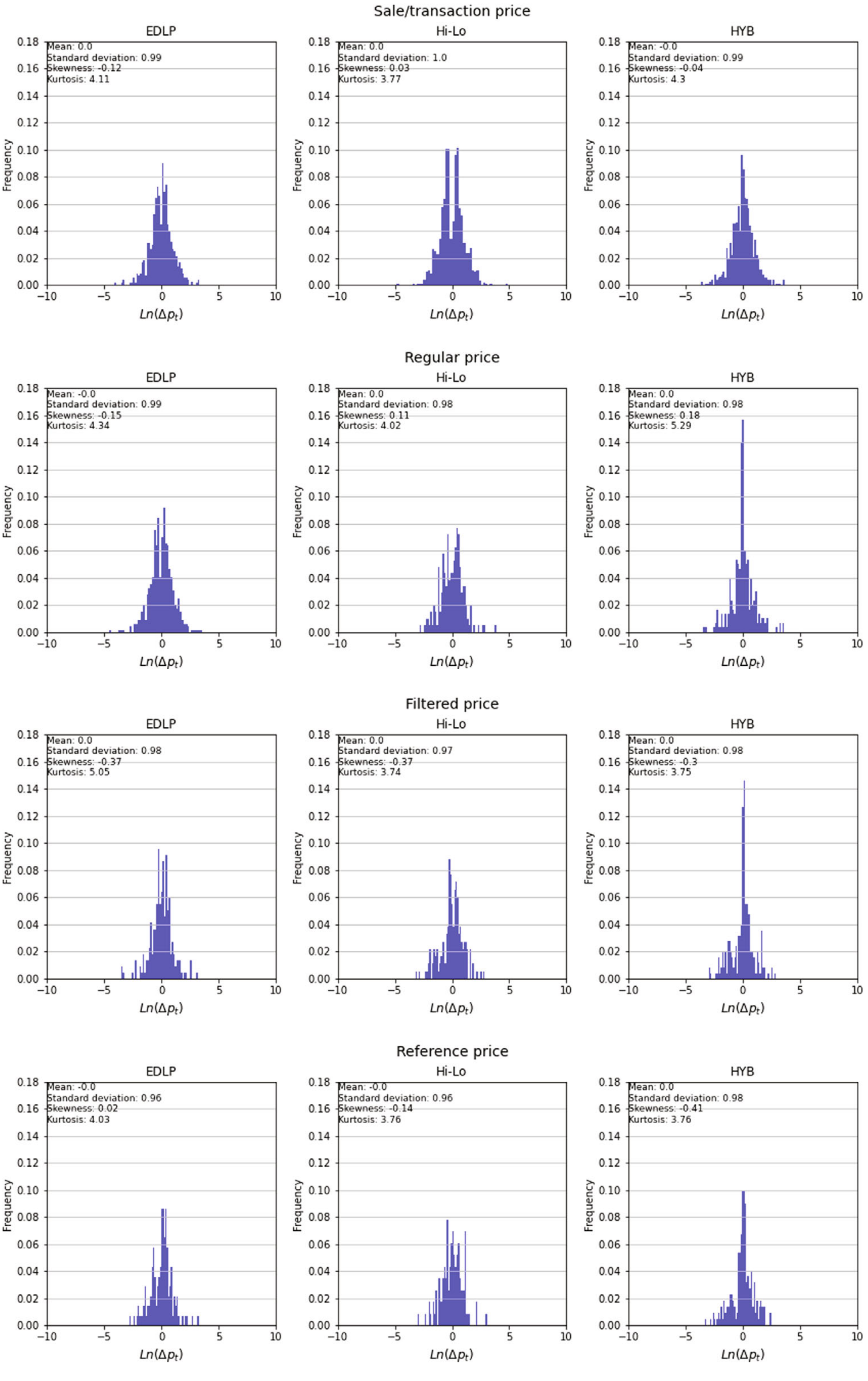

FIGURE 7 Histograms of the standardized log price differences, conditional on a price change. *Notes*: We standardize the log price differences by product category and store.

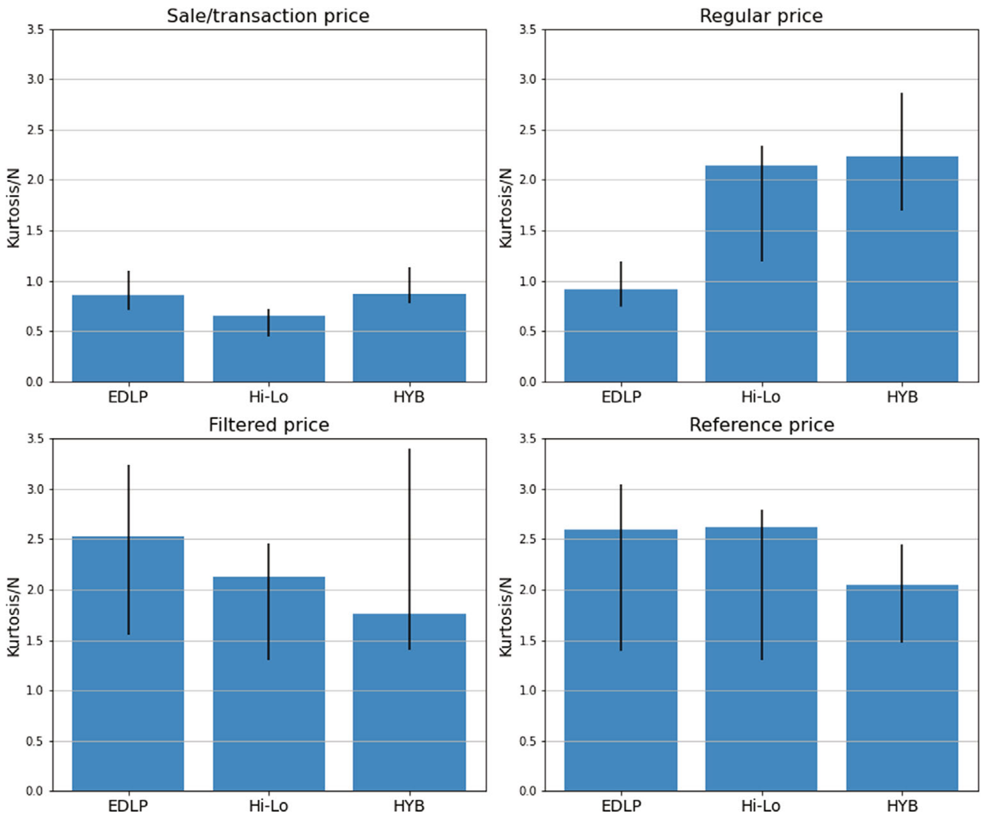

FIGURE 8 The ratio of the kurtosis of the size of price changes to the average number of price changes per year.
Notes: The vertical lines depict 95% confidence intervals.

change is temporary or more permanent (Levy *et al.* 2002). Therefore they might change their transaction price in response, but change the regular price only after they identify the competitor's price change as a regular price change. This type of behaviour will result in a more staggered pattern of regular price changes.

9 | ROBUSTNESS TESTS

9.1 | Robustness check with Canadian data

We run four robustness tests, which we summarize briefly below. The Online Appendix contains a detailed description of these tests. It also contains a discussion of how our data compare to similar but larger datasets in terms of the distribution of the last digit and the last two digits of the price (Appendix C), and a detailed list of all the products included in our sample (Appendix D).

First, in the paper, we study the price level at each store. We find that the Hi-Lo store has the highest regular and transaction prices and that the prices at the HYB store are lower than at the EDLP store. Repeating the analyses at the category level yields similar results. See Online Appendix A for details.

Second, we assess the extent of price rigidity at the level of product categories. Above, we compare the weekly frequencies of price changes at the store level. We find similar results for category-level data. See Online Appendix B for more details.

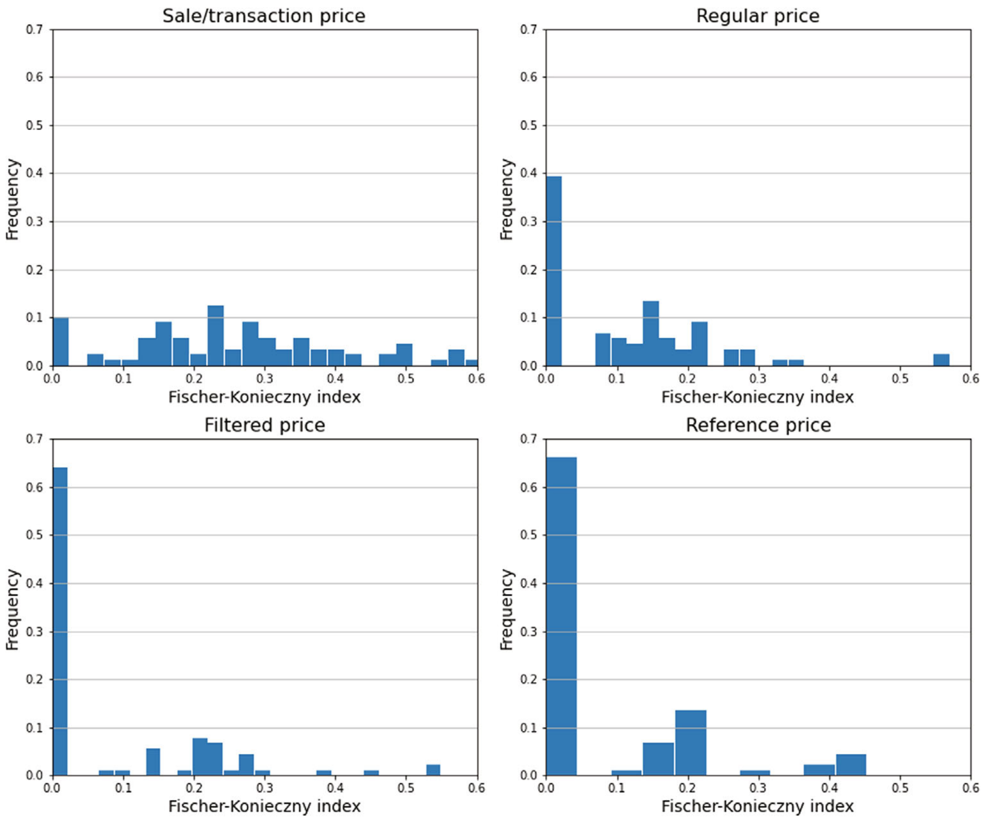

FIGURE 9 Fisher–Konieczny index of synchronization for the 89 national brand products in the sample. *Notes*: The index attains values between 0 and 1, where 0 indicates perfect staggering, and 1 indicates perfect synchronization.

Third, in Online Appendix E, we discuss alternative measures of the average price durations to gauge the effect of Jansen's inequality on the measured price durations.

Fourth, one disadvantage of sales filters such as that of Nakamura and Steinsson (2008) is that they are less precise near the endpoints. Because we have only 52 weeks of data, we cannot overcome this problem completely. As a partial solution, we exclude observations close to the endpoints and recalculate the frequency of price changes and implied price durations. Under this assumption, we find that the average frequencies of price changes, which are lower bounds on the real average frequencies, are 3.69%, 2.91%, and 4.20% for the EDLP, Hi-Lo, and HYB stores, respectively. This is compared to 4.25%, 3.55%, and 4.50% when we use all observations.[23] See Online Appendix G for more details.

9.2 | Robustness check with Israeli data

The short span of our data, only 52 weeks, creates two problems. First, for many products, the regular, filtered, and reference prices do not change at all, which leads to a downward bias in duration estimates. Second, the reduced precision of sales filters near the endpoints is more severe when the data series is short. We, therefore, employ data for a large retail food store in Israel that follows the HYB format. We have 171 weeks of data on 447 products. For each product, we have data on both the regular and transaction prices.

We use these data to estimate the frequency and duration of prices. We find that for all four data series, the frequency of price changes in the Israeli store is similar to the frequency of price changes that we find in the Canadian HYB store. The likelihood that a transaction, regular, filtered and reference price will change in a given week are 13.62%, 4.68%, 5.79%, and 4.47%, respectively.[24] When we use equation (2) to estimate the implied durations, we find that the transaction, regular, filtered and reference prices change every 18.34, 69.95, 43.97, and 47.85 weeks, respectively.

This suggests that the durations that we obtain using equation (2) for the Canadian HYB store, namely 10.55 weeks, 21.96 weeks, 24.44 weeks, and 28.30 weeks for the transaction, regular, filtered, and reference prices, are perhaps biased downwards.

Assessing the extent of price rigidity by excluding the first and final weeks, however, has only a small effect on the estimated durations. If we remove observations less than 6 weeks from the beginning or the end of each series, then we find that the implied durations are shorter by 3.0%–6.4%.

10 | DATA REPRESENTATIVENESS AND DATA LIMITATIONS

An important caveat concerns our dataset's limitations, which is due to the hand-collection process that we had to employ to collect it. We have only one year of data from three stores, and for a limited number of products, raising a question over the representativity of our data. Also, we do not have quantity data, and the dataset itself is dated. We recognize these shortcomings. An important question, therefore, is whether we can treat the stores that we sampled and their price data as reasonably representative of similar store formats, their price-setting practices, and so on.

To answer this question, we offer four observations.

First, we interviewed the managers of the three stores, and they self-identified and confirmed our information about their store formats, which was consistent also with the general knowledge at the time. They also offered details of how they manage prices in their stores, etc., and these details are consistent with the typical characteristics of their store formats.[25]

Second, we looked at the existing empirical studies that use retail price datasets, focusing on their descriptive statistics. We identified eight studies (all in marketing journals),[26] that use comparable but larger datasets from EDLP and Hi-Lo stores. The studies use prices of different products, from different locations, and address different questions, yet overall they report that (1) Hi-Lo prices are higher than EDLP prices, (2) the average change in Hi-Lo prices is higher than in EDLP prices, (3) the variance of the change in Hi-Lo prices is higher than in EDLP prices, and (4) Hi-Lo stores offer more deals than EDLP stores. We find similar attributes in our data. The average weekly frequencies of price changes reported by Levy *et al.* (1997) for Hi-Lo and EDLP chains are also consistent with the behaviour that we document here.

Third, the price behaviours that we find at the three stores are typical and consistent with textbook descriptions of similar format stores. For example, the descriptions of price setting and price adjustment practices of EDLP, Hi-Lo, and HYB stores found in textbooks on retail pricing are consistent with the pricing behaviour found in our data (e.g. Monroe 2002; Nagle and Müller 2017).

Fourth, in Online Appendix C, we compare the price-ending distribution in our data to distributions found in large scanner price datasets, and find that 9- and 99-ending prices are a dominant feature in our data, consistent with the findings in the literature (Levy *et al.* 2011; Anderson et al. 2015; Knotek 2019; Snir and Levy 2021).

Thus the descriptive statistics, and other attributes of the price behaviour that we report, as well as the pricing practices of the stores in our sample, are all in line with comparable figures and information reported in the literature for larger datasets. We believe, therefore, that our dataset, although small, is still a good representative of the price-setting practices of the retailers that follow EDLP, Hi-Lo, and HYB pricing formats.

11 | CONCLUSIONS, MACROECONOMIC IMPLICATIONS, AND FUTURE RESEARCH

We use a hand-collected dataset to study different notions of sale and regular prices, and their variability with stores' pricing format (i.e. pricing strategy). The dataset is unique for three key reasons. First, the stores in our sample follow different pricing formats—EDLP, Hi-Lo, and HYB. Second, we have both the actual transaction prices and the actual regular prices. Third, the stores are located within a 1 km radius.

We study four price series at each store—the actual transaction prices, actual regular prices, filtered prices, and reference prices. We find substantial variability in the extent of price rigidity across the three store formats and the four price series.

Irrespective of the measure of the regular price that we use, we find that the Hi-Lo store has the lowest frequency of regular price changes. If we use the stores' notion of regular prices, then the likelihood that the Hi-Lo store changes a regular price on a given week is 4.06%, compared to 13.38% at the EDLP store, and 5.34% at the HYB store. If we use the filtered series, then we find that the likelihood that the Hi-Lo store changes price is 3.55%, compared to 4.25% at the EDLP store, and 4.50% at the HYB store. If we focus on reference prices, we find that the likelihood that the Hi-Lo store changes price is 2.23%, compared to 2.70% at the EDLP store, and 3.95% at the HYB store. Thus in our data, the most flexible regular prices are 1.3–3.3 times as flexible as the least flexible regular prices, depending on the store format and the definition of the regular price.

Several conclusions follow.

First, when using data that come from stores that follow different pricing formats, the choice of the definition of regular prices can have significant effects on the measured variation in regular price rigidity: our results suggest that it will be the lowest when regular prices are generated using a sales filter, and the highest when we adopt the stores' own notions of regular prices. However, the label 'sales filter' might be misleading in this context, because the filter removes temporary price cuts, which—especially at EDLP stores—are not necessarily promoted as sales.

Second, our results suggest that the behaviour of filtered and reference price series is consistent with the predictions of sticky price models with no inflation and symmetric menu costs as discussed by Álvarez *et al.* (2016). We find, for example, that if we use either the filter or the reference prices, then the sufficient statistics scores (Álvarez *et al.* 2016) of the three stores are similar.

Third, stores with different pricing formats treat temporary price cuts differently, therefore they also have different frequencies of regular price changes, regardless of how we define regular prices. As Carvalho (2006) notes, firm-level heterogeneity in price rigidity can exacerbate market-level price rigidity. In particular, if there are strategic complementarities, then firms with rigid prices can slow down the response of the economy to a shock, increasing the real effects. We find evidence for some synchronization of price changes across stores, suggesting that strategic complementarities might indeed play a role in the market-level response to shocks.

Fourth, while it is hard to gauge the macroeconomic implications of our findings because we do not have information on quantities sold, we can expect that the geographic distribution of store pricing formats will likely affect the economy's response to monetary shocks if stores tend to respond to macroeconomic shocks through regular price changes (Coibion *et al.* 2015; Kehoe and Midrigan 2015; Anderson *et al.* 2017; DellaVigna and Gentzkow 2019). In Table J2 of Online Appendix J, we present the geographic distribution of retail store formats across the USA. Based on the figures in the table, we anticipate that the effect of sales on the aggregate price level will be higher in the Great Lakes region, which has a high share of Hi-Lo stores, than in the south-east region, which has a high share of EDLP stores. This can be important for assessing the variability in the local effects of monetary policy by regions and/or states, as in Angeloni and Ehrmann (2007) or Francis *et al.* (2012), for example. Thus our findings may have implications for the aggregate empirics and macroeconomic models of price-setting.[27]

Fifth, some studies suggest that temporary price cuts might have large effects on the aggregate effective price level (i.e. the price level that accounts for quantities purchased).[28] These studies are based partly on the premise that price cuts are promoted by stores, increasing the quantities purchased. However, because EDLP stores tend not to promote temporary price cuts, such price cuts are likely to have only a modest effect on sales volumes.[29] Therefore temporary price cuts are likely to have only a small effect on the aggregate price level in markets that are dominated by EDLP stores rather than Hi-Lo stores. This underscores the value of having the actual store-level data on regular and sale prices, rather than using mechanical algorithms, such as sales filters, to distinguish between regular and sale prices.

Sixth, to check the robustness of the results, we use data from a supermarket in Israel. We find that the frequency of price changes in the Israeli supermarket, which belongs to a chain that promotes itself as HYB, is similar to the frequency at the Canadian HYB store. Thus although the distribution of pricing formats may differ across countries, heterogeneity due to pricing formats likely affects price rigidities also in countries outside North America.

Future work could consider larger datasets that contain information on stores' pricing formats and quantities sold to explore the robustness of the results that we report. Considering our findings, we believe that it will be beneficial, when studying the behaviour of temporary price cuts and their implications, to focus on the prices from the point of view of both buyers and sellers. Depending on store formats and the corresponding notions of regular and sale prices, store managers and shoppers do not necessarily interpret price cuts as 'sales'. Therefore considering how they interpret price cuts is important for accurately assessing the effects of micro-level price changes on the aggregate price level.

Another avenue for future research that is worth exploring should be a study of the aggregate implications of our findings. We have argued that the heterogeneity that we document in pricing policies can affect the degree of nominal price rigidity. However, just because prices change more/less frequently or by smaller/larger amounts does not necessarily imply that they are more/less responsive to aggregate shocks. Exploring this more methodically requires developing a theoretical framework for assessing how stores with different pricing formats may respond to aggregate shocks. These and similar questions could also be explored empirically with larger datasets that contain information about prices and quantities sold as well as about the stores' pricing formats. We hope that the current paper offers a starting point for such explorations.

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NOTES

[1] The empirical literature on nominal price rigidity has expanded dramatically since then. For older surveys, see Gordon (1981, 1990), Romer (1993), Weiss (1993), Taylor (1999), Willis (2003), and Wolman (2007). More recent surveys include Klenow and Malin (2011), Leahy (2011), and Nakamura and Steinsson (2013).

[2] The literature uses different terms. In general, 'transaction prices' refer to 'final prices' or 'posted prices', which is the same as 'discounted prices' in the case where there are discounts, or 'regular prices' where there are no discounts.

[3] Examples include Nakamura (2008), Nakamura and Steinsson (2008, 2013), Eichenbaum *et al.* (2011), Guimaraes and Sheedy (2011), Midrigan (2011), Klenow and Malin (2011), Campbell and Eden (2014), Beradi *et al.* (2015), Coibion *et al.* (2015), Kehoe and Midrigan (2015), Anderson *et al.* (2015, 2017), Eden (2018), Nakamura *et al.* (2018), DellaVigna and Gentzkow (2019), Levy *et al.* (2020), Wu (2022), and the studies cited therein.

[4] This is an improvement over much of the literature that often uses scanner price data, which usually does not contain information on regular prices. See, for example, Barsky *et al.* (2003), Ray *et al.* (2006), Chen *et al.* (2008), and Snir *et al.* (2022).

[5] This also raises a question, of whether the term 'sales filter' is appropriate, because a large share of the prices that a sales filter tags as sale prices might not be perceived as such by shoppers.

[6] See Table J1 in Online Appendix J for details.

[7] See Table J2 in Online Appendix J for details.

[8] Source: https://www.statista.com/topics/2874/supermarkets-and-grocery-stores-in-canada/#topicOverview (accessed 27 July 2023).

[9] Online Appendix I offers more details about the retail supermarket landscape in Canada.

[10] For example, among Kroger's stores, the largest US food retailer, 13% are EDLP, 47% Hi-Lo, and 40% HYB (Ellickson and Misra 2008). The data in Table 1 and Figure 1 are based on the 1998 Trade Dimensions survey.

[11] The Warehouse Group of New Zealand switched from Hi-Lo to EDLP in 2017. In their 2018 annual report, the Group explicitly acknowledges how costly it is to switch pricing strategies. The costs include expected sales and margin declines in the near term (an expected 3-year turnaround), the need to restructure the supply chain, building up the private label lines, and even renegotiating trading cycles with business partners. Fast forward to 2020—the effectiveness of the EDLP move is still a 'work in progress' with a focus on identifying the right product portfolio and leveraging better forecasting abilities. These suggest that changing a pricing strategy is a long-term decision. See https://www.thewarehousegroup.co.nz/application/files/3815/3775/0583/2018_Annual_Report_EDLP_Case_Study.pdf, https://www.thewarehousegroup.co.nz/download_file/force/1583/174 and https://www.thewarehousegroup.co.nz/download_file/force/2600/174 (all accessed 27 July 2023). Iceland, a UK-based frozen goods retailer, ditched its EDLP strategy in 1997 and went back to Hi-Lo. See https://www.campaignlive.co.uk/article/iceland-freezes-edlp-policy/63585 (accessed 27 July 2023).

[12] The district population is 104,974, average age of 41.2, 42.8% with academic degrees, a median gross household income of \$58,178, and an 8.6% unemployment rate. As a comparison, the median gross household income in Canada is \$70,336, 54% with academic degrees, and a 6.8% unemployment rate (Statistics Canada 2016).

[13] Source: https://www.theglobeandmail.com/business/article-loblaw-profit-revenue-gain-as-bigger-baskets-help-offset-slower (accessed 27 July 2023).

[14] In November 1998, Provigo was purchased by the Loblaw's Group. Loblaw's and Provigo, however, are run independently of each other, each with its own market positioning, format, and identity. In January 2016, the Loblaw's store in our sample was turned into a Provigo store. We collected the data from July 2003 to July 2004, long before that happened. See https://www.wsj.com/articles/SB909782024300867500 (accessed 27 July 2023).

[15] The pricing format of each store was self-identified by the store managers when we interviewed them. Super-C follows a discount format, a type of HYB format. It offers low daily prices like EDLP stores, but with occasional discounts like Hi-Lo stores, to generate an image of 'best deals', in addition to the image of everyday best prices.

[16] Private-label goods are specific to each chain/store, therefore they are not comparable across the stores.

[17] The total number of observations is $n = (89 \times 52 \times 3) + (39 \times 52) = 15{,}912$. Online Appendix D lists the products included in our sample and the corresponding regular and transaction prices.

[18] Manufacturers compete for eye-level shelf spaces by paying the supermarkets various slotting and display fees.

[19] Consequently, there are many temporary price cuts at the EDLP store that visually resemble 'sales' (i.e. deep and temporary price cuts), but which the store classifies and presents as changes in *regular prices*.

[20] Eichenbaum *et al.* (2011) define a reference price as the modal price in a quarter, but we have only 52 weeks of data, thus with their algorithm we would have a maximum of four different price changes per good. Klenow and Malin (2011) define a reference price based on the modal price in a 13-observation rolling window. Chahrour (2011) and Kehoe and Midrigan (2015) suggest that such an algorithm might result in the reference price changing either too early or too late, and offer procedures for mitigating this problem.

[21] The regular and transaction prices of this product are also shown in the top row of Figure 4.

[22] Observing more price changes during Christmas week is consistent with Warner and Barsky (1995) and Levy *et al.* (2010), who find a higher frequency of price changes in the week prior to Christmas.

[23] When we exclude the final weeks from the sample, we risk biasing our estimates if the probability of sales is higher in the excluded weeks than in other weeks. However, to the best of our knowledge, neither the academic nor the practitioners' literature suggests that sales of the products that we study are particularly common in June–July (Volpe and Li 2012). See also https://maplemoney.com/canadas-yearly-sales-cycle (accessed 27 July 2023).

[24] The likelihood of a regular price change, as defined by the store, is lower than the likelihood of a filtered price change, and it is similar to that of the reference price. It turns out that the reason is that the chain tends to keep a high regular price and a low transaction price for long periods. Occasionally, it changes the transaction ('sale') price. These changes are then recorded as changes in the filtered price, and consequently, there are more filtered price changes than regular price changes.

[25] During the data collection period, one of the coauthors of this paper as well as our research assistant lived in Montreal, and as part of the general knowledge, they both knew quite well the pricing formats of the three stores.

[26] These are Hoch *et al.* (1994), Shankar (1996), Bell and Lattin (1998), Galata *et al.* (1999), Bolton and Shankar (2003), Voss and Seiders (2003), Rondan-Cataluña *et al.* (2005) and He *et al.* (2023). We were unable to find a study that considers an HYB store similar to ours that also reports the store's regular and transaction price statistics.

[27] At the technical level, the geographical variability in the pricing format suggests that removing sale prices from the analysis might be more appropriate in the context of the price data from some regions than others.

[28] See Klenow and Willis (2007), Hendel and Nevo (2013), Fox and Syed (2016), Glandon (2018), Chevalier and Kashyap (2019), Kryvtsov and Vincent (2021), and Wu (2022).

[29] Note an important difference between temporary price cuts at Hi-Lo versus EDLP stores, as seen from the point of view of consumers. A shopper at a Hi-Lo store knows that the price cut is temporary, thus she has the incentive to buy more than the usual quantity. At an EDLP store, however, even if the shopper knows that the price is low, she does not perceive it as temporary, therefore she has no incentive to buy more than the usual quantity.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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