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Sales Filters and Rigidity of Regular Prices*

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Abstract

We study price rigidity using two retail price datasets. Both datasets contain the *actual transaction prices* as well as the *actual regular prices*. We use the data to assess the rigidity of both price series. In addition, following the common practice in this literature, we employ sales filters to form a series of generated regular prices. We compare the rigidity of the filter-generated regular prices to the rigidity of the actual regular prices. We assess the implications of our findings for the effectiveness of monetary policy using sufficient statistics for both the actual and filter-generated regular prices.

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1. Introduction

"A central question in macroeconomics is whether nominal rigidities are important" (Eichenbaum et al. 2011, p. 234). Indeed, a large literature tries to assess the importance of nominal rigidities by measuring how often prices change, and how fast prices respond to changes in market conditions.[1]

Nakamura and Steinsson (2008) argue that changes in regular prices are more important than changes in transaction prices when evaluating the effects of monetary policy. This is because sale prices are usually set months in advance and, therefore, do not respond to changes in market conditions (Anderson et al. 2017, Cavallo 2018). In addition, Eichenbaum et al. (2011) find that in each period there is one price that is the most common, which they term the *reference price*, and that deviations from the reference price are quickly reversed. They also show that when the wholesale costs change, the retailers adjust the reference prices, not the transaction prices.

Building on these findings, Midrigan (2011) develops a model to explain the role of regular prices in transmitting monetary shocks. In his model, retailers pay a high menu cost for adjusting the regular price and a low menu cost for making temporary price cuts ("sales"). Although a large share of transactions occurs during sales, Midrigan finds that the transmission of a monetary shock depends only on the rigidity of the regular prices (Eichenbaum et al. 2011, Kehoe and Midrigan 2015).

Despite the theoretical importance of regular prices, direct empirical evidence on their rigidity is scarce, because most datasets contain only transaction prices. To fill this gap in the literature, we use two new datasets, which contain both variables of interest—*the actual regular prices and the actual transaction prices*. The main dataset contains ≈108 million daily prices for 2,403 products in 106 stores that belong to the 11 largest food retail chains and the largest drugstore chain in Israel. The 11 chains account for over 90% of the retail store sales in Israel, making our data representative of almost the entire country's retail food market, with a broad geographical country-wide coverage.

The second dataset is smaller (because it was hand-collected), containing data on prices of 89 national branded and 39 private label products offered in 3 stores in

[1] Earlier studies include Barro (1972), Mankiw (1985), Kashyap (1995), Carlton (1986), Cecchetti (1986), Lach and Tsiddon (1992, 1996), Levy et al. (1997, 1998, 2020), Dutta et al. (1999, 2002), Bils and Klenow (2004), and Konieczny and Skrzypacz (2005). The empirical literature on nominal price rigidity has grown dramatically since then. For surveys, see Gordon (1981, 1990), Mankiw and Romer (1991), Romer (1993), Weiss (1993), Taylor (1999), Willis (2003) and Wolman (2007). Klenow and Malin (2011), Leahy (2011), and Nakamura and Steinsson (2013).

Montréal, Canada. For each product, we have 52 weekly observations, with a total of 15,912 observations. We use the smaller dataset to assess the robustness of our findings.

Using the main dataset, we study price rigidity at weekly and daily frequencies. We find that regular prices are quite rigid. The median regular price changes every 84 weeks. There is also a large variation in the rigidity; the standard deviation of the implied duration between price changes is 62 weeks.

When we analyze the size of price changes, we find that consistent with the menu cost model, small price changes are rare. The share of regular price changes smaller than 1% is 1.2%, while the share of regular price changes smaller than 5% is 13.5%.

For comparison, Midrigan (2011) using data from a midwestern food retailer, finds that 10% of the price changes are smaller than 3%, and 25%—smaller than 5%. Beradi, et al. (2015) find that in French stores, 11.2% of all regular price changes are smaller than 1%, while 23% are smaller than 2%.

The low share of small price changes in our data leads to a "bimodal" distribution of the size of regular price changes, resembling the one predicted by the models of Golosov and Lucas (2007), and Alvarez et al. (2016) with one product and a low probability of costless price changes. However, the distribution of regular price changes in our data also includes large price changes, leading to a distribution with "thick tails" and a kurtosis that is higher than predicted by Golosov and Lucas (2007).[2]

Following a common practice in this literature, we also "generate" regular prices using 4 sales filters: (i) Nakamura and Steinsson (2008), (ii) Eichenbaum et al. (2011), (iii) Chahrour (2011), and (iv) Kehoe and Midrigan (2015). We assess the rigidity and the distribution of changes in the filter-generated regular prices. We find that sales filters underestimate both the rigidity of the regular prices and their variance while predicting too many small regular price changes, and kurtoses that are either too high or too low.

Using the (smaller) Canadian data, we find that sales filters underestimate the rigidity of regular prices, mostly because one of the sampled stores follows Every-Day-Low-Price strategy, a format that is popular in the US and Canada (Ellickson and Misra 2008, Ray et al. 2023), but does not exist in Israel. We also find that small price changes are more common in Canada than in Israel. For example, in the Canadian data, the share of regular price changes smaller than 1% is 9.2%, compared to 1.2% in the Israeli data. As

[2] The distribution of the size of price changes in our data resembles the distributions that Cavallo and Rigobon (2016) and Cavallo (2018) find using scraped data.

in the Israeli data, sales filters overestimate the share of small price changes by 36%–101%, depending on the filter employed and the definition of a "small" price change.

Our findings are important for several reasons. First, we find that actual regular prices are stickier than filter-generated regular prices. I.e., the actual regular prices change less often, and by more, than the filter-generated regular prices. One reason is that sales that last several months are common in our data, while sales filters typically assume that sales last 4–6 weeks, at most. This is significant because if sale prices can last for months, a phenomenon that was also observed in the US and elsewhere (Volpe and Li, 2012), then it is not clear what is the significance of posted regular prices.

Second, in models such as Midrigan (2011) and Kehoe and Midrigan (2015), the cost of changing a regular price exceeds the cost of changing a sale price. This seems to hold also in our data. Our findings, therefore, suggest that retailers might be using a mix of stable regular prices with lower sale prices over long periods, which gives them more degrees of freedom than is generally assumed in the literature.[3]

Second, there is a large variation in the rigidity of regular prices across products, which likely plays a role in the transmission of monetary policy (Carvalho 2006, Alvarez and Lippi 2014, Alvarez et al. 2016, Baley and Blanco 2021).

Third, as noted by Kehoe and Midrigan (2015, p. 38), the goal of algorithms designed to filter "regular" prices from transaction prices is not "… to identify a theoretical object such as the list price… but rather … [they are] a simple way to highlight key patterns in our data." Our results highlight the properties of the price trajectories generated by different sales filters, which can serve as a guide in choosing sales filters, depending on the patterns one wishes to highlight.

Fourth, the results using the Israeli data support key predictions of the menu cost model: regular price changes are rare and tend to be large. Indeed, one argument against the canonical menu cost model is that real-world data contain many small price changes, counter to the menu cost model's predictions.[4] Our results thus support the findings of Cavallo and Rigobon (2016) and Cavallo (2018). However, the results of the Canadian

[3] In Israel, adjusting a regular price has a higher cost than changing a sale price because Israel has an item pricing law. Changing a regular price, therefore, entails sticking a new price tag on *every item* that is offered for sale, which is costly (Bergen et al. 2008, Levy et al. 1997). This is in line with the model of Midrigan (2011) and Kehoe and Midrigan (2015). Changing a regular price might also be more costly than changing sale prices because of consumer antagonization costs (Kahneman et al. 1986, Rotemberg 2005, Anderson and Simester 2010), and implicit contracts (Blinder 1991 and 1994, Blinder et al. 1998, Levy and Young 2004 and 2021, Young and Levy 2014).

[4] See Eichenbaum et al. (2011), Midrigan (2011), Alvarez and Lippi (2014), and Alvarez et al. (2016). Sayag et al. (2024) argue that if we consider the sales volume, then small price changes can be consistent with the menu cost model.

dataset show that in some markets, small price changes are common, suggesting that the size of menu costs likely varies across markets.

Fifth, sales filters tend to produce too many "spurious" small price changes, leading to kurtosis that is too high, and making the data look more "Calvoish" than is implied by the size of the true regular price Changes.

Sixth, Alvarez et al. (2016) show that the real effects of a monetary shock depend on the size of the sufficient statistic. We calculate sufficient statistics using data on actual regular price changes and find that a monetary shock is likely to have a large effect because regular price changes are rare. Calculating sufficient statistics for filter-generated regular prices significantly underestimates the expected effects of a monetary shock. Thus, using sales filters and their choice can have a significant effect on findings regarding the effects of monetary policy.

Finally, the extent of price rigidity we find is the same in daily and weekly data which means that little information is lost when using weekly price data compared to daily data.

We proceed as follows. In section 2, we describe the data. In section 3, we study the rigidity of the actual and filter-generated regular prices. In section 4, we discuss the size of price changes. In section 5, we use sufficient statistics to assess the implications of our findings for the effects of monetary policy. In section 6, we summarize the robustness of our findings. We conclude in section 7. The Appendix describes the two datasets, details the robustness tests, and presents the results of additional analyses.

2. Data

Our primary dataset consists of daily prices from Israeli supermarkets and drugstores. Since May 20, 2015, all large food retailers operating in Israel have been required by law (known as the price transparency law) to publish online their daily prices for all products sold in each one of their stores. As of July 1, 2017, large drugstore chains are also required to publish their prices.[5] The goal of the law was to make price information more accessible to shoppers.[6] To this end, the government offered prizes to developers of price comparison apps that would reach certain traffic levels. Ater and Rigbi (2023) show that

[5] The data we use was provided by CHP, a price comparison company that scrapes data from the website where the retailers must post their price data. The website, https://www.gov.il/he/pages/cpfta_prices_regulations (in Hebrew), is not very user-friendly. CHP's platform makes the price data accessible in a more user-friendly format.

[6] Retailers are fined NIS 45,000 each time they fail to publish the prices of all products in all stores. See, for example, Israel Financial Insider, June 22, 2022: "Shufersal has not published price files and promotions of some of its stores and will pay a fine of NIS 180,000," https://www.ifi.today/news/2287-Shufersal-has-not-published-price-files-and-promot/, accessed January 4, 2025.

although the traffic in price comparison sites remains law, the price transparency law led to a decrease in price dispersion and the price level.

We have data on 2,403 products sold in 106 stores that belong to the 11 largest food retailers and the largest drugstore chain. Appendices A and B report summary statistics about the retailers, and the products in our sample, respectively.

The 11 food retailers included in our sample are responsible for over 90% of the sales by chain stores.[7] The number of stores of each retailer included in our data corresponds to their respective market share. For example, the largest retailer, Shufersal, has a market share of 37% while the second largest retailer, Rami Levi, has a market share of 16%. They are represented by 36 and 16 regular (brick-and-mortar) stores, respectively.[8] For each chain, we selected the store locations randomly. As Map 1 shows, the locations of the stores broadly cover much of Israel's territory within the 1967 borders.[9] Appendix C contains the list of the sampled stores and their locations.

The 2,403 products in our sample are all the UPCs that belong to the ELIs whose average prices are included in a representative basket of goods published by Israel's Ministry of Economy and Industry and the Central Bureau of Statistics.[10] The Ministry publishes the average prices of these goods to help consumers find stores that offer the lowest prices. ELIs included in this basket satisfy the following criteria: (a) they have a large weight in the CPI, (b) they are consumed by households of all income levels, (c) the nominal expenditure on each of the goods is similar across income levels, and (d) the products are consumed throughout the year. We divide these products into 25 categories, such as dairy products, grooming products, bread, fresh meat and fish, etc.

In total, we have 107,739,819 daily price observations from January 1, 2018 – April 8, 2021. Importantly, the price transparency law requires that retailers continuously post the regular prices. If a product is offered at a discount, the retailer has to post the discounted price in addition to the regular price. This way, a shopper can immediately find the amount of a discount relative to the regular price. Therefore, for each product in each sampled stores, we have the regular price as well as the transaction price for each day that

[7] According to Israel's 2013 Household Expenditure Survey, 71% of the food is purchased in chain stores. The remaining 29% is purchased in grocery stores, open markets, and specialty stores.
[8] We also have data from both retailers' online stores. Appendix A presents summary statistics for the sampled chains.
[9] A more detailed map can be accessed at http://tinyurl.com/4dx8bvu8.
[10] Entry Level Items (ELI) are the most granular, complete, and mutually exclusive categorization of CPI items. ELI examples include fresh tomatoes, red wine, laundry detergents, etc. Universal Product Code (UPC) is a unique product identifier. For example, different flavors or different package sizes of the same item have different UPCs.

the product was offered for sale.[11] By law, these prices are the final prices that shoppers pay (including VAT and any other tax). The average regular (transaction) price in our data is NIS 16.93 (NIS 15.88), with a standard deviation of NIS 13.40 (12.84).[12]

Over our sample period, the average annual (food price) inflation rate was 0.3% (0.9%). In addition, during our sample period, the prices of 20 UPCs included in our sample were capped by the government. This is unlikely to affect our results, because the products with capped prices comprise only 0.8% of the 2,403 UPCs in our data.[13]

3. Price rigidity

To make our results comparable with the existing literature (which usually uses weekly data), we study price rigidity at a weekly frequency.[14] We define a weekly price as the mode price of the week (Karadi et al. 2024). If there was more than one mode price, we chose the first (Kehoe and Midrigan 2015). This yields 16,676,881 observations.

Because missing observations can affect the measured price rigidity, we follow Chahrour (2011) and Eichenbaum et al (2011) by focusing on store-product combinations that have no more than 3 missing observations over the sample period. This yields 3,910,261 observations on 1,506 products sold in 79 stores that belong to 10 chains.[15]

Before presenting the findings, consider as an example the behavior of the prices of 4 products offered in Store 18 of Shufersal (the largest chain). The top panel of Figure 1 depicts the regular price (green dashed line) and transaction price (red dotted line) of red peppers. We find that the regular price is volatile. We also observe temporary cuts in the transaction price (sales).

Tapuchips Potato Chips (second panel) has a stable regular price, but the transaction price is rarely set at the regular price. In other words, for a large part of the sample period, the transaction price is below the regular price, where it stays for long periods.

Spring strawberry-banana flavored nectar (third panel) also has stable regular prices. Its transaction price is more volatile, with several temporary price cuts (sales).

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[11] The regular price is the price before sales. The transaction price is equal to the regular price if no discount is offered, and to the discounted price if a discount is offered.
[12] The average exchange rate during the sample period was NIS3.49/$1.
[13] In Appendix D, we show that dropping these UPCs has little effect on the results. Appendix B presents the sampled products' summary statistics, at the category level.
[14] The results of the analysis of daily data are summarized below in section 6.1 and discussed in detail in Appendix G.
[15] Stores not included in the final list either opened or closed in the middle of the sample period. For example, one of the largest chains, Yenot-Bitan, and its subsidiary chain Mega, came close to bankruptcy during the sample period, forcing the chain to close some branches and sell some branches to other chains. Data for another chain, Tiv-Taam, was not recorded for about 2 months for technical reasons. The final list includes 9 food retailers and one drugstore chain.

Cremissimo ice cream (fourth panel) had a stable regular price in the first part of the data, when the transaction price was more volatile, with some long-lasting price cuts. In the second part of the data, after September 2019, the regular price became more volatile.

3.1. Filter-generated regular prices

For lack of direct observations on regular prices, the literature often uses sales filters to generate regular prices. Sales filters are computational algorithms that use transaction price information to identify and generate the corresponding regular prices. We take advantage of our data which contains both the actual regular and the actual transaction prices, to form filter-generated regular prices, and compare their rigidity to the rigidity of the actual regular prices.

We use 4 sales filters: Nakamura and Steinsson's (2008) sales filter A, Eichenbaum et al.'s (2011), Chahrour's (2011), and Kehoe and Midrigan's (2015).[16] Nakamura and Steinsson's (2008) filter is a one-sided filter, designed to identify regular prices by removing V-shaped price cut patterns. We applied the filter assuming that the maximum length of both symmetrical and asymmetrical sales is 6 weeks. Eichenbaum et al.'s (2011) filter computes the mode price in each quarter (13 weeks) which they define as a reference price.[17] Chahrour's (2011) and Kehoe and Midrigan's (2015) filters also focus on the mode price. Their filters, however, find the mode prices for moving windows rather than for set time periods. They also use a second-stage procedure for smoothing the resulting series of modal prices. The two filters differ in the length of the moving window they use (13 weeks for Chahrour's filter, 11 weeks for Kehoe and Midrigan's filter) and in the algorithm they employ to smooth the price series.

Figure 2 illustrates the results of applying the filters. It shows, for each product included in Figure 1, the time series of the actual regular and transaction prices along with filter-generated regular prices. Consider first red peppers. We find that the filters fail to correctly identify the movements in regular prices because they are highly volatile. Nakamura and Steinsson's (2008) and Kehoe and Midrigan's (2015) filters do a better job than Eichenbaum et al.'s (2011) and Chahrour's (2011) filters, although they also overestimate the regular price rigidity.

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[16] Other sales filters found in the literature include Nakamura and Steinsson's (2008) sales filter B, Dutta et al.'s (2002) moving average filter, A.C. Nielsen's filter (as implemented by Kehoe and Midrigan 2015), Syed's (2015) and Fox and Syed's (2016) sale spotter, Klenow and Malin's (2011) filter, Campbel and Eden's (2014) filter, and Butters, et al.'s (forthcoming) base price filter.

[17] In the case of ties, we follow Chahrour (2011) and Kehoe and Midrigan (2015), by setting the reference price equal to the mode price that appears first in the relevant period.

In the case of potato chips, we find the opposite. Because the transaction price stays below the regular price for long periods, all four filters underestimate the rigidity of the regular price. Nakamura and Steinsson's (2008) and Kehoe and Midrigan's (2015) filters which are more flexible, underestimate the regular price rigidity by more than Eichenbaum et al.'s (2011) and Chahrour's (2011) filters.

In the case of the flavored nectar, all four filters identify well the movements in the regular price.[18] In the case of Cremissimo ice cream, the filters underestimate the price rigidity in the first part of the data where the regular price remains unchanged, while the transaction price is more volatile. In the second part of the data, where the regular price is more volatile, the filters overestimate the regular price rigidity.

Overall, as shown below, products with price series such as the second and fourth products, are quite common. Consequently, the sales filters that allow a few price changes do a better job of replicating the median frequency of regular price changes in comparison to the sales filters that follow the transaction prices more closely.

3.2. Actual regular prices vs. filter-generated regular prices

Below, we report the median frequency of price changes along with the implied median duration between price changes, calculated as $-[\ln(1-f)]^{-1}$, where f is the median frequency of price changes (Nakamura and Steinsson, 2008). We calculate these statistics at the store–product level, and then report the median at the category level.[19] We report the statistics for the actual regular and transaction prices and for the 4 filter-generated regular price series. We also report 95% confidence intervals obtained by bootstrapping 1,000 times. Table 1 reports the median frequencies of price changes, and Table 2 reports the median implied durations between price changes.

Consistent with Bils and Klenow (2004) and Nakamura and Steinsson (2008), we find that the transaction prices are quite volatile. Across categories, transaction prices change every 4–28 weeks, with the median price changing every 7 weeks.[20]

Note two observations on the behavior of the actual regular prices. First, the median price changes every 84 weeks, i.e., every 1.6 years. Second, there is a large cross-

[18] Eichenbaum et al.'s (2011) filter is not accurate in the timing of the regular price change because it allows for price changes only at the beginning of each quarter. The filter is correct, however, about the number of price changes.
[19] A possible concern is that retailers use uniform pricing (DellaVigna and Gentzkow, 2019), resulting in identical prices across stores belonging to the same retailer and limiting the variation in the data. In Appendix J, we show that there is variation even within retailers, probably due to a zone-based pricing strategy.
[20] We focus on regular prices, but the rigidity of transaction prices might also play a role in the monetary policy transmission of monetary policy (Alvarez and Lippi, 2020, Sudo et al., 2020, Kryvtsov and Vincent, 2021).

category variation. The prices are quite flexible in the categories of fruits and vegetables, with a median price changing every 4 weeks, and cooking oil, condiments, and ice cream, with a median price changing every 12 weeks. In other categories, the median regular price changes only once in 3+ years. Examples include baking goods, canned food, coffee and tea, dairy products, snacks and sweets, and soft drinks. Overall, the standard deviation of the implied duration between price changes is 62 weeks.

None of the sales filters succeed in fully replicating these two attributes. First, the sales filters overestimate (underestimate) the price rigidity when the actual regular price is flexible (rigid), yielding standard deviations of the implied durations of 51 weeks, 53 weeks, 52 weeks, and 49 weeks for Nakamura and Steinsson's (2008), Eichenbaum et al.'s (2011), Chahrour's (2011), and Kehoe and Midrigan's (2015) filters, respectively. These figures are 17.7%, 14.5%, 16.1%, and 21.0%, respectively, smaller than the standard deviation of the regular prices.

Second, all 4 filters underestimate the rigidity of the median regular prices. According to Nakamura and Steinsson's (2008), Eichenbaum et al.'s (2011), Chahrour's (2011), and Kehoe and Midrigan's (2015) filters, the median prices change every 24, 55, 33 and 27 weeks, respectively. Even Eichenbaum et al.'s (2011) filter, which outperforms the other filters, underestimates both the median rigidity of the regular prices and the variation in the rigidity of the regular prices.

4. Size of price changes

Consistent with Bonomo et al. (2022), the size of price changes is relatively large. The mean absolute values of price changes (standard deviations) are 17.3% (14.1%), 15.9% (12.7%), 15.8% (12.2%), 16.5% (12.5%), 16.4% (12.4%) and 18.7% (13.5%), for the regular, Nakamura and Steinsson's (2008), Eichenbaum et al.'s (2011), Chahrour's (2008), Kehoe and Midrigan's (2015), and the transaction prices, respectively.

Alvarez et al. (2016) show that if there is heterogeneity in the variance of the size of price changes across products, then estimates of aggregate statistics might be biased. We, therefore, report statistics for $z_{is,t}$, where $z_{is,t} = \left(\Delta p_{is,t} - \overline{\Delta p_{is}}\right)/\sigma_{is}$, where $p_{is,t}$ is the price of product i in store s at week t, $\Delta p_{is,t}$ are log price changes, $ln\left(\frac{p_{is,t}}{p_{is,t-1}}\right)$, $p_{is,t} \neq p_{is,t-1}$, $\overline{\Delta p_{is}}$ is the average log price changes at the store-category level, and σ_{is} is the standard deviation of log price changes at the store-category level. Figure 3 depicts the

histograms of $z_{is,t}$ for the actual regular prices, for the filter-generated regular prices, and for the transaction prices. Table 3 reports key statistics of the distributions.[21]

Several features of the size of regular price changes stand out. First, the distribution is almost symmetric with a skewness of 0.005. Second, the distribution is slightly leptokurtic with a kurtosis of 3.79. This is slightly higher than the kurtosis reported by Bonomo, et al. (2022), but lower than the kurtosis reported for other countries (Midrigan 2011, Alvarez, et al. 2016, Cavallo 2018, Ray, et al. 2023), possibly because the quality of our data is better, reducing measurement errors (Eichenbaum, et al. 2014).

Third, the share of small price changes in our data is low in comparison to the data from other countries. The share of log price changes smaller than 0.5 of the average log price change is 24.4%. For comparison, Bhattarai and Schoenle (2014) find that in the US PPI data, the corresponding value is in the range 38%–55%.

Very small regular price changes are particularly rare in our data. Table 4 reports the share of price changes smaller than 1%–5%. 1.2% of all price changes are smaller than 1%, 3.6% are smaller than 2%, and 13.5% are smaller than 5%.[22]

The kurtosis of transaction prices, 3.24, is lower than that of the regular prices. Small price changes are even less common among transaction prices than among regular prices, because transaction prices contain large price changes associated with sales (Nakamura and Steinsson, 2008). Among transaction prices, 1.7% of the price changes are smaller than 1%, 3.0% are smaller than 2%, and 9.6% are smaller than 5%.

The histogram of regular price changes suggests that the reason for the low share of small price changes in our data is that the distribution is bimodal, with a low likelihood of very small price changes. The low share of small price changes could be explained by the current Israeli law that prohibits price changes smaller than the smallest currency denomination NIS 0.10 (Ater and Gerlitz 2017, Snir et al 2017 2022). However, in Appendix F, we show that the lack of price changes in the range NIS 0.01–0.09 can only account for a fraction of this finding because price changes below NIS 0.5 are rare.

A more likely explanation is the quality of our data. Cavallo and Rigobon (2016) and

[21] Following Bonomo et al. (2022), we exclude observations falling in the top and bottom 0.5% of the distribution. Appendix E shows that including all observations has a very modest effect on the results we report in the paper.
[22] For comparison, Beradi et al. (2015) find that in France, 11.2% of all price changes are smaller than 1%, and 23.7% are smaller than 2%. Gautier et al. (2024) find that 15% of the price changes in the EU are smaller than 2%. Midrigan (2011) finds that 10% of all price changes in the US are smaller than 3%, and 25% are smaller than 5%. Klenow and Kryvtsov (2008) and Vermeulen et al. (2012) find that 25% of all price changes are smaller than 2.5% and 1.5%, respectively.

Cavallo (2018) use scraped data, and, like us, find that small price changes are rare.[23] They suggest that the share of small price changes in scanner data like in Midrigan (2011) is probably inflated due to measurement errors. They also suggest that the share of small price changes in datasets produced by official agencies for the computation of the CPI might be affected by the imputation of missing prices that lead to spurious price changes.

Another possible explanation is that in Israel, the "item pricing law" requires that retailers post a price tag on every item. Consequently, the menu cost is higher in Israel than in the US (Levy et al. 1997, 1998, Dutta et al. 1999, Bergen, et al. 2008). In addition, Sayag et al. (2025) argue that small price changes can be profitable when the sales volume is sufficiently large. This suggests that in countries with small sales volumes, the likelihood of small price changes will be lower than in large countries.

Also, the number of products in a typical Israeli supermarket is smaller than in the US. Bonomo et al. (2022) report that an average Israeli supermarket offers 7,217 products. In contrast, Levy, et al. (1997) and Kackmeister (2007) report that a typical US supermarket carries ≈25,000 products, while Ray et al. (2023) report that large Canadian chain stores carry ≈30,000 products. Alvarez et al. (2016) show that when stores sell a small number of products and price changes are costly, the distribution of the size of price changes approximates the bimodal distribution of Golosov and Lucas (2007). Yet the kurtosis of our data 3.79, is much higher than predicted by the Golosov and Lucas (2007) model, suggesting that the distribution in our data is bimodal, but also has thick tails.

Comparing the behaviors of the actual and filter-generated regular prices, we find the following. First, except for Nakamura and Steinsson's (2008) filter, which indicates a slightly positive skewness, all other filters generate regular prices with a skewness close to zero. The filter-generated price distributions also resemble the bimodal distribution of the actual regular prices. However, in the filter-generated regular prices of Nakamura and Steinsson (2008), Eichenbaum, et al. (2011), Chahrour (2011), and Kehoe and Midrigan (2015), we find that the shares of price changes smaller than 25% of the average change are respectively 25%, 38%, 26%, and 22% higher than what we find in the actual data. In particular, in the filter-generated series, we find that price changes smaller than 1% are 117%–125% higher than in the actual data. The filters of Eichenbaum et al. (2011), Chahrour (2011), and Kehoe and Midrigan (2015) also lead to slightly platykurtic

[23] Giulietti et al (2020) find that small transaction price changes are common but small reference price changes are rare.

kurtosis, while Nakamura and Steinsson's filter leads to excessive leptokurtic kurtosis.

5. Implications for monetary policy

The dataset we study comes from an economy with low inflation, in which the shares of price increases and decreases are similar. For such economies, Alvarez, et al. (2016) show that in sticky price models, the real effects of small monetary shocks depend on a sufficient statistic given by the ratio of two quantities: the kurtosis of the size of price changes, and the average annual number of price changes.

We calculate the sufficient statistics for the actual regular prices, the transaction prices, and 4 filter-generated regular prices. The LHS panel of Figure 4 depicts the results.[24] The black lines denote 95% confidence intervals obtained by bootstrapping 1,000 times.

The predicted effect of a small monetary shock is significantly greater if we use the actual regular prices than the filter-generated regular prices of Eichenbaum et al. (2011), Chahrour (2011), or Kehoe and Midrigan (2015). This is because the actual regular prices have a bigger kurtosis and a smaller probability of change than the filter-generated prices.

We cannot reject, however, the null hypothesis that the sufficient statistic of the actual regular prices is indifferent from the sufficient statistic of the prices generated by Nakamura and Steinsson's (2008) filter. This is because Nakamura and Steinsson's (2008) filter generates a price series with a kurtosis that is too big relative to the actual regular prices, together with a higher than actual likelihood of price changes. Thus, although Nakamura and Steinsson's filter predicts an effect of a small monetary shock that is similar to the one that the sufficient statistic predicts for the actual regular prices, the mechanism of the effect seems different from what the actual data predicts.

6. Robustness

We assess the robustness of our findings by discussing the results of the (1) analyses of daily data, and (2) Canadian data, (3) a hypothetical situation where a sales indicator flag is included in the dataset, and (4) the generalizability of the results we report.

6.1. Results of the analysis of daily data

In daily data, the frequency of regular price changes is slightly higher than in weekly

[24] The RHS panel of Figure 4 depicts the same for daily data, which we discuss briefly below, in Section 6.1, and in greater detail in Appendix G.

data. The median duration between price changes decreases from 1.6 years in the weekly data to about 1.5 years in the daily data. The difference is due to cases where a price changes twice within the same week. However, we find that in the vast majority of cases, when a price changes twice within 7 days, the changes completely or partially cancel each other out, suggesting that their effect on the price level is limited.

Consistent with Bonomo et al. (2022), the share of small regular price changes is slightly lower in the daily data than in the weekly data. In daily data, the share of regular price changes smaller than 1% (5%) is 0.9% (11.0%), compared to 1.2% (13.5%).

The sufficient statistic of the actual regular prices, depicted on the RHS panel of Figure 4, is almost unchanged compared to the weekly data. However, all 4 filters generate price series with sufficient statistics smaller than what we obtained with weekly data. In other words, because these filters are not designed to work with daily data, they all predict that a small monetary shock would have an effect that is much smaller than predicted by the properties of the actual regular price series.

Thus, overall, the analyses of daily data yield results similar to the results obtained with weekly data. See Appendix G for details.

6.2. Results of the analysis using Canadian data

For robustness, in Appendix I, we present results of using hand-collected data from three Canadian supermarket stores in Montréal. Here we briefly summarize the findings.

In Canada, the median regular price changes every 17 weeks. The high frequency of regular price changes is driven mostly by one store that employs an EDLP strategy, implying that it hardly promotes any discounts. Instead, it presents even temporary price changes as changes in the regular price (Ray et al., 2023). This format does not exist in Israel, which might explain why the regular price rigidity in Israel is higher than what is reported for the US (Nakamura and Steinsson, 2008, Midrigan, 2011).

Sales filters underestimate the frequency of regular price changes and thus overestimate the regular price rigidity. The median filter-generated regular price changes every 25, 51, 25, and 25, respectively, for Nakamura and Steinsson's (2008), Eichenbaum's et al. (2011), Chahrour's (2011), and Kehoe and Midrigan's (2015) filters.

Small regular price changes are more common in Canada than in Israel. In Canada, 9.2% of all regular price changes are smaller than 1%, and 32.1% are smaller than 5%, which are higher than the corresponding values in the Israeli data, 1.2% and 13.5%.

Sales filters overestimate the share of small price changes, like in Israel. For example, the shares of price changes smaller than 1% (5%) are 13.9% (47.0%), 17.8% (51.8%), 14.3% (45.6%) and 13.7% (44.1%) for Nakamura and Steinsson (2008), Eichenbaum et al. (2011), Chahrour (2011), and Kehoe and Midrigan (2015) sales filters, respectively. Thus, depending on the filter and the definition of a small price change, sales filters overestimate the share of small price changes by 36%–101%. See Appendix I for details.

6.3. Could sale indicators suffice?

We find that sales filters generate "regular" prices that can deviate considerably from the true regular prices. A possible remedy is to use datasets that contain sale flags indicating sale prices. For example, the BLS dataset used by Nakamura and Steinsson (2008) and Dominick's dataset used, among others, by Levy et al. (2011), Midrigan (2011), and Alvarez et al. (2016), contain sale indicator flags. In both these cases, there are reasons to think that the sale flags might be imprecise, as discussed in Peltzman (2000), Barsky et al. (2003), and Nakamura and Steinsson (2008). However, to the extent that databases with reliable sale indicator flags exist, it is of interest to explore whether sale flags can replace the use of exact information on the regular prices.

The main disadvantage of sale flags in comparison to actual regular prices is that if one relies on sale flags, s/he might miss regular price changes that occur during sales. In our data, there are 24,957 such price changes, 16.6% of all regular price changes.

Thus, regular price changes during sales are quite common. However, as long as there is no more than one price change per sale period, then a researcher that uses sale flags might make a mistake in identifying the timing of regular price changes, but not in the frequency. We therefore look for instances with more than one regular price change during a sale period. We find that in our data, there were 2,703 such sale events, with a total of 6,876 regular price changes. Therefore, we would miss 4,173 regular price changes (2.8% of all regular price changes) if we relied on sale flags.

In Appendix H, we show that missing sales would not change the overall conclusion about the median frequency of price changes, but it would lead to a slight overestimation of the regular price rigidity in 5 out of 25 categories. Thus, sale flags could be a reasonable substitute for information on regular prices. The main concern when using sale flags is that it might lead to slightly overestimating the price rigidity, especially in product categories with volatile prices, such as fresh produce, and in categories

characterized by long sales (sausages, juices, and grooming products in our data).

We also find that 55.4% and 16.4% of all price changes during sales take place in the first and last weeks of the sale period, respectively. Only 28.2% of the price changes during sales occur in other weeks. Thus, if one is concerned about the timing of a regular price change during a sale, the best guess is that the change occurred in the first week of the sale. The sales filter of Nakamura and Steinsson's (2008) is based on this assumption.

6.4. Generalizability of the results

Our data come from retail supermarkets and drugstores in Israel. Therefore, it is not clear whether our results can be generalized to other sectors of the economy, or whether they can be extrapolated to other countries.

There are, however, reasons to believe that the results can be generalized to other countries. First, Volpe and Li (2012) find that sales that last several months are common in the US. In addition, in our Canadian data, we find that 13% of the sales last more than 6 weeks, with the longest sales lasting 13 weeks. Also, when retailers hold long sales and set the price at the regular price only occasionally, the resulting transaction price series is characterized by occasional short-lived price hikes. Syed (2015) reports that such patterns are common in a dataset of a large US food retailer as well.

In addition, our results using the Canadian data suggest that filter-generated regular prices can deviate significantly from the actual regular prices. We find that although the actual regular prices are fairly flexible with the median price changing every 4 months, the median filter-generated regular prices change every 6–11.75 months.

We also find that although small regular price changes are more common in Canada than in Israel, sales filters lead to overestimation. Thus, although the results from Canada should be taken with a grain of salt because the sample is small and not necessarily representative, they are in line with the results from Israel about the effect of sales filters: in both datasets, the filter-generated regular prices differ from the actual regular prices.

Both our datasets focus on food retailers and drugstores. We therefore acknowledge that it is not immediately clear whether they are representative of the full spectrum of the products and services CPI covers. Nevertheless, although our data covers only a portion of the CPI, it might still be important. First, food retailers and drugstores of the type that we cover in this work are responsible for about 16%–17% of the Israeli CPI, which is not trivial. Second, as Eichenbaum et al. (2011) argue, the median price change frequency of

food products is often close to the median of the CPI basket. Third, other manufactured goods also tend to be offered at stores that offer discounts (Nakamura and Steinsson 2008). Our results might, therefore, be relevant for a broad spectrum of products.

7. Conclusion

We study regular and transaction price data using two unique datasets. We find that transaction prices are quite flexible, while regular prices are rigid: the median transaction (regular) price changes every 0.13 (1.61) years in weekly data, and every 0.11 (1.5) years in daily data. We also find that small regular price changes are rare: In weekly data, 1.2% of all price changes are smaller than 1%, and 13.5% are smaller than 5%. In daily data, 0.9% of all price changes are smaller than 1%, and 11% are smaller than 5%.

We also find that filter-generated regular prices fail to capture many properties of the actual regular prices. First, the filter-generated regular prices change too often. In weekly (daily) data, the median regular price changes every 24 (193), 55 (293), 33 (190), and 27 (146) weeks (days) according to Nakamura and Steinsson (2008), Eichenbaum, et al. (2011), Chahrour (2011), and Kehoe and Midrigan (2011) filters, respectively. These figures are much smaller than the corresponding figures for the actual regular prices.

Filter-generated regular prices also contain too many small price changes. In weekly (daily) data, 2.6% (1.8%), 2.7% (3.0%), 2.7% (2.8%), and 2.6% (2.7%) of all price changes are smaller than 1% according to sales filters of Nakamura and Steinsson (2008), Eichenbaum et al (2011), Chahrour (2011), and Kehoe and Midrigan (2011), respectively. These figures are more than double the corresponding figures for the true regular prices.

These results are important for several reasons. First, our findings suggest that studying price rigidity at weekly and daily frequency yields similar results. Second, Alvarez et al. (2016) show that in many sticky price models, the effect of a small monetary shock on the real economy is proportional to the ratio of the kurtosis of the distribution of the size of price changes and the average annual number of price changes. We find that the kurtosis of the distribution of the size of regular price changes is slightly leptokurtic, 3.79 in weekly data and 3.75 in daily data. Combined with rigid regular prices, this implies that the expected effect of a monetary shock is large.

Third, these findings are consistent with Cavallo and Rigobon (2016) and Cavallo (2018) who use scraped data from several countries, including the US, the UK, Japan, and Germany. They show that the likelihood of observing a small price change in scraped

data is much lower than in scanner data or CPI data. They argue that scanner datasets contain too many small price changes (and too many price changes in general) due to measurement errors, and that CPI data contain too many small price changes due to imputation of missing observations. Our results corroborate their conclusions by showing that when the quality of the data is high, small price changes are rare. We also extend their work, first because we use data from brick-and-mortar stores as well as online stores. Second, because we have direct observations on the actual regular prices, we are able to show that the results they report using transaction and filter-generated regular prices, hold for the actual regular prices as well.

Fourth, based on their findings, Cavallo and Rigobon (2016) and Cavallo (2018) argue that literature gives too much weight to models that generate large numbers of small price changes. Consistent with their findings, our results suggest that in high-quality data, the main predictions of menu cost models hold quite well: price changes are rare, and when prices do change, the changes are usually large.

Fifth, sales filters generate regular price series whose properties differ from those of the actual regular prices. In particular, sales filters generate frequent "spurious" regular price changes, and especially, small regular price changes. Consequently, menu cost estimates based on filter-generated regular prices, are likely downward biased. In this respect, sales filters introduce systematic noise that resembles the noise generated by measurement errors in scanner data and by imputed prices in CPI data. Sales filters also tend to underestimate the variation in the price rigidity across products.

Our results further suggest that in an environment of low inflation, the simple filter of Eichenbaum et al. (2011) performs somewhat better, in terms of the median and variance of the spells between price changes, than other filters. This is so because the filter's emphasis on set periods makes it more resilient to changes in long-lasting sale prices. However, it is possible that combining several filters might yield even better results. For example, using flexible filters, such as Nakamura and Steinsson's (2008), Chahrour's (2011), or Kehoe and Midrigan's (2015) for product categories with more volatile regular prices, such as fresh produce and condiments, while using Eichenbaum's et al.'s (2011) filter for product categories with rigid prices (see Tables 1 and 2).

Our Canadian dataset also suggests that when regular prices are more flexible, Eichenbaum et al.'s (2011) filter underestimates price rigidity. When choosing a sales filter, therefore, it is important to consider the properties of the price data.

Sixth, sales filters mistakenly identify changes in sale prices as changes in regular prices because sales often last long periods, whereas sales filters typically assume that sales do not last more than 4–6 weeks. Indeed, the price trajectories of some products, such as Potato Chips in Figure 1, are dominated by long periods of "sale" prices, with the price trajectory hitting the "regular" price for only short periods. In such cases, the actual regular prices are much more rigid than the corresponding filter-generated regular prices.

This raises a question about the "best" definition of regular prices. If sale prices last several months, should we consider them to be the "true" regular prices? It is important to note, however, that the cost of changing a posted regular price is higher than the cost of changing a sale price, even if it is a long-lasting sale price. In Israel, this is partly because the retailers are subject to an item-pricing law (Bergen et al. 2008). But the cost of changing a posted regular price is likely to be higher than the cost of changing a sale price even in the absence of such laws, for example, because of consumer antagonization costs (Rotemberg 2005, Anderson and Simister 2010) or implicit contracts (Blinder 1991 and 1994, Blinder et al. 1998, Levy and Young, 2004).

Seventh, a possible explanation for the existence of long-lasting sales in our data is that retailers that are uncertain about future demand might prefer to change sale prices rather than regular prices. Long-lasting sale prices, a phenomenon that was observed in the US and other countries (Li and Volpe, 2012), might serve retailers as a mechanism for maintaining price flexibility in the face of high price adjustment costs of regular prices.

Eighth, the setting in Israel, with high costs of regular price changes and low costs of sale price changes, resembles the setting modeled in Midrigan (2011) and Kehoe and Midrigan (2015). However, these models predict more frequent small price changes and higher kurtoses than we find in the data.

Future work should consider models with multi-product retailers, where menu costs lead to a low likelihood of price changes and a distribution of the size of price changes that include both a very low likelihood of small price changes, together with fatter tails than predicted by Golosov and Lucas (2007). In addition, it will be beneficial to consider the role that long "sales" play in retail pricing strategies when studying price rigidity.

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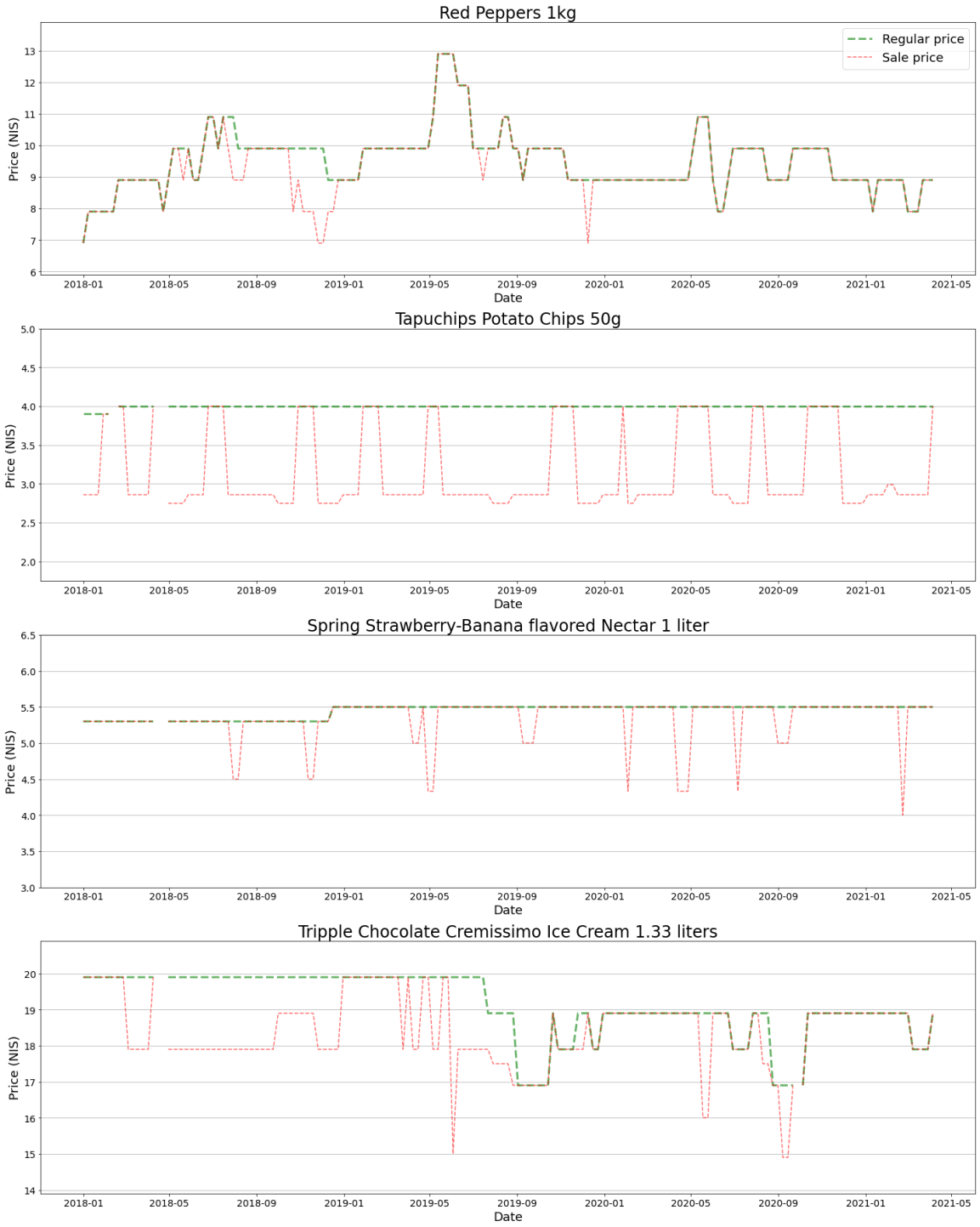
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Map 1. The location of the sampled stores



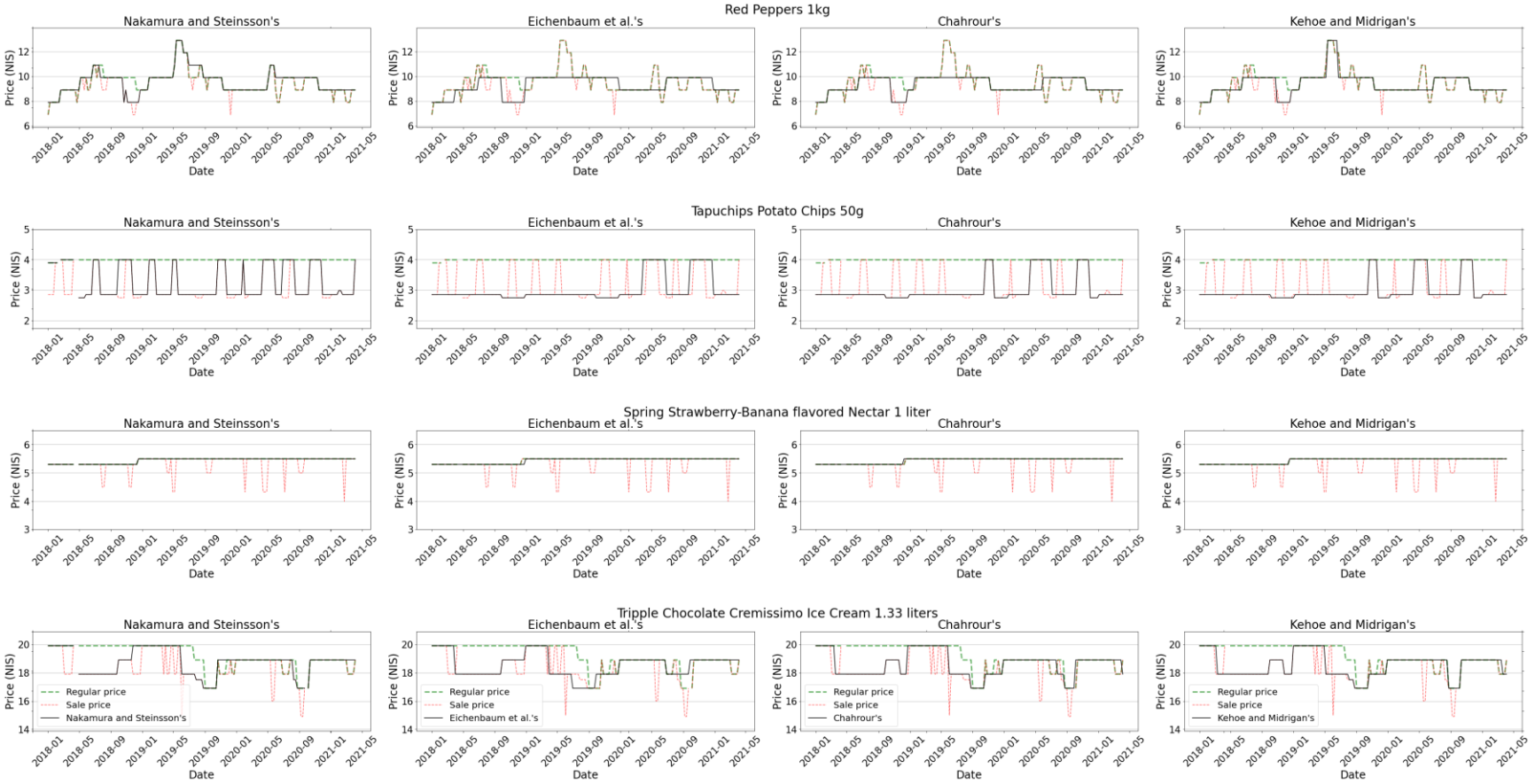
Note: The Southern part of Israel, which is mostly desert, and which includes the city of Eilat, is not shown. The full map can be accessed at http://tinyurl.com/4dx8bvu8.

Figure 1. Actual regular and transaction prices of four products, weekly frequency



Notes: Weekly data from store 18 of Shufersal.

Figure 2. Actual regular prices vs. generated regular prices, weekly frequency



Notes: Weekly data from store 18 of Shufersal.

Figure 3. Histograms of the size of the normalized regular (actual and generated) and transaction price changes, weekly data

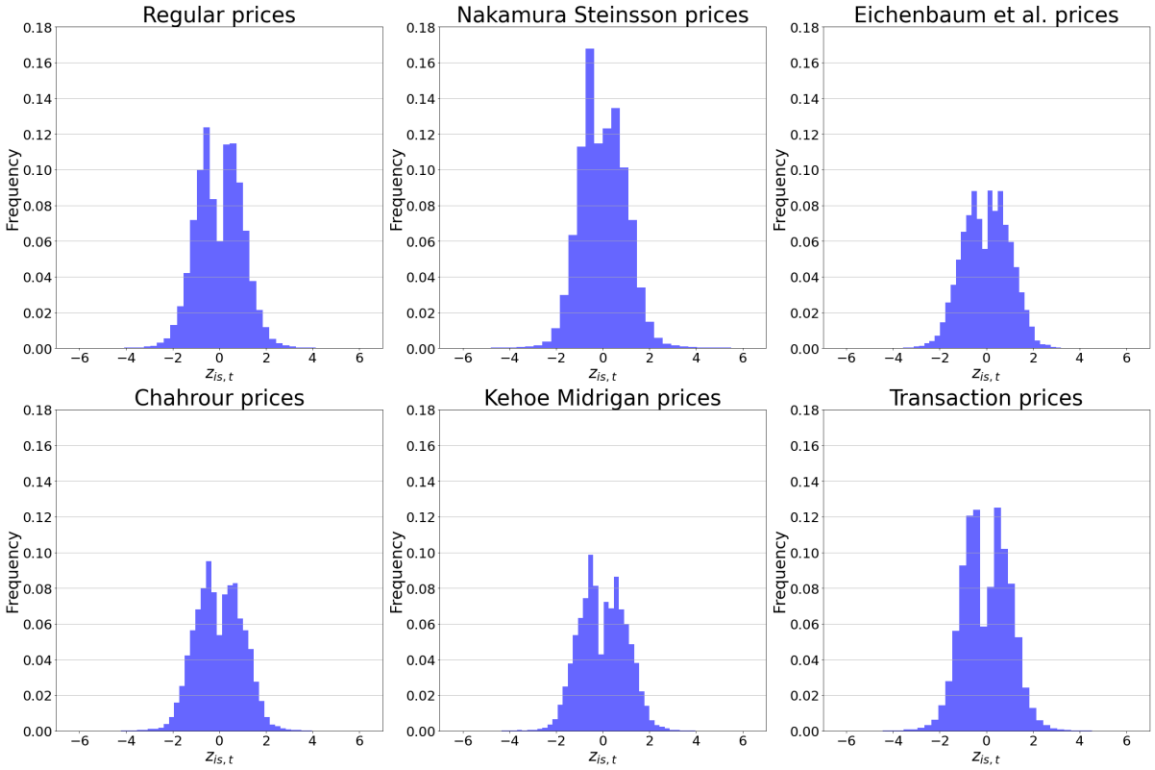
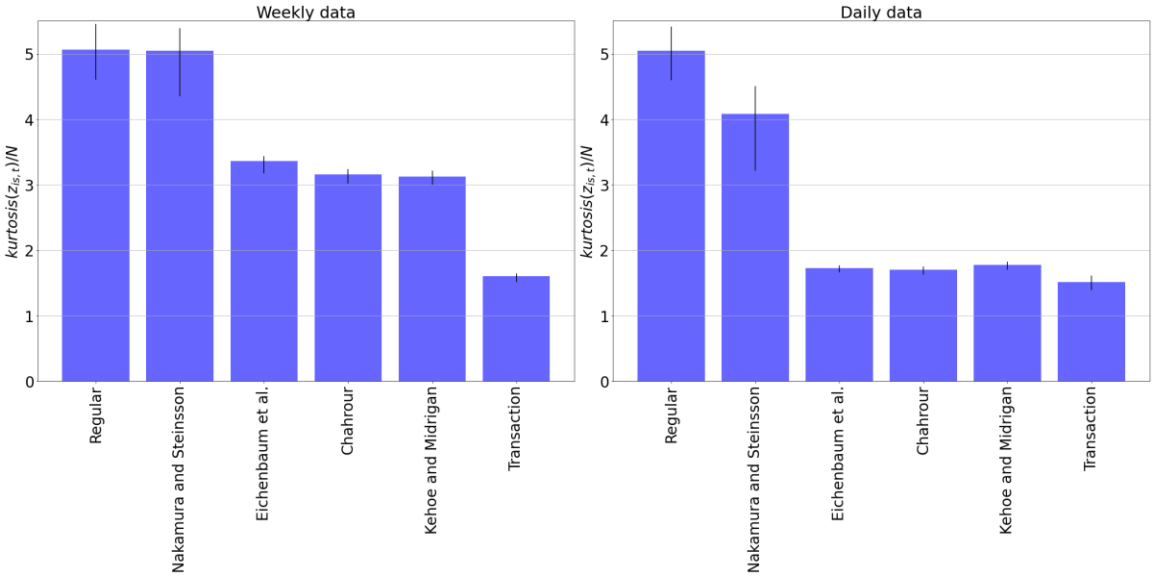


Figure 4. Sufficient statistics, weekly and daily data



Notes: The figure depicts $kurtosis(z_{is,t})/N$, where $z_{is,t}$ is the normalized log price change, and N is the average number of price changes per year (Alvarez et al., 2016). The LHS panel uses weekly data. The RHS panel uses daily data. The black lines denote 95% bootstrapped confidence intervals.

Table 1. Frequency of price changes

categories	Actual regular prices	Generated regular prices, Nakamura-Steinsson	Generated regular prices, Eichenbaum et al.	Generated regular prices, Chahrour	Generated regular prices, Kehoe and Midrigan	Actual transaction prices
alcoholic beverages	0.036 (0.030, 0.047)	0.095 (0.089, 0.095)	0.036 (0.030, 0.036)	0.060 (0.059, 0.065)	0.065 (0.065, 0.071)	0.167 (0.155, 0.178)
baby products	0.018 (0.012, 0.018)	0.053 (0.047, 0.060)	0.030 (0.030, 0.030)	0.048 (0.042, 0.053)	0.048 (0.047, 0.053)	0.272 (0.260, 0.290)
baking goods	0.006 (0.006, 0.006)	0.012 (0.006, 0.012)	0.006 (0.006, 0.012)	0.012 (0.006, 0.018)	0.012 (0.006, 0.018)	0.030 (0.012, 0.042)
bread	0.024 (0.024, 0.030)	0.006 (0.006, 0.012)	0.006 (0.006, 0.006)	0.006 (0.006, 0.006)	0.006 (0.006, 0.012)	0.101 (0.089, 0.107)
canned food	0.006 (0.006, 0.006)	0.047 (0.047, 0.053)	0.024 (0.024, 0.024)	0.036 (0.036, 0.041)	0.041 (0.036, 0.042)	0.095 (0.089, 0.101)
cereals	0.024 (0.018, 0.024)	0.083 (0.071, 0.089)	0.030 (0.024, 0.036)	0.041 (0.036, 0.053)	0.047 (0.036, 0.053)	0.207 (0.195, 0.225)
cleaning materials	0.036 (0.036, 0.041)	0.047 (0.047, 0.053)	0.024 (0.024, 0.030)	0.041 (0.041, 0.041)	0.047 (0.047, 0.048)	0.155 (0.149, 0.160)
coffee & tea	0.006 (0.006, 0.006)	0.006 (0.006, 0.006)	0.006 (0.000, 0.006)	0.006 (0.006, 0.006)	0.006 (0.006, 0.012)	0.036 (0.024, 0.036)
condiments	0.077 (0.054, 0.083)	0.054 (0.053, 0.059)	0.024 (0.024, 0.030)	0.053 (0.047, 0.053)	0.053 (0.053, 0.054)	0.143 (0.136, 0.149)
cooking oil	0.083 (0.071, 0.089)	0.059 (0.048, 0.065)	0.036 (0.030, 0.036)	0.059 (0.054, 0.059)	0.065 (0.059, 0.071)	0.183 (0.178, 0.195)
dairy products	0.006 (0.006, 0.006)	0.012 (0.012, 0.012)	0.012 (0.012, 0.012)	0.012 (0.012, 0.018)	0.018 (0.018, 0.018)	0.065 (0.065, 0.071)
Fish & meat	0.024 (0.012, 0.041)	0.027 (0.018, 0.041)	0.018 (0.018, 0.018)	0.024 (0.024, 0.024)	0.024 (0.024, 0.030)	0.107 (0.077, 0.107)
frozen fish & meat	0.030 (0.030, 0.036)	0.095 (0.089, 0.107)	0.041 (0.041, 0.042)	0.071 (0.062, 0.071)	0.077 (0.071, 0.077)	0.201 (0.195, 0.202)
Fruits & vegetables	0.211 (0.193, 0.222)	0.094 (0.088, 0.099)	0.041 (0.035, 0.041)	0.058 (0.053, 0.058)	0.058 (0.058, 0.064)	0.274 (0.251, 0.292)
grooming products	0.065 (0.041, 0.083)	0.095 (0.083, 0.107)	0.036 (0.036, 0.041)	0.053 (0.053, 0.059)	0.071 (0.065, 0.083)	0.179 (0.166, 0.219)
humus & spreads	0.012 (0.006, 0.012)	0.012 (0.012, 0.018)	0.012 (0.006, 0.012)	0.012 (0.012, 0.018)	0.018 (0.018, 0.024)	0.077 (0.065, 0.077)
ice cream	0.083 (0.071, 0.101)	0.065 (0.065, 0.071)	0.047 (0.042, 0.048)	0.071 (0.065, 0.071)	0.071 (0.071, 0.071)	0.183 (0.167, 0.183)
juices	0.012 (0.012, 0.012)	0.095 (0.095, 0.095)	0.036 (0.036, 0.041)	0.065 (0.054, 0.065)	0.077 (0.065, 0.077)	0.178 (0.172, 0.189)
rice & pasta	0.012 (0.006, 0.012)	0.036 (0.030, 0.041)	0.018 (0.012, 0.018)	0.030 (0.030, 0.036)	0.030 (0.030, 0.036)	0.112 (0.107, 0.124)
sausages	0.059 (0.047, 0.065)	0.071 (0.059, 0.071)	0.024 (0.024, 0.036)	0.041 (0.030, 0.047)	0.053 (0.047, 0.059)	0.137 (0.131, 0.148)
shampoo & bath soap	0.047 (0.047, 0.048)	0.083 (0.077, 0.089)	0.036 (0.036, 0.041)	0.059 (0.053, 0.065)	0.071 (0.065, 0.071)	0.201 (0.195, 0.213)
Snacks and sweets	0.006 (0.006, 0.006)	0.059 (0.054, 0.065)	0.030 (0.030, 0.030)	0.042 (0.041, 0.047)	0.054 (0.048, 0.059)	0.166 (0.160, 0.167)
soft drinks	0.006 (0.006, 0.006)	0.024 (0.018, 0.030)	0.018 (0.012, 0.018)	0.018 (0.018, 0.024)	0.024 (0.018, 0.024)	0.065 (0.059, 0.071)
toilet paper, wipes and plastic bags	0.042 (0.036, 0.053)	0.036 (0.036, 0.042)	0.024 (0.018, 0.024)	0.036 (0.036, 0.042)	0.041 (0.036, 0.048)	0.118 (0.112, 0.130)
toothpaste & toothbrush	0.036 (0.030, 0.042)	0.047 (0.041, 0.056)	0.018 (0.018, 0.024)	0.036 (0.030, 0.041)	0.047 (0.041, 0.053)	0.160 (0.148, 0.181)
Total	0.012 (0.012, 0.012)	0.041 (0.041, 0.041)	0.018 (0.018, 0.018)	0.030 (0.030, 0.036)	0.036 (0.036, 0.041)	0.125 (0.124, 0.130)

Notes: The median frequency of the actual regular price changes, the generated regular price series using the sales filters of Nakamura and Steinsson (2008), Eichenbaum et al. (2011), Chahrour (2008), and Kehoe and Midrigan's (2015), and the actual transaction prices. The observations are at a weekly frequency.

Table 2. The expected number of weeks between price changes

categories	Actual regular prices	Generated regular prices, Nakamura-Steinsson	Generated regular prices, Eichenbaum et al.	Generated regular prices, Chahrour	Generated regular prices, Kehoe and Midrigan	Actual transaction prices
alcoholic beverages	28 (21, 33)	11 (10, 11)	28 (28, 33)	16 (15, 16)	15 (14, 15)	5 (5, 6)
baby products	56 (55, 83)	18 (16, 21)	33 (33, 33)	20 (18, 23)	20 (18, 21)	3 (3, 3)
baking goods	168 (168, 168)	84 (83, 168)	167 (84, 168)	84 (56, 168)	84 (56, 167)	33 (23, 83)
bread	41 (41, 42)	84 (84, 167)	168 (168, 168)	167 (167, 168)	167 (84, 167)	9 (9, 11)
canned food	168 (168, 168)	20 (18, 21)	42 (41, 42)	27 (24, 28)	24 (23, 27)	10 (9, 11)
cereals	42 (41, 55)	13 (11, 13)	33 (28, 41)	24 (18, 28)	21 (18, 27)	4 (4, 5)
cleaning materials	28 (24, 28)	20 (18, 21)	41 (33, 42)	24 (24, 24)	21 (20, 21)	6 (6, 6)
coffee & tea	168 (168, 168)	168 (167, 168)	168 (168, Inf)	168 (168, 168)	168 (84, 168)	28 (27, 41)
condiments	12 (12, 18)	18 (16, 18)	41 (33, 42)	18 (18, 21)	18 (18, 18)	6 (6, 7)
cooking oil	12 (11, 14)	16 (15, 20)	28 (28, 33)	16 (16, 18)	15 (14, 16)	5 (5, 5)
dairy products	167 (167, 168)	84 (83, 84)	84 (84, 84)	83 (56, 83)	56 (56, 56)	15 (14, 15)
Fish & meat	42 (24, 84)	37 (24, 56)	56 (55, 56)	42 (41, 42)	42 (33, 42)	9 (9, 12)
frozen fish & meat	33 (28, 33)	10 (9, 11)	24 (24, 24)	14 (9, 16)	12 (12, 14)	4 (4, 5)
Fruits & vegetables	4 (4, 5)	10 (10, 11)	24 (24, 28)	17 (17, 18)	17 (15, 17)	3 (3, 3)
grooming products	15 (12, 24)	9 (9, 12)	28 (24, 28)	18 (16, 18)	14 (12, 15)	5 (4, 6)
humus & spreads	84 (84, 167)	83 (56, 84)	84 (84, 167)	83 (56, 84)	55 (42, 56)	12 (12, 15)
ice cream	12 (9, 13)	15 (14, 15)	21 (20, 23)	14 (14, 15)	14 (13, 14)	5 (5, 5)
juices	84 (84, 84)	10 (10, 10)	27 (24, 28)	15 (15, 18)	12 (12, 15)	5 (5, 5)
rice & pasta	84 (84, 167)	28 (24, 33)	56 (56, 83)	33 (28, 33)	33 (28, 33)	8 (8, 9)
sausages	16 (15, 21)	14 (14, 16)	41 (28, 42)	24 (21, 33)	18 (16, 21)	7 (6, 7)
shampoo & bath soap	21 (20, 21)	11 (11, 12)	27 (24, 28)	16 (15, 18)	14 (14, 15)	4 (4, 5)
Snacks and sweets	168 (168, 168)	16 (15, 18)	33 (33, 33)	23 (21, 24)	18 (16, 20)	6 (5, 6)
soft drinks	168 (167, 168)	42 (33, 55)	56 (56, 84)	55 (42, 56)	42 (41, 55)	15 (14, 16)
toilet paper, wipes and plastic bags	23 (18, 27)	24 (23, 28)	42 (41, 55)	27 (23, 28)	24 (20, 27)	8 (7, 8)
toothpaste & toothbrush	28 (23, 33)	23 (17, 24)	56 (42, 56)	27 (23, 33)	21 (18, 24)	6 (5, 6)
Total	84 (84, 84)	24 (24, 24)	55 (55, 56)	33 (28, 33)	27 (24, 27)	7 (7, 8)

Notes: The implied duration between price changes, in weeks, calculated as $-[ln(1-f)]^{-1}$, where f is the median frequency of price changes, taken from Table 1.

Table 3. Summary statistics of the size of price changes

	Skewness	Kurtosis	$\sigma_{\lvert z_{is,t}\rvert}/\bar{z}_{is}$	$\lvert z_{is,t}\rvert$<0.5× $\bar{z}_{is}$	$\lvert z_{is,t}\rvert$<0.25× $\bar{z}_{is}$
Actual regular prices	0.005	3.791	0.687	0.244	0.090
Generated regular prices, Nakamura and Steinsson	0.216	5.137	0.742	0.264	0.113
Generated regular prices, Eichenbaum et al.	–0.061	2.810	0.683	0.263	0.124
Generated regular prices, Chahrour	0.011	2.938	0.675	0.255	0.114
Generated regular prices, Kehoe and Midrigan	0.022	2.956	0.671	0.249	0.110
Actual transaction prices	0.009	3.243	0.657	0.227	0.083

Notes: The table reports summary statistics of the distribution of the size of price changes. $z_{is,t} = \left(\Delta p_{is,t} - \overline{\Delta p_{is}}\right)/\sigma_{is}$, where $p_{is,t}$ is the price of product i in store s at week t, $\Delta p_{is,t}$, are log price changes, $\overline{\Delta p_{is}}$ is the average log price changes at the store-category level, and σ_{is} is the standard deviation of the log price changes at the store-category level. Data at weekly frequency.

Table 4. Share of price changes smaller than 1%–5%

	< 1%	< 2%	< 3%	< 4%	< 5%
Actual regular prices	0.012	0.036	0.063	0.108	0.135
Generated regular prices, Nakamura and Steinsson	0.026	0.050	0.076	0.123	0.150
Generated regular prices, Eichenbaum et al.	0.027	0.052	0.080	0.147	0.173
Generated regular prices, Chahrour	0.027	0.048	0.071	0.124	0.149
Generated regular prices, Kehoe and Midrigan	0.026	0.046	0.069	0.120	0.145
Actual transaction prices	0.017	0.030	0.045	0.077	0.096

Notes: The table reports the share of non-zero log price changes that are smaller than 1%, 2%, 3%, 4% and 5%. Weekly data.

Online Supplementary Web Appendix

Sales Filters and Rigidity of Regular Prices

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Table of contents **Page**

Appendix A.	Summary statistics of the Chains	2
Appendix B.	Summary statistics of the products, by product category	4
Appendix C.	The locations of the sampled stores	6
Appendix D.	The effect of capped prices	9
Appendix E.	Summary statistics of the size of price changes, with the outliers included	12
Appendix F.	Histograms of the size of price changes in NIS	15
Appendix G.	Analyses of the Daily Data	18
Appendix H.	Excluding sales that cannot be detected by using a sale flag	28
Appendix I.	Analyses of the Canadian Data	31
Appendix J.	Uniform pricing	36
References		39

Appendix A. Summary statistics of the Chains

Our data come from the 11 largest food retail chains and one drugstore chain (SuperPharm) in Israel. Table A1 summarizes the descriptive statistics for the products offered by each chain. The first column contains the list of the chains. The second column gives the number of stores that are included in our data sample for each chain.[1] The third column reports the number of products (as identified by their UPCs), for which we have data. In total, we have information on 2,403 different products. The drugstore chain, SuperPharm, offers only 536 of these products, while the largest food retailer, Shufersal, offers 2,370 of them.

The fourth and fifth columns give information about the average regular and transaction prices, respectively. If we focus on food retailers and ignore Maayan 2000 which offers only a small selection of the products in our dataset, the lowest average prices are offered by Osher-Ad and Rami Levi Shivuk Hashikma, with average transaction prices of NIS 15.34 and NIS 15.35, respectively. The highest average transaction price is offered by Tiv-Taam, which promotes itself as a premium retailer, NIS 19.79.

The sixth column gives the share of prices that are promoted as sales by each chain. It seems that most of the retailers in our dataset use sales extensively. On average, 31.66% of all the prices in the dataset are promoted as sale prices. Tiv-Taam is an exception: it promotes only 9.51% of all prices as sales.

The final column gives the total number of observations per retailer, where an observation is the price of product i offered in store s on day t. In total, our data set contains 107,739,819 observations.

[1] The number of brick-and-mortar stores we sampled for each chain, corresponds to their respective market shares. If a chain operates an online store, we have also collected information on the prices of the online store. See also Appendix C.

Table A1. Summary statistics of the sampled chains and the products offered by each chain

Retail chain	**No. of stores**	**No. of products**	**Average regular price (NIS)**	**Average transaction price (NIS)**	**% of sales**	**No. of observations**
Maayan 2000	1	706	13.38 (10.34)	12.18 (9.55)	42.61%	16,130
Freshmarket	3	1,632	16.19 (12.27)	15.54 (12.20)	22.84%	2,388,701
Kol Bo Hatzi Hinam	3	1,672	17.39 (14.12)	16.43 (13.52)	21.19%	2,769,167
Machsanei-Hashuk	3	1,844	17.97 (14.45)	16.09 (13.30)	50.26%	3,382,639
Tiv-Taam	4	1,727	20.17 (17.68)	19.79 (17.54)	9.51%	4,149,349
Victory	6	1,753	17.55 (13.78)	16.04 (12.81)	37.97%	6,179,834
M. Yohananof and his sons	8	1,664	16.09 (12.39)	15.39 (12.09)	25.98%	9,613,243
Osher-Ad	10	1,081	16.06 (11.93)	15.34 (11.78)	30.14%	6,979,455
Yenot Bitan	13	1,712	16.18 (12.77)	15.45 (12.54)	26.43%	8,081,907
Rami Levy Shivuk Hashikma	17	1,791	16.62 (12.87)	15.35 (12.10)	38.96%	20,926,120
Shufersal	37	2,370	16.97 (13.42)	15.86 (12.79)	31.66%	42,870,451
SuperPharm (drugstore)	1	536	30.34 (20.32)	28.93 (20.20)	17.40%	382,823
Total	106	2,403	16.93 (13.40)	15.88 (12.84)	31.66%	107,739,819

Notes: The table gives descriptive summary statistics about the chains, stores, and products that are included in our dataset. The first column lists the chains sampled. The second column gives the number of stores for which we have information. The third column gives the number of products for which we have information and that were offered by the retailer. The fourth and fifth columns give the average regular and transaction prices, respectively (standard deviations in parenthesis). The sixth column gives the % of observations that are defined as sale prices by retailer. The last column gives the total number of observations for each chain.

Appendix B. Summary statistics of the products, by product category

Table B1 gives summary statistics of the products in our sample, by product categories. The first column lists the product categories. The second column gives the number of products per category, where a product is defined by its UPC. The third and fourth columns give the average regular and transaction prices, respectively. The average prices vary significantly across categories. The lowest average regular and transaction prices are found in the fruits and vegetables category, NIS 7.54 and NIS 7.29, respectively. The highest average regular and transaction prices are found in the baby products category, NIS 46.66 and NIS 43.86, respectively. I.e., the lowest and the highest average prices differ by a factor of 6.

The fifth column gives the share of sale prices in each category. Again, there is a large variation across categories. The minimum share of sale prices is found in the baking goods category, with 8.47% of the prices promoted as sales. The maximum share of sale prices is found in the juices category, with 53.70% of the prices promoted as sales. The final column gives the total number of observations per category, where an observation is the price of product i offered in store s on day t.

Table B1. Summary statistics of the products sampled

Product category	No. of products	Average regular price (NIS)	Average transaction price (NIS)	% sales	No. of observations
alcoholic beverages	169	34.00 (21.10)	31.30 (20.16)	44.67%	6,332,550
baby products	99	46.66 (16.84)	43.86 (17.37)	38.78%	4,147,373
baking goods	81	11.04 (7.10)	10.89 (7.12)	8.47%	2,382,858
bread	72	13.01 (3.05)	12.67 (3.14)	12.60%	2,485,371
canned food	103	10.78 (5.96)	10.24 (5.93)	25.87%	3,932,491
cereals	64	20.07 (5.06)	17.53 (4.91)	41.93%	2,588,744
cleaning materials	196	20.40 (10.69)	19.26 (10.48)	30.52%	9,261,884
coffee & tea	61	18.24 (7.84)	17.74 (7.65)	11.76%	3,157,551
condiments	33	11.79 (4.11)	11.39 (4.13)	16.84%	1,399,529
cooking oil	40	28.37 (9.74)	27.46 (9.91)	21.12%	1,566,809
dairy products	261	10.16 (6.79)	9.86 (6.69)	15.36%	16,470,457
fish & meat	8	28.65 (11.82)	26.61 (11.59)	33.13%	520,713
frozen fish & meat	37	32.73 (8.43)	29.10 (8.17)	42.13%	1,752,192
fruits & vegetables	13	7.54 (3.77)	7.29 (3.86)	11.80%	1,294,580
grooming products	75	20.67 (18.86)	19.19 (18.71)	31.26%	1,516,288
hummus & spreads	44	12.96 (7.48)	12.21 (7.35)	32.04%	2,415,371
ice cream	41	20.13 (2.94)	18.90 (2.79)	31.76%	2,068,116
juices	99	9.68 (6.14)	8.93 (6.23)	53.70%	5,704,229
rice & pasta	107	9.86 (7.81)	9.17 (7.99)	44.82%	4,756,875
sausages	39	23.06 (6.20)	21.81 (5.99)	30.06%	2,031,843
shampoo & bath soap	195	15.61 (6.91)	14.26 (6.70)	40.94%	6,241,754
snacks & sweets	313	10.76 (7.56)	9.88 (7.47)	41.78%	14,400,660
soft drinks	73	10.45 (9.24)	9.92 (9.31)	37.95%	4,873,141
toilet paper, wipes and plastic bags	79	25.89 (9.21)	24.96 (9.34)	20.67%	3,163,593
toothpaste & toothbrush	101	20.55 (8.44)	19.00 (7.97)	27.81%	3,274,847
Total	2403	16.93 (13.40)	15.88 (12.84)	31.66%	107,739,819

Notes: The table gives summary statistics about products sampled by category. The first column lists the product categories. The second column gives the number of products (UPCs), by category. The third and fourth columns give the average regular and transaction prices, respectively with standard deviations in the parenthesis. The fifth column gives the % of observations that are defined as sale prices, by category. The last column gives the total number of observations.

Appendix C. The locations of the sampled stores

Table C1. The stores' addresses

Chain	Store	Street address	City
Freshmarket	21	Big Center	Kiryat-Ata
Freshmarket	22	Ofer Hasharon Mall	Netanya
Freshmarket	35	Yoseftal 92	Bat-Yam
Kol Bo Hatzi Hinam	1	Hachsharat Hayeshuv 3	Rishon-Lezion
Kol Bo Hatzi Hinam	6	Racoon 2	Hod-Hasharon
Kol Bo Hatzi Hinam	101	Online	Online
M. Yohananof and his sons	5	Star Center	Ashdod
M. Yohananof and his sons	7	King Hasan 1	Kiryat-Akron
M. Yohananof and his sons	13	Hutzot Hamifratz, Haifa	Haifa
M. Yohananof and his sons	17	Yishparo Center	Modiin
M. Yohananof and his sons	24	Atir Yeda 1	Kfar-Sava
M. Yohananof and his sons	30	Hatzoran 2	Netanya
M. Yohananof and his sons	31	Centro Center	Rehovot
M. Yohananof and his sons	32	Ben Tzvi 112	Tel Aviv
Maayan 2000	50	Online	Online
Machsanei-Hashuk	40	Yahadut Drom Afrika 14	Ofakim
Machsanei-Hashuk	51	Bar Yehuda 147	Nesher
Machsanei-Hashuk	80	Derech Hamehachrerim 100	Beer-Sheeva
Osher-Ad	1	Haitztadion 11	Migdal Haemek
Osher-Ad	3	Beit Hadfus 29, Givat Shaul	Jerusalem
Osher-Ad	5	Hans Mueller 6	Kiryat-Bialik
Osher-Ad	9	Baalei Hamelacha 4	Ashdod
Osher-Ad	10	Ben Tzion Glis 30	Petah-Tikva
Osher-Ad	11	Hakishon 11	Bnei-Brak
Osher-Ad	13	Hakotzer 15	Beer-Sheeva
Osher-Ad	14	Hamasger 22	Hadera
Osher-Ad	15	Gilboa 1	Nazareth-Ilit
Osher-Ad	24	Kramnitzki 3	Tel-Aviv
Rami Levy Shivuk Hashikma	3	Derch Hachoresh 90	Jerusalem
Rami Levy Shivuk Hashikma	7	Mevaseret Tzion Mall	Mevaseret Zion
Rami Levy Shivuk Hashikma	11	Hankin Yehushua 14	Afula
Rami Levy Shivuk Hashikma	14	Hamvreg 1	Tiberias
Rami Levy Shivuk Hashikma	19	Halutzei Hataasia 73	Haifa
Rami Levy Shivuk Hashikma	24	Haorzim 4	Netanya
Rami Levy Shivuk Hashikma	31	Tzomet Beit Hagdi	Netivot
Rami Levy Shivuk Hashikma	32	Hayotzrim 2	Neharia
Rami Levy Shivuk Hashikma	33	Galgalei Hapladas 2	Kfar-Sava
Rami Levy Shivuk Hashikma	39	Online	Online
Rami Levy Shivuk Hashikma	40	Hakishon 9	Yavne
Rami Levy Shivuk Hashikma	42	Shderot Hatzionut 1	Lod
Rami Levy Shivuk Hashikma	43	Cinema City	Rishon-Lezion
Rami Levy Shivuk Hashikma	45	Haamal 20	Bat-Yam

Rami Levy Shivuk Hashikma	55	Dvora Hanevia 127	Tel-Aviv
Rami Levy Shivuk Hashikma	56	Tzahal 99	Ashkelon
Rami Levy Shivuk Hashikma	57	Azrieli Center, Haifa	Haifa
Shufersal	18	Keren Hayesod 3	Holon
Shufersal	22	Smilanski 22	Netanya
Shufersal	28	Tzahal 71	Tel-Aviv
Shufersal	33	Tsharnihovski 35	Haifa
Shufersal	61	Haarava 17	Tzur Moshe
Shufersal	71	Bar Yehuda 147	Nesher
Shufersal	72	Lev Reut Center	Reut
Shufersal	84	Yonatan 1	Bet Hashmonai
Shufersal	95	Orot Mall	Or Akiva
Shufersal	118	Hasatat 15	Eilat
Shufersal	128	Nahum Hat 5	Tirat-Hakarmel
Shufersal	132	Hashalom Center	Tel-Aviv
Shufersal	147	Hohit 16	Zichron-Yaacov
Shufersal	151	Renanim Shopping Center	Raanana
Shufersal	152	Yishpao Center, Kiryat Haomanim	Arad
Shufersal	171	Osteshinski 15	Kfar-Sava
Shufersal	189	Derech Habanim 17	Pardes-Hana
Shufersal	190	Hagalil Haelyon Mall	Hatzor-Haglilit
Shufersal	199	Ort Israel 25	Bat-Yam
Shufersal	205	Altalef 4	Yahud
Shufersal	208	Yerushalaim Hashlema 52	Eilat
Shufersal	227	Derech Haifa 40	Kiryat-Ata
Shufersal	230	Weitzman 29	Kfar-Sava
Shufersal	232	Alonim St.	Tzfat
Shufersal	241	Ayalon Mall	Bnei-Brak
Shufersal	260	Talpyot Mall	Jerusalem
Shufersal	265	Zalman Aran 1	Holon
Shufersal	269	Harav Pintu Masud Asher 18	Petah-Tikva
Shufersal	274	Florentin 27	Tel-Aviv
Shufersal	277	Bnei Binyamin 23	Hertzelia
Shufersal	300	Beerot-Yitzhak	Beerot-Yitzhak
Shufersal	311	Bustanai 14	Rehovot
Shufersal	314	Derech Tzarfat 14	Haifa
Shufersal	359	Grand Kenyon Mall	Haifa
Shufersal	413	Online	Online
Shufersal	438	Tzamarot 2	Hertzelia
Shufersal	445	Harav Yehuda Tzvi Meltzer 20	Rehovot
SuperPharm	667	Online	Online
Tiv-Taam	2	Beni Gaon 2	Netanya
Tiv-Taam	3	Jabotinski 45	Ashdod
Tiv-Taam	5	Online	Online
Tiv-Taam	6	Ehud Kinamon 14	Bat-Yam
Victory	9	Rehov Haarbaa 6	Tel Aviv

Victory	46	Shbazi 26	Rosh Haain
Victory	51	Nesher	Nesher
Victory	79	Engel 78	Kfar-Sava
Victory	81	Hakishor 8	Gan Yavne
Victory	97	Online	Online
Yenot Bitan	3	Shmotkin 29	Rishon-Lezion
Yenot Bitan	60	Hashayatim 9	Ashdod
Yenot Bitan	61	Haari 29	Netanya
Yenot Bitan	64	Rabi Akiva 50	Hertzelia
Yenot Bitan	80	Kakal 16	Kiryat-Tivon
Yenot Bitan	90	Gdalya Neuman 6	Neve Yaakov
Yenot Bitan	91	Raynes 6, Kiryat Moshe	Jerusalem
Yenot Bitan	92	Haatzmaut 42	Kiryat-Ata
Yenot Bitan	2310	Hertzel pinal Kibutz Galuyot	Gan Yavne
Yenot Bitan	2730	Nitzanim 39	Migdal Haemek
Yenot Bitan	3740	Shderot Yerushalim 5	Ashkelon
Yenot Bitan	9006	Online	Online
Yenot Bitan	9090	Online (Mega)	Online

Appendix D. The effect of capped prices

During our sample period, the prices of 21 narrowly defined basic food products were capped by government regulations. This might bias our results because the prices of these products are not set freely by the retailers. Our sample contains 20 UPCs with price caps, which comprise only 0.8% of the 2,403 UPCs in our sample.[2]

Below, we show that excluding these products from the sample has little effect on the results. Table D1 reports the median frequency of price changes, by category, after we exclude observations pertaining to the 20 UPCs with price caps. Comparing the results with those of the full sample (Table 1 in the paper), we find that excluding the 20 UPCs has very little effect on the median durations between price changes.

Indeed, we find only 3 instances where excluding the products with price caps affects the results. In the baking goods category, the frequency of the median change in the Eichenbaum et al.'s (2011) filter generated regular prices is 0.012 when we exclude the products with price caps, and 0.006 when we do not. In the dairy products category, the frequency of the median change in the Chahrour's (2011) filter generated regular prices is 0.018 when we exclude the products with price caps, and 0.012 when we do not. Also in the dairy products category, the frequency of the median transaction price change is 0.071 when we exclude the products with price caps, and 0.065 when we do not.

Table D2 summarizes the information on the distribution of the size of price changes. Comparing the results in this table with the results reported in the paper in Table 6 for the full sample, we find that the results are hardly affected by the exclusion of the products with price caps. The distribution of the size of price changes of the transaction and the regular prices remains slightly leptokurtic, while the distribution of the Nakamura and Steinsson (2008) filter generated regular price changes is excessively leptokurtic. The distributions of the regular prices generated by the filters of Eichenbaum et al. (2011), Chahrour (2011), and Kehoe and Midrigan (2015), remain slightly platykurtic.

In addition, similar to the findings reported in Table 6 in the paper, when we exclude from the analysis the products with price caps, we find that the share of log price changes smaller than 0.5 (0.25) of the average log price change is 24.3% (8.90%), compared with 24.4% (9.00%) when we do not exclude these products.

Thus, excluding the products with price caps, does not affect our findings regarding the frequency and size of price changes.

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[2] The UPCs in our sample that are subject to the price cap regulations are eggs in the baking goods category, and milk and soft cheese with 5% fat, in the dairy products categories.

Table D1. Frequency of price changes – weekly data, excluding products with price caps

categories	Actual regular prices	Nakamura-Steinsson's filter-generated regular prices	Eichenbaum et al.'s filter-generated regular prices	Chahrour's filter generated regular prices	Kehoe and Midrigan's filter generated regular prices	Actual transaction prices
alcoholic beverages	0.036 (0.030, 0.047)	0.095 (0.089, 0.095)	0.036 (0.030, 0.036)	0.060 (0.059, 0.065)	0.065 (0.065, 0.071)	0.167 (0.155, 0.178)
baby products	0.018 (0.012, 0.018)	0.053 (0.047, 0.060)	0.030 (0.030, 0.030)	0.048 (0.042, 0.053)	0.048 (0.047, 0.053)	0.272 (0.260, 0.290)
baking goods	0.006 (0.006, 0.006)	0.012 (0.006, 0.018)	0.012 (0.006, 0.012)	0.012 (0.006, 0.024)	0.012 (0.012, 0.030)	0.036 (0.018, 0.053)
bread	0.024 (0.024, 0.030)	0.006 (0.006, 0.012)	0.006 (0.006, 0.006)	0.006 (0.006, 0.006)	0.006 (0.006, 0.012)	0.101 (0.089, 0.107)
canned food	0.006 (0.006, 0.006)	0.047 (0.047, 0.053)	0.024 (0.024, 0.024)	0.036 (0.036, 0.041)	0.041 (0.036, 0.042)	0.095 (0.089, 0.101)
cereals	0.024 (0.018, 0.024)	0.083 (0.071, 0.089)	0.030 (0.024, 0.036)	0.041 (0.036, 0.053)	0.047 (0.036, 0.053)	0.207 (0.195, 0.225)
cleaning materials	0.036 (0.036, 0.041)	0.047 (0.047, 0.053)	0.024 (0.024, 0.030)	0.041 (0.041, 0.041)	0.047 (0.047, 0.048)	0.155 (0.154, 0.160)
coffee & tea	0.006 (0.006, 0.006)	0.006 (0.006, 0.006)	0.006 (0.000, 0.006)	0.006 (0.006, 0.006)	0.006 (0.006, 0.012)	0.036 (0.024, 0.036)
condiments	0.077 (0.054, 0.083)	0.054 (0.053, 0.059)	0.024 (0.024, 0.030)	0.053 (0.047, 0.053)	0.053 (0.053, 0.054)	0.143 (0.136, 0.149)
cooking oil	0.083 (0.071, 0.089)	0.059 (0.048, 0.065)	0.036 (0.030, 0.036)	0.059 (0.054, 0.059)	0.065 (0.059, 0.071)	0.183 (0.178, 0.195)
dairy products	0.006 (0.006, 0.006)	0.012 (0.012, 0.018)	0.012 (0.012, 0.012)	0.018 (0.012, 0.018)	0.018 (0.018, 0.018)	0.071 (0.065, 0.071)
Fish & meat	0.024 (0.012, 0.041)	0.027 (0.018, 0.041)	0.018 (0.018, 0.018)	0.024 (0.024, 0.024)	0.024 (0.024, 0.031)	0.107 (0.077, 0.107)
frozen fish & meat	0.030 (0.030, 0.036)	0.095 (0.089, 0.107)	0.041 (0.041, 0.041)	0.071 (0.060, 0.071)	0.077 (0.071, 0.077)	0.201 (0.195, 0.202)
Fruits & vegetables	0.211 (0.193, 0.222)	0.094 (0.088, 0.099)	0.041 (0.035, 0.041)	0.058 (0.053, 0.058)	0.058 (0.058, 0.064)	0.274 (0.251, 0.292)
grooming products	0.065 (0.041, 0.083)	0.095 (0.083, 0.107)	0.036 (0.036, 0.041)	0.053 (0.053, 0.059)	0.071 (0.065, 0.083)	0.179 (0.166, 0.219)
humus & spreads	0.012 (0.006, 0.012)	0.012 (0.012, 0.018)	0.012 (0.006, 0.012)	0.012 (0.012, 0.018)	0.018 (0.018, 0.024)	0.077 (0.065, 0.077)
ice cream	0.083 (0.071, 0.101)	0.065 (0.065, 0.071)	0.047 (0.042, 0.048)	0.071 (0.065, 0.071)	0.071 (0.071, 0.071)	0.183 (0.167, 0.183)
juices	0.012 (0.012, 0.012)	0.095 (0.095, 0.095)	0.036 (0.036, 0.041)	0.060 (0.054, 0.065)	0.077 (0.065, 0.077)	0.178 (0.172, 0.189)
rice & pasta	0.012 (0.006, 0.012)	0.036 (0.030, 0.041)	0.018 (0.012, 0.018)	0.030 (0.024, 0.036)	0.030 (0.030, 0.036)	0.112 (0.107, 0.124)
sausages	0.059 (0.047, 0.065)	0.071 (0.059, 0.071)	0.024 (0.024, 0.036)	0.041 (0.030, 0.047)	0.053 (0.047, 0.059)	0.137 (0.131, 0.148)
shampoo & bath soap	0.047 (0.047, 0.048)	0.083 (0.077, 0.089)	0.036 (0.036, 0.041)	0.054 (0.054, 0.059)	0.071 (0.065, 0.071)	0.201 (0.195, 0.213)
Snacks and sweets	0.006 (0.006, 0.006)	0.059 (0.054, 0.065)	0.030 (0.030, 0.030)	0.042 (0.041, 0.047)	0.054 (0.048, 0.059)	0.166 (0.160. 0.167)
soft drinks	0.006 (0.006, 0.006)	0.024 (0.018, 0.030)	0.018 (0.012, 0.018)	0.018 (0.018, 0.024)	0.024 (0.018, 0.024)	0.065 (0.059, 0.071)
toilet paper, wipes and plastic bags	0.042 (0.036, 0.053)	0.036 (0.036, 0.042)	0.024 (0.018, 0.024)	0.036 (0.036, 0.042)	0.041 (0.036, 0.048)	0.118 (0.112, 0.130)
toothpaste & toothbrush	0.036 (0.030, 0.042)	0.047 (0.041, 0.056)	0.018 (0.018, 0.024)	0.036 (0.030, 0.41)	0.047 (0.041, 0.053)	0.160 (0.148, 0.181)
Total	0.012 (0.012, 0.012)	0.041 (0.041, 0.041)	0.018 (0.018, 0.018)	0.036 (0.030, 0.036)	0.041 (0.036, 0.041)	0.130 (0.125, 0.130)

Notes: The median frequency of the actual regular price changes, the generated regular price series using the sales filters of Nakamura and Steinsson (2008), Eichenbaum et al. (2011), Chahrour (2008), and Kehoe and Midrigan's (2015), and the actual transaction prices. The observations are at a weekly frequency. Bootstrapped standard errors are reported in the parentheses. The data excludes 20 UPCs with price caps.

Table D2. Summary statistics of the size of price changes, weekly data, excluding products with price caps

	Skewness	**Kurtosis**	$\sigma_{\lvert z_{is,t}\rvert}/\bar{z}_{is,t}$	$\lvert z_{is,t}\rvert$<0.5× $\bar{z}_{is,t}$	$\lvert z_{is,t}\rvert$<0.25× $\bar{z}_{is,t}$
Actual regular prices	0.007	3.781	0.685	0.243	0.089
Generated regular prices, Nakamura and Steinsson	0.217	5.134	0.741	0.264	0.111
Generated regular prices, Eichenbaum et al.	–0.060	2.798	0.680	0.261	0.121
Generated regular prices, Chahrour	0.012	2.928	0.673	0.254	0.112
Generated regular prices, Kehoe and Midrigan	0.023	2.952	0.670	0.248	0.108
Actual transaction prices	0.010	3.240	0.657	0.226	0.083

Notes: The table reports summary statistics of the distribution of the size of price changes. $z_{is,t} = \left(\Delta p_{is,t} - \overline{\Delta p_{is}}\right)/\sigma_{is}$, where $p_{is,t}$ is the price of product i in store s at week t, $\Delta p_{is,t}$, are log price changes, $\overline{\Delta p_{is}}$ is the average log price changes at the store-category level, and σ_{is} is the standard deviation of the log price changes at the store-category level. The data is at weekly frequency. We Exclude the products with price caps.

Appendix E. Summary statistics of the size of price changes, with the outliers included

In Tables 6 and 8 in the paper, we report the summary statistics of the distribution of the size of price changes at weekly and daily frequencies, respectively. Following Bonomo et al. (2022), in these tables we report the results after excluding price changes in the top and bottom 0.5% of the distribution.

As a test of robustness, Table E1 (E2) reports the summary statistics of the distribution of the size of price changes at weekly (daily) frequency, with the outliers included.

It turns out that including all observations has only a modest effect on the results. Looking at the data at weekly (daily) frequency, we find that the kurtosis of the size of regular price changes is 3.816 (3.811), compared to 3.791 (3.756) when we exclude the outliers. The share of price changes smaller than 25% of the average price change is 0.090 (0.086), unchanged relative to using the data with the outliers excluded.

Table E1. Summary statistics of the size of price changes including outliers, weekly frequency

	Skewness	**Kurtosis**	$\sigma_{\lvert z_{is,t}\rvert}/\bar{z}_{is,t}$	$\lvert z_{is,t}\rvert$<**0.5**× $\bar{z}_{is,t}$	$\lvert z_{is,t}\rvert$<**0.25**× $\bar{z}_{is,t}$
Actual regular prices	0.001	3.816	0.688	0.244	0.090
Generated regular prices, Nakamura and Steinsson	0.221	5.267	0.744	0.265	0.113
Generated regular prices, Eichenbaum et al.	–0.063	2.823	0.684	0.263	0.124
Generated regular prices, Chahrour	0.012	2.944	0.675	0.255	0.114
Generated regular prices, Kehoe and Midrigan	0.020	2.986	0.672	0.250	0.110
Actual transaction prices	0.011	3.302	0.658	0.227	0.083

Notes: The table reports summary statistics of the distribution of the size of price changes. $z_{is,t} = \left(\Delta p_{is,t} - \overline{\Delta p_{is}}\right)/\sigma_{is}$, where $p_{is,t}$ is the price of product i in store s at week t, $\Delta p_{is,t}$, are log price change, $\overline{\Delta p_{is}}$ is the average log price change at the store-category level, and σ_{is} is the standard deviation of the log price change at the store-category level. Data at weekly frequency.

Table E2. Summary statistics of the size of price changes including outliers, daily frequency

	Skewness	**Kurtosis**	$\sigma_{\lvert z_{is,t}\rvert}/\bar{z}_{is,t}$	$\lvert z_{is,t}\rvert$<0.5× $\bar{z}_{is,t}$	$\lvert z_{is,t}\rvert$<0.25× $\bar{z}_{is,t}$
Actual regular prices	0.039	3.811	0.671	0.228	0.086
Generated regular prices, Nakamura and Steinsson	0.240	4.213	0.677	0.239	0.098
Generated regular prices, Eichenbaum et al.	–0.028	2.838	0.681	0.260	0.120
Generated regular prices, Chahrour	0.019	3.006	0.674	0.251	0.113
Generated regular prices, Kehoe and Midrigan	0.026	2.933	0.661	0.243	0.106
Actual transaction prices	0.074	3.504	0.644	0.217	0.072

Notes: The table reports summary statistics of the distribution of the size of price changes. $z_{is,t} = \left(\Delta p_{is,t} - \overline{\Delta p_{ıs}}\right)/\sigma_{is}$, where $p_{is,t}$ is the price of product i in store s at week t, $\Delta p_{is,t}$, are log price changes, $\overline{\Delta p_{ıs}}$ is the average log price changes at the store-category level, and σ_{is} is the standard deviation of the log price changes at the store-category level. Data at weekly frequency.

Appendix F. Histograms of the size of price changes in NIS

In the paper, we show that the share of small price changes in our data is smaller than reported for other countries. For example, in our (weekly) data, the share of price changes up to 1% is 1.2%, compared to 11.2% in France (Beradi et al., 2015).

One possible explanation is mechanical. In Israel, price changes smaller than 0.1 NIS are allowed only for fresh produce, and for a very small number of products whose prices are capped by government regulations, because there is no NIS denomination smaller than NIS 0.1. It is, therefore, possible that small price changes are rare in Israel because they are largely prohibited. However, Figure F1 suggests that this is not the only, nor the main, reason.

The figure depicts the histograms of the size of price changes, where we measure the size of price changes in NIS. I.e., the figure depicts the distribution of the size of $\Delta p_{is,t}$, where $\Delta p_{is,t} = p_{is,t} - p_{is,t-1}$, where $p_{is,t}$ is the price of product i in store s in week t, and $p_{is,t} \neq p_{is,t-1}$. Focusing on the actual regular price changes, we see that there are peaks around price changes that are multiples of NIS 0.1. We also find that small regular price changes are rare.

Table F1 underscores this finding. It gives the shares of the price changes of up to NIS 0.1, between NIS 0.1 and NIS 0.2, etc. The table presents these values for the actual regular and transaction prices, as well as for the four generated regular price series which are the results of applying the sales filters of Nakamura and Steinsson (2008), Eichenbaum et al. (2011), Chahrour (2011), and Kehoe and Midrigan (2015).

Focusing on the actual regular prices, we find that price changes smaller than NIS 0.1 are, as expected, very rare, comprising about 0.1% of all price changes. However, bigger price changes are also rare. 2.7% of all price changes are bigger than or equal to NIS 0.1 and smaller than NIS 0.2, while 1.5% of all price changes are in the range of NIS 0.2 – NIS 0.3. Together, all price changes of up to NIS 0.5 comprise 7.0% of all price changes. By comparison, Sayag et al. (2025) report that in a US supermarket, 26.6% of all price changes are smaller than or equal to 10¢ (about NIS 0.35).

It, therefore, seems that small price changes are rare in our data, and this is not only because price changes smaller than NIS 0.1 are illegal.

Figure F1. Histograms of the size of price changes, in NIS, weekly frequency

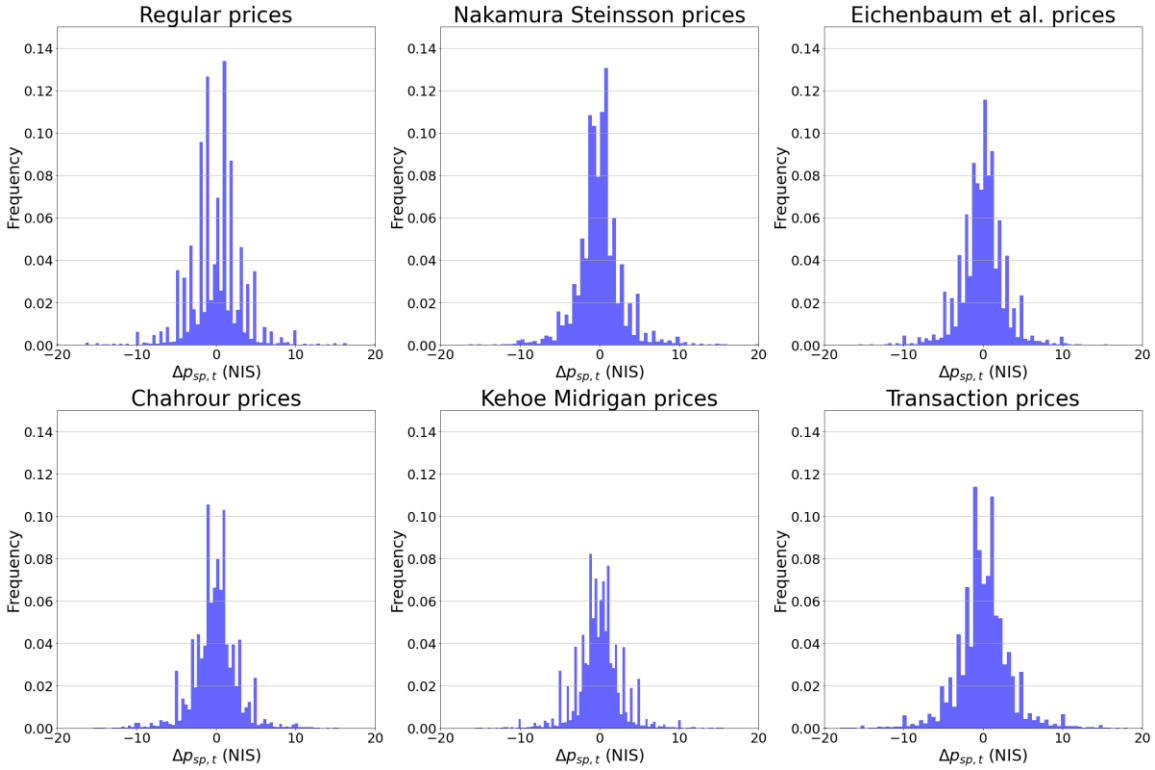


Table F1. The shares of price-changes by size in NIS, weekly data

	Size of price changes (NIS)						
	$0 < \Delta p_{is,t} < 0.1$	$0.1 \leq \Delta p_{is,t} < 0.2$	$0.2 \leq \Delta p_{is,t} < 0.3$	$0.3 \leq \Delta p_{is,t} < 0.4$	$0.4 \leq \Delta p_{is,t} < 0.5$	$0.5 \leq \Delta p_{is,t} < 1$	$1 \leq \Delta p_{is,t} < 1.5$
Actual regular prices	0.001	0.027	0.015	0.014	0.013	0.040	0.127
Generated regular prices, Nakamura and Steinsson	0.019	0.031	0.015	0.023	0.018	0.086	0.099
Generated regular prices, Eichenbaum et al.	0.007	0.045	0.016	0.029	0.020	0.080	0.104
Generated regular prices, Chahrour	0.127	0.032	0.012	0.023	0.017	0.070	0.086
Generated regular prices, Kehoe Midrigan	0.007	0.033	0.013	0.026	0.019	0.078	0.097
Actual transaction prices	0.003	0.021	0.009	0.018	0.013	0.076	0.099

Notes: The share of price changes by size. Weekly data.

Appendix G. Analyses of the Daily Data

A. Frequency of price changes

Figure G1 illustrates the behavior of the *daily* time series of the regular and transaction prices of the same 4 products as in Figure 1 in the paper. Not surprisingly, when the data is at daily frequency, the transaction prices become more erratic, especially for the products with relatively more volatile prices—red peppers and Cremissimo ice cream. The transaction prices of potato chips are also somewhat more volatile, as can be seen, for example, in October 2019 and the first half of 2020.

Perhaps more surprisingly, we find that the frequency of regular price changes is higher in the daily data. For example, we see a regular price increase for red peppers that is quickly reversed in September 2019, followed by a series of price increases and decreases in the second half of 2020. A series of successive price increases and decreases is found also in the regular prices of Cremissimo ice cream, in the 4th quarters of 2019 and 2020. These findings are consistent with Bonomo et al. (2022) who study regular prices of products at Israeli supermarkets and find that aggregating prices to weekly frequency, leads to a loss of both small and large price changes.

Table G1 summarizes information about price changes that occur within 7 days of each other. It turns out that such price changes are quite common. Across categories, they comprise between 10.3% and 32.2% of all price changes, with an average of 18.5%.

However, 62.6% of these short-lived price changes completely cancel each other out. In 23.4% of cases, the changes occur in the opposite direction, suggesting that the retailer has either increased or decreased the price and then decided that the change was too large. In only 14.1% of the cases, the price changes occur in the same direction. In 6.6% (7.4%) of the cases, both price changes are increases (decreases).

Figure G2 illustrates the effect of applying the four sales filters to the data. It is important to note that these filters were not designed to work with daily data. Therefore, the results of this exercise should not be interpreted as reflecting on the performance of the filters' algorithms. Rather, it should be seen as a study of the desired properties of a filter that is designed to work with daily price data.[3]

Because daily transaction prices are more volatile than weekly, the sales filters identify more price changes in the daily prices than in the weekly prices. This can be seen in the performance of Nakamura and Steinsson's (2011) filter in the case of red peppers, potato

[3] To implement the filter algorithms, we follow Sudo et al. (2018) in multiplying all parameters by 7.

chips in early 2021, and Cremissimo ice cream in mid-2019. The other filters are also affected by the volatility of the daily prices. For example, Chahrour's (2011) filter finds 3 "steps" in the 2nd quarter of 2019 in the daily data of Cremissimo ice cream. These "steps" are absent in the weekly data. Compared to the weekly data, Kehoe and Midrigan's (2015) filter adds a price hike followed by a price cut in the 2nd quarter of 2020.

Tables G2 and G3 summarize the findings on price rigidity for daily data. When we use daily observations, the median duration between regular price changes decreases from 1.61 years in the weekly data, to 1.50 years in the daily data. The median durations between price changes according to Nakamura and Steinsson's (2008), Eichenbaum's (2011), Chahrour's (2011) and Kehoe and Midrigan's (2015) filters are 0.53 years, 0.80 years, 0.52 years, and 0.40 years, respectively.

Compared to the weekly data, these figures are 15% longer, and 24%, 18%, and 23% shorter for Nakamura and Steinsson's (2008), Eichenbaum's (2011), Chahrour's (2011) and Kehoe and Midrigan's (2015) filters, respectively. Thus, it seems that when we use daily data, the filters, except for Nakamura and Steinsson's (2008), underestimate the median rigidity of regular prices by more than when we use weekly data.

B. Size of price changes

In the daily data (Table G4), we find that the share of regular price changes smaller than 25% of the average price change, 0.086, is smaller than in the weekly data, 0.09. Consistent with this finding, Table 8 reports that the shares of regular price changes smaller than 1%–5% are lower than their counterparts in the weekly data. The lower share of small price changes in the daily data is consistent with Bonomo et al. (2022) who find that aggregating price changes that occur within the same week, eliminates some of the small price changes.

We also find that the sales filters are less successful in replicating the properties of the actual regular prices when we use daily rather than weekly data. Figure G3 depicts the histograms of the size of price changes in the daily data. Nakamura and Steinsson's (2008) filter succeeds in capturing the bimodal distribution of the regular prices, but its kurtosis, 4.17, is excessive.

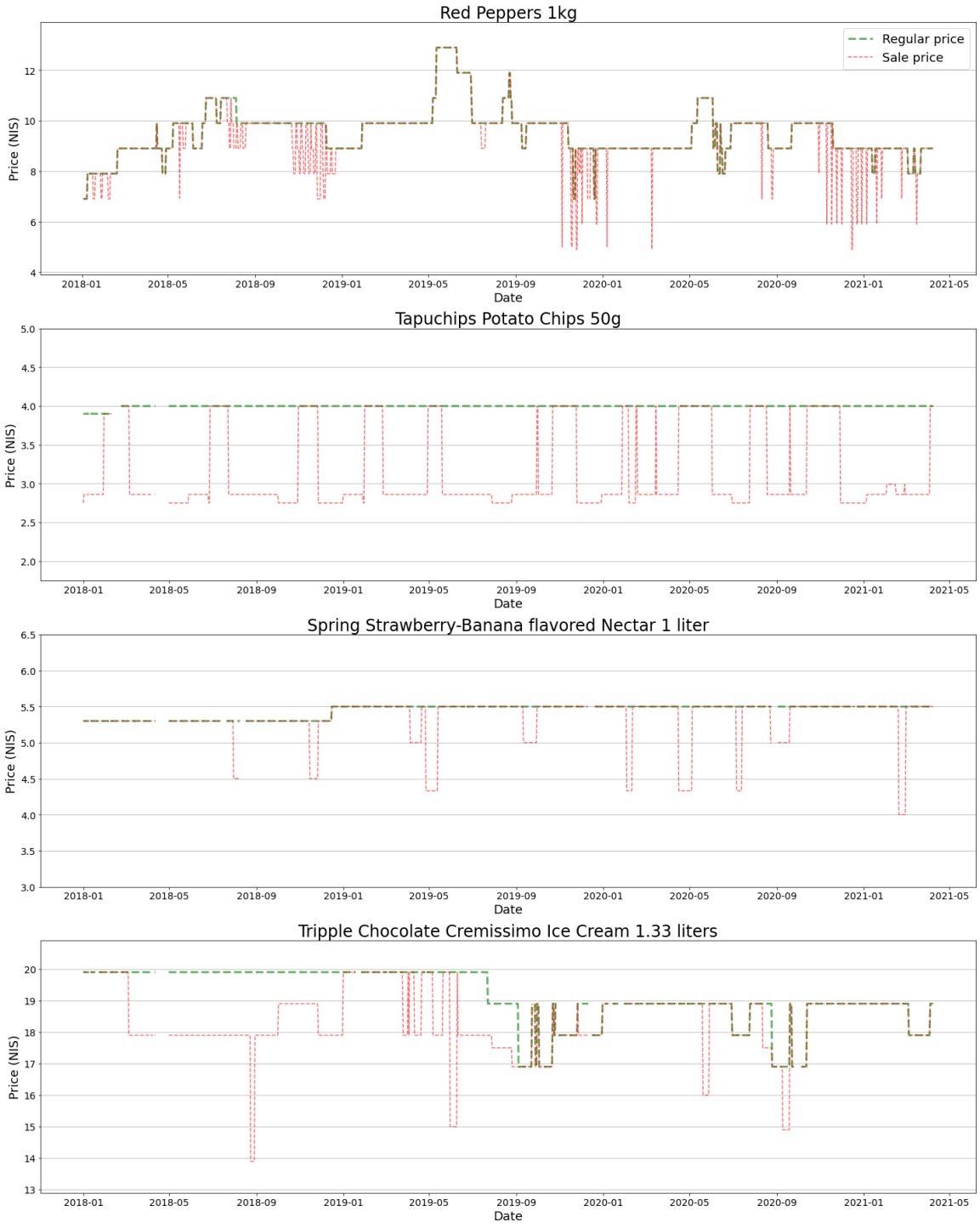
The filters of Eichenbaum et al. (2011), Chahrour (2011), and Kehoe and Midrigan (2015) fail to replicate the bimodal distribution of the actual regular prices. Consequently, they produce too many small price changes—12.6%, 11.8%, and 11.5% price changes

smaller than 0.25 of the average price change, respectively.

Eichenbaum et al.'s (2011) and Nakamura and Steinsson's (2008) filters generate regular price series with slightly excessive kurtosis, 4.06 and 4.17, respectively. The filters of Chahrour (2011) and Kehoe and Midrigan (2015) lead to kurtoses that are slightly smaller than the kurtosis of the actual regular prices—3.29 and 3.43, respectively.

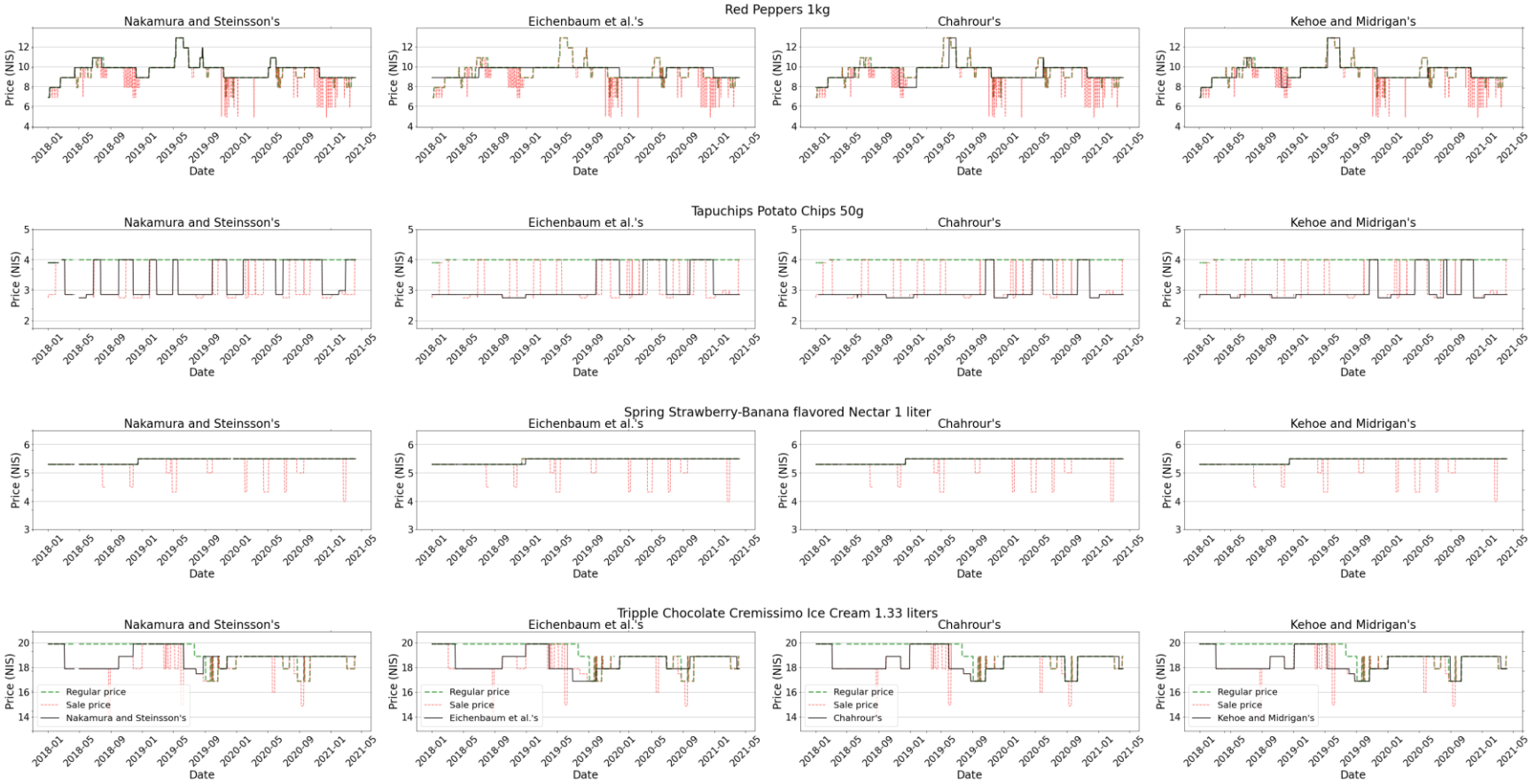
Consistent with the findings in the paper regarding very small regular price changes, we find that also when using daily data, very small price changes are rare. Table G5 reports the share of price changes smaller than 1%–5%. 0.9% of all price changes are smaller than 1%, 3.0% are smaller than 2%, and 11.0% are smaller than 5%. The regular price series generated by the filters overestimate these figures.

Figure G1. Actual regular and transaction prices of four products, daily frequency



Notes: Daily data from store 18 of Shufersal.

Figure G2. Actual regular prices vs. generated regular prices, daily frequency



Notes: Daily data from store 18 of Shufersal.

Figure G3. Histograms of the size of the normalized regular (actual and generated) and transaction price changes, daily data

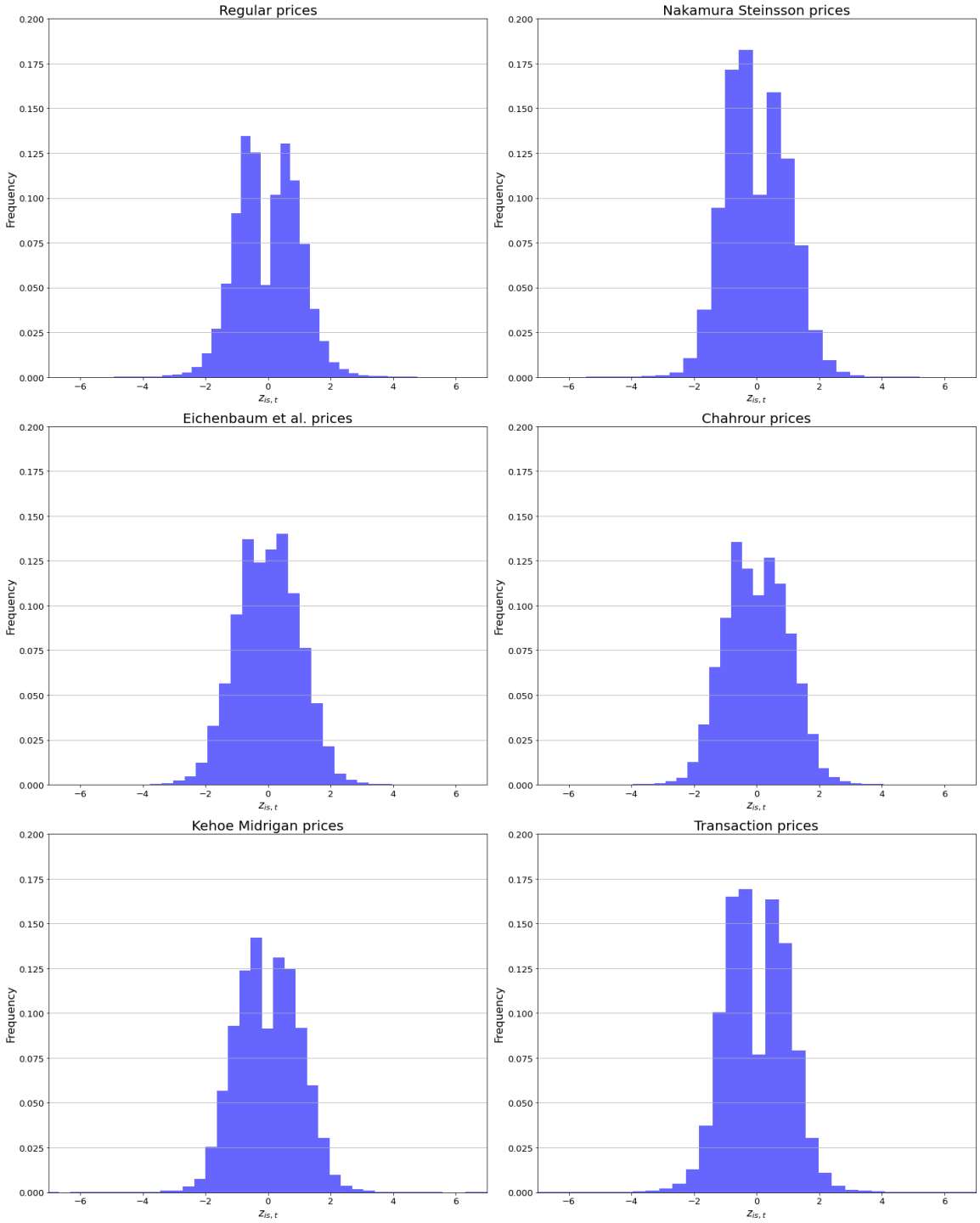


Table G1. Information on price changes within 7 days of each other

categories	All price changes (1)	Price changes within 7 days (2)	% price changes within 7 days (3)	% no change (4)	% positive changes (5)	% negative changes (6)	% mixed changes (7)
alcoholic beverages	11,905	2,529	21.2%	57.5%	2.5%	7.8%	32.3%
baby products	6,904	1,050	15.2%	51.4%	8.8%	12.4%	27.4%
baking goods	1,714	300	17.5%	71.0%	3.3%	6.3%	19.3%
bread	3,197	328	10.3%	76.2%	4.9%	2.4%	16.5%
canned food	4,932	1,128	22.9%	75.5%	2.6%	5.1%	16.8%
cereals	2,597	362	13.9%	57.5%	4.4%	6.4%	31.8%
cleaning materials	21,984	3,514	16.0%	64.0%	4.1%	7.3%	24.6%
coffee & tea	3,933	607	15.4%	67.1%	2.3%	3.8%	26.9%
condiments	4,456	1,090	24.5%	81.8%	3.7%	5.4%	9.1%
cooking oil	7,505	1,387	18.5%	77.4%	2.7%	3.3%	16.6%
dairy products	23,230	2,777	12.0%	58.9%	7.0%	9.3%	24.8%
Fish & meat	1,044	336	32.2%	56.0%	8.3%	5.4%	30.4%
frozen fish & meat	3,064	366	11.9%	53.8%	2.5%	6.3%	37.4%
Fruits & vegetables	43,680	10,794	24.7%	52.4%	12.8%	9.9%	24.9%
grooming products	2,750	623	22.7%	77.0%	1.6%	3.0%	18.3%
humus & spreads	4,083	711	17.4%	80.0%	3.0%	6.0%	11.0%
ice cream	3,647	613	16.8%	71.9%	1.8%	8.3%	17.9%
juices	8,714	945	10.8%	61.3%	4.1%	7.5%	27.1%
rice & pasta	5,227	669	12.8%	49.9%	10.2%	9.9%	30.0%
sausage	8,767	2,058	23.5%	73.8%	2.8%	3.2%	20.3%
shampoo & bath soap	12,651	1,761	13.9%	74.7%	4.1%	3.7%	17.5%
snacks & sweets	14,874	2,878	19.3%	62.3%	6.5%	8.2%	23.0%
soft drinks	6,597	882	13.4%	70.1%	3.4%	3.3%	23.2%
toilet paper, wipes and plastic bags	8,364	1,815	21.7%	58.3%	5.1%	8.8%	27.9%
toothpaste & toothbrush	7,022	1,725	24.6%	74.1%	3.1%	4.6%	18.1%
Total	222,841	41,248	18.5%	62.6%	6.6%	7.4%	23.4%

Notes: The table summarizes information on price changes that occur within 7 days of each other. Column (1) reports the total number of price changes in each category. Column (2) reports the number of price changes that occur within 7 days of each other. Column (3) reports the share of prices that are within 7 days of each other out of all price changes. Column (4) reports the % of the price changes that occur within 7 days of another price change, such that the total change is zero. Column (5) reports the % of the price changes that occur within 7 days of another price change, such that both changes are positive. Column (6) reports the % of the price changes that occur within 7 days of another price change, such that both changes are negative. Column (7) reports the % of the price changes that occur within 7 days of another price change, such that one of the two price changes is negative, but their sum is not zero.

Table G2. Frequency of price changes, daily observations

categories	Actual regular prices	Generated regular prices, Nakamura-Steinsson	Generated regular prices, Eichenbaum et al.	Generated regular prices, Chahrour	Generated regular prices, Kehoe and Midrigan	Actual transaction prices
alcoholic beverages	0.007 (0.005, 0.008)	0.015 (0.014, 0.016)	0.005 (0.004, 0.005)	0.010 (0.009, 0.011)	0.011 (0.011, 0.012)	0.034 (0.031, 0.037)
baby products	0.003 (0.003, 0.004)	0.008 (0.007, 0.009)	0.004 (0.004, 0.004)	0.009 (0.007, 0.009)	0.008 (0.008, 0.009)	0.050 (0.048, 0.053)
baking goods	0.001 (0.001, 0.002)	0.001 (0.001, 0.002)	0.001 (0.001, 0.002)	0.002 (0.001, 0.003)	0.002 (0.002, 0.003)	0.005 (0.003, 0.008)
bread	0.003 (0.003, 0.004)	0.002 (0.002, 0.002)	0.001 (0.001, 0.001)	0.001 (0.001, 0.002)	0.003 (0.003, 0.004)	0.016 (0.015, 0.017)
canned food	0.001 (0.001, 0.001)	0.006 (0.005, 0.007)	0.003 (0.003, 0.004)	0.006 (0.006, 0.006)	0.007 (0.007, 0.008)	0.023 (0.22, 0.025)
cereals	0.003 (0.003, 0.004)	0.015 (0.015, 0.016)	0.004 (0.004, 0.005)	0.007 (0.007, 0.008)	0.008 (0.006, 0.010)	0.048 (0.047, 0.049)
cleaning materials	0.006 (0.005, 0.007)	0.005 (0.005, 0.005)	0.004 (0.004, 0.004)	0.007 (0.006, 0.007)	0.008 (0.008, 0.009)	0.033 (0.032, 0.035)
coffee & tea	0.001 (0.001, 0.001)	0.001 (0.000, 0.001)	0.001 (0.001, 0.001)	0.001 (0.001, 0.001)	0.001 (0.001, 0.002)	0.005 (0.005, 0.006)
condiments	0.015 (0.010, 0.018)	0.005 (0.003, 0.006)	0.004 (0.003, 0.004)	0.008 (0.008, 0.009)	0.010 (0.009, 0.010)	0.033 (0.028, 0.036)
cooking oil	0.014 (0.012, 0.016)	0.005 (0.005, 0.006)	0.005 (0.005, 0.005)	0.010 (0.009, 0.010)	0.010 (0.010, 0.011)	0.035 (0.031, 0.038)
dairy products	0.001 (0.001, 0.001)	0.002 (0.002, 0.003)	0.002 (0.002, 0.002)	0.003 (0.003, 0.003)	0.003 (0.003, 0.003)	0.012 (0.011, 0.012)
Fish & meat	0.005 (0.002, 0.012)	0.004 (0.003, 0.005)	0.003 (0.003, 0.003)	0.003 (0.003, 0.004)	0.005 (0.004, 0.005)	0.017 (0.013, 0.018)
frozen fish & meat	0.005 (0.004, 0.007)	0.014 (0.013, 0.015)	0.006 (0.006, 0.006)	0.012 (0.012, 0.012)	0.013 (0.012, 0.014)	0.041 (0.039, 0.042)
Fruits & vegetables	0.044 (0.040, 0.049)	0.014 (0.013, 0.015)	0.006 (0.005, 0.006)	0.009 (0.009, 0.010)	0.010 (0.009, 0.010)	0.080 (0.075, 0.086)
grooming products	0.016 (0.006, 0.020)	0.014 (0.012, 0.016)	0.006 (0.005, 0.006)	0.010 (0.009, 0.011)	0.011 (0.010, 0.014)	0.038 (0.031, 0.046)
humus & spreads	0.002 (0.001, 0.002)	0.002 (0.002, 0.002)	0.002 (0.002, 0.002)	0.003 (0.003, 0.003)	0.003 (0.003, 0.003)	0.015 (0.013, 0.018)
ice cream	0.017 (0.015, 0.021)	0.009 (0.009, 0.010)	0.007 (0.007, 0.008)	0.009 (0.009, 0.010)	0.011 (0.010, 0.011)	0.042 (0.034, 0.045)
juices	0.002 (0.002, 0.002)	0.016 (0.015, 0.016)	0.006 (0.005, 0.006)	0.010 (0.009, 0.011)	0.012 (0.011, 0.013)	0.043 (0.042, 0.044)
rice & pasta	0.002 (0.001, 0.002)	0.007 (0.006, 0.008)	0.003 (0.003, 0.003)	0.005 (0.004, 0.005)	0.006 (0.005, 0.007)	0.034 (0.027, 0.038)
sausages	0.017 (0.012, 0.020)	0.013 (0.010, 0.014)	0.004 (0.003, 0.005)	0.008 (0.006, 0.008)	0.009 (0.008, 0.010)	0.030 (0.025, 0.035)
shampoo & bath soap	0.009 (0.009, 0.010)	0.013 (0.012, 0.014)	0.006 (0.005, 0.006)	0.009 (0.009, 0.010)	0.011 (0.011, 0.012)	0.047 (0.045, 0.049)
Snacks and sweets	0.001 (0.001, 0.001)	0.009 (0.009, 0.010)	0.004 (0.004, 0.004)	0.008 (0.008, 0.009)	0.010 (0.009, 0.010)	0.036 (0.035, 0.037)
soft drinks	0.002 (0.001, 0.002)	0.003 (0.003, 0.003)	0.003 (0.002, 0.003)	0.003 (0.003, 0.003)	0.003 (0.003, 0.004)	0.013 (0.011, 0.016)
toilet paper, wipes and plastic bags	0.008 (0.007, 0.009)	0.005 (0.004, 0.006)	0.003 (0.003, 0.004)	0.006 (0.005, 0.007)	0.007 (0.006, 0.008)	0.021 (0.019, 0.023)
toothpaste & toothbrush	0.008 (0.007, 0.011)	0.007 (0.006, 0.009)	0.003 (0.003, 0.004)	0.007 (0.006, 0.007)	0.008 (0.008, 0.008)	0.038 (0.032, 0.040)
Total	0.002 (0.002, 0.003)	0.005 (0.005, 0.005)	0.003 (0.003, 0.003)	0.005 (0.005, 0.005)	0.007 (0.006, 0.007)	0.025 (0.025, 0.026)

Notes: The median frequency of price changes for the actual regular prices, for the generated regular prices using the sales filters of Nakamura and Steinsson (2008), Eichenbaum et al. (2011), Chahrour (2008), and Kehoe and Midrigan (2015), and the actual transaction prices. The observations are at a daily frequency.

Table G3 The expected number of days between price changes

categories	Actual regular prices	Generated regular prices, Nakamura-Steinsson	Generated regular prices, Eichenbaum et al.	Generated regular prices, Chahrour	Generated regular prices, Kehoe and Midrigan	Generated regular prices, Transaction prices
alcoholic beverages	145 (125, 192)	68 (64, 72)	193 (187, 224)	97 (94, 106)	87 (82, 89)	28 (26, 31)
baby products	371 (280, 385)	129 (116, 145)	231 (228, 233)	115 (105, 143)	127 (108, 130)	20 (18, 20)
baking goods	1143 (586, 1161)	1137 (571, 1173)	1145 (586, 1173)	581 (390, 1147)	575 (379, 581)	193 (130, 292)
bread	285 (232, 287)	577 (574, 581)	1147 (1144, 1151)	1139 (576, 1147)	287 (232, 289)	61 (60, 67)
canned food	1158 (1150, 1163)	165 (146, 187)	285 (234, 289)	166 (165, 167)	135 (130, 146)	42 (40, 44)
cereals	290 (285, 291)	64 (63, 68)	226 (190, 274)	142 (129, 145)	124 (103, 165)	20 (20, 21)
cleaning materials	166 (146, 193)	193 (188, 195)	234 (233, 284)	146 (145, 164)	121 (117, 128)	29 (28, 31)
coffee & tea	1151 (585, 1164)	1168 (1162, 2347)	1169 (1166, 1171)	1158 (1106, 1166)	1112 (584, 1156)	192 (159, 194)
condiments	67 (54, 103)	218 (164, 379)	282 (234, 288)	128 (116, 129)	103 (95, 105)	30 (27, 36)
cooking oil	73 (61, 82)	194 (166, 203)	193 (189, 194)	104 (96, 116)	97 (90, 101)	28 (26, 32)
dairy products	1140 (1103, 1149)	549 (391, 571)	585 (584, 585)	390 (389, 390)	292 (292, 293)	83 (82, 89)
Fish & meat	194 (83, 466)	282 (188, 291)	385 (293, 391)	288 (232, 293)	195 (191, 283)	59 (56, 77)
frozen fish & meat	189 (144, 224)	71 (67, 75)	163 (160, 165)	82 (81, 83)	76 (71, 82)	24 (23, 25)
Fruits & vegetables	22 (20, 24)	70 (66, 74)	170 (169, 188)	108 (99, 116)	99 (98, 107)	12 (11, 13)
grooming products	64 (49, 166)	72 (61, 83)	167 (161, 190)	97 (90, 116)	88 (73, 96)	26 (21, 31)
humus & spreads	585 (583, 1122)	581 (541, 584)	585 (585, 586)	390 (388, 391)	292 (290, 378)	67 (55, 78)
ice cream	58 (48, 66)	105 (97, 111)	138 (130, 143)	105 (103, 106)	94 (89, 96)	23 (22, 29)
juices	581 (579, 582)	61 (61, 64)	167 (167, 192)	97 (90, 106)	83 (78, 89)	23 (22, 23)
rice & pasta	584 (574, 1131)	145 (130, 165)	386 (293, 390)	195 (193, 232)	164 (144, 193)	29 (26, 36)
sausages	57 (49, 82)	78 (73, 103)	232 (195, 286)	130 (127, 164)	115 (102, 130)	33 (28, 39)
shampoo & bath soap	106 (97, 117)	77 (73, 83)	167 (165, 187)	105 (97, 111)	87 (83, 94)	21 (20, 22)
Snacks and sweets	1169 (1165, 1171)	111 (105, 116)	232 (230, 233)	128 (117, 130)	102 (92, 105)	27 (27, 28)
soft drinks	586 (586, 1108)	389 (386, 390)	391 (389, 566)	293 (288, 387)	287 (232, 293)	77 (64, 88)
toilet paper, wipes and plastic bags	124 (106, 145)	195 (166, 234)	287 (234, 291)	165 (142, 193)	143 (126, 165)	46 (43, 52)
toothpaste & toothbrush	122 (91, 145)	141 (117, 165)	319 (281, 388)	146 (141, 167)	129 (126, 130)	26 (24, 31)
Total	548 (391, 564)	193 (191, 194)	293 (293, 341)	190 (185, 192)	146 (146, 160)	39 (38, 40)

Notes: The implied duration between price changes, in weeks, calculated as $-[ln(1-f)]^{-1}$, where f is the median frequency of price changes, taken from Table 1.

Table G4. Summary statistics of the size of price changes, daily data

	Skewness	Kurtosis	$\sigma_{\lvert z_{is,t}\rvert}/\bar{z}_{is}$	$\lvert z_{is,t}\rvert$<0.5× $\bar{z}_{is}$	$\lvert z_{is,t}\rvert$<0.25× $\bar{z}_{is}$
Actual regular prices	0.036	3.756	0.669	0.228	0.086
Generated regular prices, Nakamura and Steinsson	0.158	4.171	0.674	0.240	0.095
Generated regular prices, Eichenbaum et al.	0.059	4.060	0.725	0.279	0.126
Generated regular prices, Chahrour	0.040	3.295	0.694	0.263	0.118
Generated regular prices, Kehoe and Midrigan	0.062	3.437	0.687	0.257	0.115
Actual transaction prices	0.057	3.315	0.642	0.216	0.071

Notes: The table reports summary statistics of the distribution of the size of price changes. $z_{is,t} = \left(\Delta p_{is,t} - \overline{\Delta p_{is}}\right)/\sigma_{is}$, where $p_{is,t}$ is the price of product i in store s at week t, $\Delta p_{is,t}$, are log price changes, $\overline{\Delta p_{is}}$ is the average log price changes at the store-category level, and σ_{is} is the standard deviation of the log price changes at the store-category level. Data at daily frequency.

Table G5. Share of price changes smaller than 1%–5%, daily data

	< 1%	< 2%	< 3%	< 4%	< 5%
Actual regular prices	0.009	0.030	0.054	0.087	0.110
Generated regular prices, Nakamura and Steinsson	0.018	0.038	0.062	0.102	0.126
Generated regular prices, Eichenbaum et al.	0.030	0.057	0.092	0.164	0.194
Generated regular prices, Chahrour	0.028	0.050	0.077	0.135	0.162
Generated regular prices, Kehoe Midrigan	0.027	0.047	0.073	0.129	0.155
Actual transaction prices	0.010	0.022	0.034	0.058	0.074

Notes: The table reports the share of non-zero log price changes that are smaller than 1%, 2%, 3%, 4%, and 5%. Daily data.

Appendix H. Excluding sales that cannot be detected by using a sale flag

A researcher who has access to sale flags that indicate the timing of a sale but does not have information on regular prices, would underestimate the frequency of regular price changes if more than one regular price change occurs during the sale period.

In the paper, we report that the number of such occurrences is small – there are only 4,173 regular price changes (2.8% of the total) that occur during a sale period in which there was at least one more regular price change. Yet, a few price changes might affect the median price rigidity, depending on their distribution within product categories.

We therefore calculate the frequency of regular price changes after we exclude regular price changes that occur within the same sale period. The results are reported in the second column of Table H1. For comparison, the first column reports the results of the regular price changes, as they are reported in Table 1 in the paper. Table H2 reports the corresponding duration between price changes, calculated as $-ln\left(1-\bar{f}_{i,s}\right)^{-1}$, where $\bar{f}_{i,s}$ is the frequency of price changes of product i offered in store s.

We find that excluding these price changes does not affect the median frequency of regular price changes in the pooled data. However, it does affect the estimates of the frequency of price changes in 5 of the 25 categories: baby products, fruits and vegetables, grooming products, juices, and sausages. Thus, although using sale flags would not affect the estimation of the median frequency of regular price changes in the pooled data, it could affect the estimation within certain product categories. In particular, it affects the estimated median frequency between price changes in product categories with volatile prices, such as fruits and vegetables, and in product categories characterized by long sales, such as grooming products, juices, and sausages.

Still, in 3 of the 5 categories, the estimation of the frequency of price changes after the removal of the price changes is within the standard errors of the original estimates. Only in two categories, grooming products, and juices, estimates based on sale flags would lead to estimates in which the values in column 1 are outside of the standard errors.

In sum, estimation based on sales filters can lead to some deviations from the values based on the actual regular prices. In certain categories, these deviations can be significant. However, in the pooled data, these deviations are likely to have only a small effect, if any, on the estimates of the median frequency of price rigidity.

Table H1. Frequency of price changes – weekly observations, excluding price changes during sales

categories	Actual regular prices	Actual regular prices, using a sales flag
alcoholic beverages	0.036 (0.030, 0.047)	0.036 (0.030, 0.047)
baby products	0.018 (0.012, 0.018)	0.012 (0.012, 0.018)
baking goods	0.006 (0.006, 0.006)	0.006 (0.006, 0.006)
bread	0.024 (0.024, 0.030)	0.024 (0.024, 0.030)
canned food	0.006 (0.006, 0.006)	0.006 (0.006, 0.006)
cereals	0.024 (0.018, 0.024)	0.024 (0.018, 0.024)
cleaning materials	0.036 (0.036, 0.041)	0.036 (0.036, 0.041)
coffee & tea	0.006 (0.006, 0.006)	0.006 (0.006, 0.006)
condiments	0.077 (0.054, 0.083)	0.077 (0.054, 0.083)
cooking oil	0.083 (0.071, 0.089)	0.083 (0.071, 0.089)
dairy products	0.006 (0.006, 0.006)	0.006 (0.006, 0.006)
Fish & meat	0.024 (0.012, 0.041)	0.024 (0.012, 0.041)
frozen fish & meat	0.030 (0.030, 0.036)	0.030 (0.030, 0.036)
Fruits & vegetables	0.211 (0.193, 0.222)	0.193 (0.187, 0.205)
grooming products	0.065 (0.041, 0.083)	0.041 (0.030, 0.059)
humus & spreads	0.012 (0.006, 0.012)	0.012 (0.006, 0.012)
ice cream	0.083 (0.071, 0.101)	0.083 (0.071, 0.101)
juices	0.012 (0.012, 0.012)	0.006 (0.006, 0.006)
rice & pasta	0.012 (0.006, 0.012)	0.012 (0.006, 0.012)
sausages	0.059 (0.047, 0.065)	0.048 (0.036, 0.059)
shampoo & bath soap	0.047 (0.047, 0.048)	0.047 (0.047, 0.048)
Snacks and sweets	0.006 (0.006, 0.006)	0.006 (0.006, 0.006)
soft drinks	0.006 (0.006, 0.006)	0.006 (0.006, 0.006)
toilet paper, wipes and plastic bags	0.042 (0.036, 0.053)	0.042 (0.036, 0.053)
toothpaste & toothbrush	0.036 (0.030, 0.042)	0.036 (0.030, 0.042)
Total	0.012 (0.012, 0.012)	0.012 (0.012, 0.012)

Table H2. The expected number of weeks between price changes, excluding price changes during sales

categories	Actual regular prices	Actual regular prices, using a sales flag
alcoholic beverages	28 (21, 33)	28 (21, 33)
baby products	56 (55, 83)	83 (56, 83)
baking goods	168 (168, 168)	168 (168, 168)
bread	41 (41, 42)	41 (41, 42)
canned food	168 (168, 168)	168 (168, 168)
cereals	42 (41, 55)	42 (41, 55)
cleaning materials	28 (24, 28)	28 (24, 28)
coffee & tea	168 (168, 168)	168 (168, 168)
condiments	12 (12, 18)	12 (12, 18)
cooking oil	12 (11, 14)	12 (11, 14)
dairy products	167 (167, 168)	167 (167, 168)
Fish & meat	42 (24, 84)	42 (24, 84)
frozen fish & meat	33 (28, 33)	33 (28, 33)
Fruits & vegetables	4 (4, 5)	5 (4, 5)
grooming products	15 (12, 24)	24 (16, 33)
humus & spreads	84 (84, 167)	84 (84, 167)
ice cream	12 (9, 13)	12 (9, 13)
juices	84 (84, 84)	167 (167, 168)
rice & pasta	84 (84, 167)	84 (84, 167)
sausages	16 (15, 21)	20 (15, 28)
shampoo & bath soap	21 (20, 21)	21 (20, 21)
Snacks and sweets	168 (168, 168)	168 (168, 168)
soft drinks	168 (167, 168)	168 (167, 168)
toilet paper, wipes and plastic bags	23 (18, 27)	23 (18, 27)
toothpaste & toothbrush	28 (23, 33)	28 (23, 33)
Total	84 (84, 84)	84 (84, 84)

Appendix I. Analyses of the Canadian Data

Our results show that regular prices change infrequently. In the paper, we report that the median regular price changes roughly every 1.6 years. We also find that small price changes are rare. Sales filters, which are designed to filter out the regular prices out of an observed series of transaction prices, fail in replicating these characteristics.

One shortcoming of our data, however, is that it comes from a small country, Israel, and a specific point in time, 2018–2021, a period of very low inflation, with an average annual inflation rate of 0.3%.

As a test of robustness, we use the data from Ray et al. (2023).

Data

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.[4] Loblaw's is the largest Canadian retailer, operating 400 stores.[5] Super-C operates 97 stores and Provigo 300 stores.[6]

In each store, we hand-collected weekly price data from July 30, 2003–July 23, 2004. Over this period, the average annual inflation rate was 2.4%.

Every week, for each good, we hand-collected and 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.

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. On any week, the two prices of a good differ from each other if the good is on sale on that week. Otherwise, the two prices coincide.

From each store, we have observations for 89 national brand (*NB*) goods in 11 product

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

[5] Sources: https://mtltimes.ca/Montreal/local-businesses/loblaws-cavendish-store-in-notre-dame-de-grace-becomes-a-provigo/, and https://www.theglobeandmail.com/business/article-loblaw-profit-revenue-gain-as-bigger-baskets-help-offset-slower/, both accessed May 13, 2020.

[6] 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 during July 2003–July 2004, long before that happened. See: https://www.wsj.com/articles/SB909782024300867500, accessed November 18, 2021.

categories. In addition, we have price data for 39 private label (*PL*) goods (10 at the EDLP store, 10 at the Hi-Lo store, and 19 at the HYB store).[7] 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.

This dataset is small because it was hand collected. Also, the sampled products are not representative of all goods sold in Canadian supermarkets. However, it has the advantage of including information on both the regular and the transaction price. We can therefore use this dataset to conduct an analysis like the one that we conducted in the paper using Israeli data.

Analyses

Frequency of price changes

Table I1 is the equivalent of Table 2 in the paper. It summarizes information on the median frequency of price changes. We calculate these statistics at the store–product level, and then report the median at the category level. We report the statistics for the actual regular and transaction prices and for the 4 filter-generated regular prices. We also report the 95% confidence intervals, obtained by bootstrapping 1,000 times.

We find that in the Canadian data, the sales filters underestimate the frequency of price changes. This result should be taken with a grain of salt because the short time span implies that many products didn't have even one regular (and/or generated) price change in the sample period. In addition, the small sample of products implies that the bootstrapped standard errors tend to be large, particularly at the category level.

These limitations aside, we find that the median likelihood that a regular price will change is 0.058. The median likelihood that a filter-generated regular price will change is 0.019–0.038. This implies that the median duration between regular price changes is 17 weeks. The corresponding values for the filter-generated regular prices are 25, 51, 25, and 25 for Nakamura and Steinsson's (2008), Eichenbaum et al.'s (2011), Chahrour's (2011), and Kehoe and Midrigan's (2015) sales filters, respectively.

The sales filters, thus, overestimate the time span between regular price changes by 52%–102%. A large part of the discrepancy between the frequency of regular price changes and that of the filter-generated regular price is because one of the stores in the Canadian sample is an Every-Day-Low-Price (EDLP) store. Such stores, which comprise

[7] PL goods are specific to each chain/store and therefore they are not comparable across the stores.

about a third of US supermarkets (Ellickson and Misra, 2008), are characterized by low prices and a very low frequency of sales. Therefore, in such stores, even temporary price changes are usually treated as regular price changes (Ray et al., 2023). Sales filters tend to filter out such temporary price changes.

In the Israeli data, this does not happen because no Israeli food retailer follows an EDLP strategy. With the absence of EDLP stores, in the Israeli data, we find that the sales filters overestimate the frequency of regular price changes and, therefore, underestimate the time span between regular price changes.

Frequency of small price changes

In the Israeli data, we find that sales filters lead to an overestimation of the share of small price changes in comparison to the share of small price changes in the actual regular prices. Table I2, which is the equivalent of Table 4 in the paper, summarizes information on the shares of price changes smaller than 1%–5%.

We find that in the Canadian data, the share of small regular price changes is higher than in the Israeli data. For example, the share of regular price changes smaller than 1% (5%) in the Israeli data is 1.2% (13.5%), compared to 9.2% (32.1%) in the Canadian data.

Thus, the results for the Canadian data are consistent with papers that find that in certain markets, small price changes are common (Klenow and Kryvtsov, 2008, Midrigan, 2011, Beradi et al., 2015). However, we also find that like the Israeli data, the use of sales filters leads to overestimation of the share of small price changes. We find, for example, that among the filter-generated price series, the shares of price changes smaller than 1% (5%) are 13.7%–17.8% (44.1%–51.6%). Thus, in the Canadian data, like in the Israeli data, the use of sales filters leads to estimates of the share of small price changes that are 37%–94% larger than the actual share of regular price changes, depending on the sales filter used and the definition of small price changes.

Table I1. Frequency of price changes – Canadian data

categories	Actual regular prices	Generated regular prices, Nakamura-Steinsson	Generated regular prices, Eichenbaum et al.	Generated regular prices, Chahrour	Generated regular prices, Kehoe and Midrigan	Actual transaction prices
Baby Products & Foods	0.019 (0.000, 0.038)	0.019 (0.000, 0.019)	0.000 (0.000, 0.000)	0.000 (0.000, 0.019)	0.000 (0.000, 0.019)	0.019 (0.000, 0.038)
Beverage	0.077 (0.038, 0.115)	0.038 (0.038, 0.058)	0.019 (0.019, 0.019)	0.019 (0.019, 0.038)	0.019 (0.019, 0.038)	0.212 (0.154, 0.308)
Breakfast/Cereals	0.058 (0.038, 0.077)	0.038 (0.019, 0.058)	0.019 (0.019, 0.019)	0.019 (0.019, 0.029)	0.019 (0.019, 0.038)	0.192 (0.135, 0.221)
Condiments, Sauces & Spread	0.058 (0.038, 0.135)	0.038 (0.019, 0.058)	0.019 (0.019, 0.019)	0.038 (0.019, 0.038)	0.038 (0.019, 0.038)	0.173 (0.135, 0.231)
Dairy Products	0.058 (0.038, 0.096)	0.038 (0.038, 0.058)	0.038 (0.038, 0.038)	0.038 (0.038, 0.038)	0.038 (0.038, 0.038)	0.154 (0.087, 0.173)
Frozen Food	0.058 (0.038, 0.077)	0.038 (0.038, 0.058)	0.019 (0.019, 0.038)	0.019 (0.019, 0.038)	0.019 (0.019, 0.038)	0.135 (0.077, 0.192)
Health & Beauty Aid	0.067 (0.058, 0.077)	0.038 (0.038, 0.058)	0.029 (0.019, 0.038)	0.038 (0.038, 0.058)	0.038 (0.038, 0.058)	0.125 (0.096, 0.154)
Households	0.038 (0.038, 0.058)	0.038 (0.019, 0.038)	0.019 (0.019, 0.029)	0.019 (0.019, 0.038)	0.029 (0.019, 0.038)	0.125 (0.096, 0.154)
Juices	0.058 (0.038, 0.077)	0.038 (0.019, 0.058)	0.029 (0.019, 0.038)	0.038 (0.000, 0.048)	0.038 (0.019, 0.058)	0.231 (0.077, 0.269)
Paper Towel, Tissue & Pet Supplies	0.038 (0.019, 0.038)	0.038 (0.019, 0.038)	0.019 (0.019, 0.019)	0.019 (0.000, 0.038)	0.019 (0.000, 0.038)	0.077 (0.038, 0.115)
Soup / Canned Foods	0.058 (0.038, 0.077)	0.038 (0.019, 0.058)	0.038 (0.019, 0.038)	0.038 (0.019, 0.058)	0.038 (0.019, 0.058)	0.173 (0.154, 0.212)
Total	0.058 (0.038, 0.058)	0.038 (0.038, 0.038)	0.019 (0.019, 0.019)	0.019 (0.019, 0.038)	0.038 (0.038, 0.038)	0.154 (0.125, 0.154)

Notes: The median frequency of the actual regular price changes, the generated regular price series using the sales filters of Nakamura and Steinsson (2008), Eichenbaum et al. (2011), Chahrour (2008), and Kehoe and Midrigan's (2015), and the actual transaction prices. The observations are at a weekly frequency.

Table I2. Share of price changes smaller than 1%–5%, Canadian data

	< 1%	< 2%	< 3%	< 4%	< 5%
Actual regular prices	0.092	0.132	0.194	0.264	0.321
Generated regular prices, Nakamura and Steinsson	0.139	0.208	0.293	0.395	0.470
Generated regular prices, Eichenbaum et al.	0.178	0.265	0.356	0.434	0.516
Generated regular prices, Chahrour	0.143	0.214	0.303	0.372	0.456
Generated regular prices, Kehoe and Midrigan	0.137	0.199	0.283	0.358	0.441
Actual transaction prices	0.039	0.058	0.092	0.127	0.158

Notes: The table reports the share of non-zero log price changes that are smaller than 1%, 2%, 3%, 4% and 5%. Weekly data.

Appendix J. Uniform pricing

Chakraborty et al. (2015) note that large UK retailers follow a uniform pricing strategy, setting an identical price for the same products in their stores. DellaVigna and Gentzkow (2019) show that although US retailers do not have an explicit "uniform pricing" policy, many US retailers follow such a policy de facto.

If Israeli chains follow a similar pricing strategy, then that might weaken our results, because all the variation would come from between-chain comparisons. To examine the pricing policy of the retailers included in our dataset, Figures J1 and J2 present a heat map depicting the prices of the four products that we study in Figures 1 and 2 in the paper. Figure J1 depicts the prices in stores belonging to the largest supermarket chain, "Shufersal," and Figure J2 depicts the prices in stores belonging to the second largest supermarket chain, "Rami Levi Shivuk Hashikma" ("Rami Levi").

In both figures, the colors depict the prices, with darker colors indicating lower prices. If the retail chains followed a uniform pricing strategy, then at each date, the color would be the same across all stores. We see that pricing policies vary across chains, as well as across products.

Across products, prices with more volatile prices, such as red peppers, also have different prices across stores. In both Shufersal and Rami Levi stores, there is a large variance in the prices across stores. For other products, there is more uniformity across stores, although the prices are usually not the same across all stores.

Across chains, Rami Levi, the smaller chain, seems to have almost uniform pricing for the three products other than red peppers. However, there is some variation across stores. In particular, Store No. 39 seems to have a different pricing strategy than the other stores, suggesting that Rami Levi employs a zone pricing strategy (DellaVigna and Gentzkow, 2019).[8] There is also some variation in the prices across stores that appear to be in the same pricing zone.

Shufersal also seems to employ a pricing zone strategy. This is seen most clearly in the prices of potato chips. However, as in Rami Levi, prices at Shufersal's stores seem to vary somewhat even when the stores are in the same pricing zone.

[8] Dominick's, a large US retailer, whose price database was used in dozens of studies, is also known for employing several pricing zones. See, for example, Dutta et al. (2002), Levy, et al. (2002, 2010, 2011, 2020), Barsky et al. (2003), Ray et al. (2006), Müller, et al. (2006, 2007), Chen, et al. (2008), Snir and Levy (2021), and Snir et al. (2022).

Figure J1. Heat map of the prices in Shufersal's stores

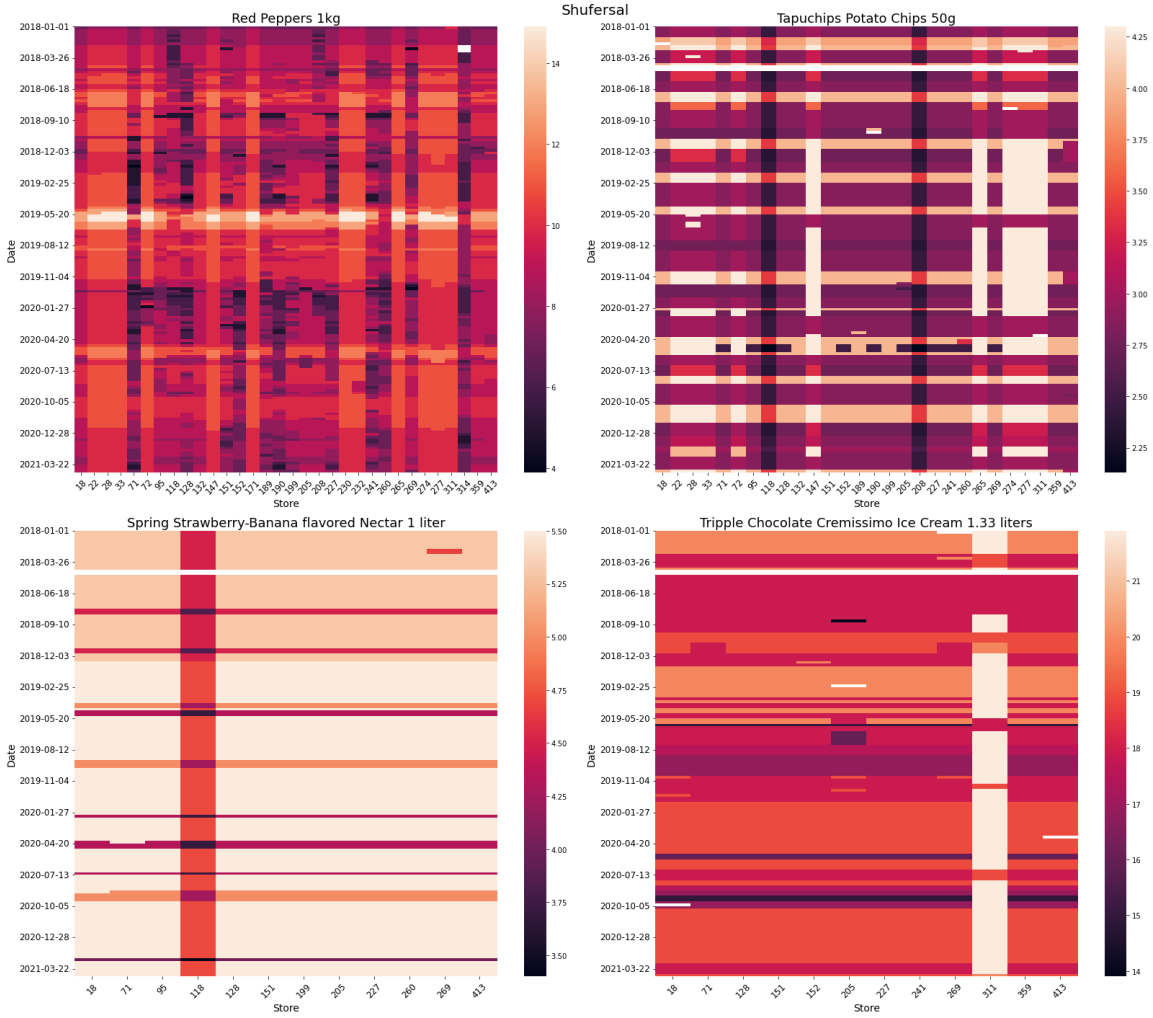
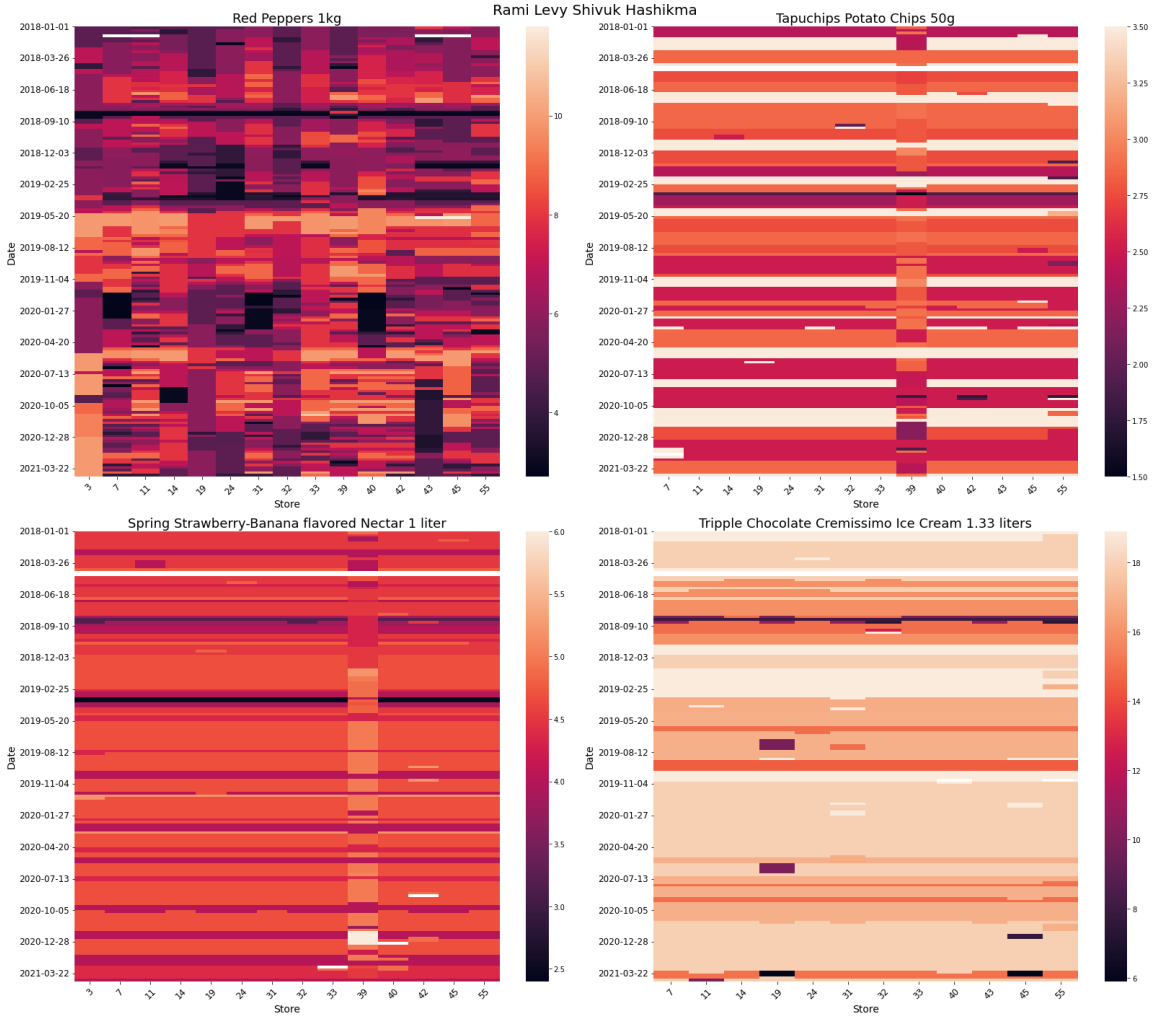


Figure J2. Heat map of the prices in Rami Levi's stores



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