Sales Filters and Regular Price Rigidity

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Sales Filters and Regular Price Rigidity

Abstract

We use new daily retail price data from 12 supermarket chains and one drugstore chain. The data covers 2,403 products sold in 106 stores, over the period January 1, 2018–April 8, 2021, with a total of about 108 million price observations. A unique aspect of the data is that it contains the *actual* regular prices along with the *actual* transaction prices. We use the data to study the rigidity of both the transaction prices and the regular prices. We employ four commonly used sales filters to generate regular price series and compare their rigidity to the rigidity of the actual regular price series. We conduct the analyses at both daily and weekly frequencies. We assess the implications of our findings for the effectiveness of monetary policy using sufficient statistics for both actual and generated series.

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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 whether or not prices respond to changes in market conditions.[1]

Nakamura and Steinsson (2008) argue that for evaluating the effects of monetary policy, changes in regular prices are more important than changes in transaction prices. This is because sale prices are usually set months in advance and, therefore, they 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 show that reference prices are set such that the firm would earn a constant average markup. They also show that when the wholesale costs change, the retailers adjust the reference prices, not the transaction prices.

Building on these empirical findings, Midrigan (2011) develops a model to explain the role of regular prices in the transmission of 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"). He finds that although a large share of the transactions take place during sales, 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 the rigidity of regular prices is missing, because most datasets contain information only on transaction prices. We use a new dataset of supermarket prices to fill this gap in the literature. The dataset contains more than 107 million daily price observations for 2,403 products sold in 106 stores that belong to the 12 largest food retail chains as well as to the largest drugstore chain in Israel. The 12 food retail chains account for over 90% of the

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

sales by chain stores in Israel, which makes our data a representative of much of the Israel's retail food market. In addition to its country-wide coverage, the sample size, and the daily frequency, the dataset is unique particularly because it includes the actual regular and transaction prices, both as posted by the stores.

We study price rigidity at both weekly and daily frequencies. We find that regular prices are quite rigid. The median regular price changes every 84 weeks (548 days). There is also a large variance in the rigidity; the standard deviation of the implied duration between price changes is 62 weeks (424 days).

When we analyze the size of price changes, we find that, consistent with menu cost theory, small price changes are rare. In the weekly (daily) data, the share of regular price changes smaller than 1% is 1.2% (0.9%), while the share of regular price changes smaller than 5% is 13.5% (11%). In contrast, Midrigan (2011) finds that in a US supermarket (Dominick's), 10% of the price changes are smaller than 3%, and that 25% of all price changes are smaller than 5%. Beradi et al. (2015) report 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 very small price changes in our data leads to a "bimodal" distribution of the size of price changes. Thus, the distribution of regular price changes ostensibly resembles the one predicted by 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 much higher than predicted by Golosov and Lucas (2007).[2]

For comparison, we "generate" regular price series using the four "sales filter" algorithms of (i) Nakamura and Steinsson (2008), (ii) Eichenbaum et al. (2011), (iii) Chahrour (2011), and (iv) Kehoe and Midrigan (2015), and use them to assess the rigidity of regular prices and the distribution of small regular price changes. We find that for both, the time spell between price changes and the variance of the rigidity, the sale filter of Eichenbaum et al. (2011) performs the best. However, even Eichenbaum et al.'s (2011) filter underestimates both the rigidity of the median regular prices and the variance of the

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

regular price rigidity. When it comes to the size of price changes, we find that all four algorithms fail to replicate the distribution of the size of price changes, predicting too many small price changes and kurtoses that are either too high or too low.

Our results are important for several reasons. First, we find that actual regular prices are stickier than the regular prices that are generated by applying “sales filters.” I.e., the actual regular prices change less often, and by more, than the 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.

Second, we find that there is a large variation in the rigidity of regular prices across products, suggesting that variation in the rigidity is likely to play an important 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), algorithms designed to filter the “regular” prices from transaction prices are not “an attempt to identify a theoretical object such as the list price in our model, but rather as a simple way to highlight key patterns in our data.” As they point out, different algorithms highlight different patterns in the data. Therefore, the choice of an algorithm depends on the patterns that need to be highlighted. However, our results suggest that Eichenbaum et al.’s (2011) simple algorithm manages best at capturing a key parameter: in a low inflationary environment, the regular prices firms set are very rigid. Transaction prices often deviate from these regular prices, and these deviations sometimes last long periods (Volpe and Li 2012). Eventually, however, prices revert to the regular price.

Fourth, our results support key predictions of the menu cost model: price changes are rare and tend to be large. Indeed, one argument against the canonical menu cost model is that real-world data contains many small price changes, whereas the menu cost model predicts that price changes should be relatively large (Eichenbaum et al. 2011, Midrigan 2011, Alvarez and Lippi 2014, Alvarez et al. 2016). Our results therefore support the findings of Cavallo and Rigobon (2016) and Cavallo (2018) that point at a possible role that measurement errors play in generating spurious small price changes.

Fifth, we find that sales filters tend to produce too many small price changes. Thus, our results suggest that using “sales filter” algorithms to identify regular prices leads to "spurious" small price changes.

Sixth, Alvarez et al. (2016) show that the real effects of a monetary shock depend on the size of a sufficient statistic. Our results suggest that because regular price changes are rare, a monetary shock is likely to have a large effect. Assessing the likelihood and the size of price changes using sales filters underestimates this effect.

Finally, our results suggest that the extent of price rigidity found in daily data is close to the price rigidity found in weekly data.

The paper is organized as follows. In section 2, we describe the data. In section 3, we study price rigidity for the weekly and daily data. In section 4, we study the size of price changes for the weekly and daily data. In section 5, we discuss the implications of our findings for the effect of monetary policy using sufficient statistic information. We conclude in section 6.

2. Data

We use daily price data from Israeli supermarkets and drugstores. Since May 20, 2015, all large food retailers operating in Israel have been required by law to publish online their daily prices for all products sold in each of their stores (Bonomo et al. 2022). As of July 1, 2017, large drugstore chains are also required to publish their prices.

The data we use was provided by CHP, a price comparison company that scrapes the above price data (which is not consumer-friendly) and makes it accessible for consumers and businesses. We have data on 2,403 products sold in 106 stores belonging to the 12 largest food retailers and to the largest drugstore chain. Appendices A and B report summary statistics about the retailers and the products, respectively.

The 12 food retailers included in our sample are responsible to over 90% of the sales by chain stores.[3] 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 38 and 17 stores, respectively.[4] For each chain, we selected the

[3] According to Israel's Household Expenditure Survey (2013), 71% of the food is purchased in chain stores. The remaining 29% is purchased in grocery stores, open markets, and specialty stores.
[4] The 38 (17) stores of Shufersal (Rami-Levi) include 37 (16) brick-and-mortar stores and the chains' online stores.

store locations randomly. Appendix C contains a list of the stores in our sample.
The 2,403 products in our sample are all the UPCs that belong to the ELIs whose average prices appear in a representative basket of goods published the Israel's Ministry of Economy and Industry and the Central Bureau of Statistics.[5] The Ministry of Economy and Industry publishes the average prices of these goods to help consumers find stores that offer the lowest prices. ELIs that are 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., according to the department in which they are sold.

In total, we have 107,743,561 observations on daily prices for the period January 1, 2018–April 8, 2021. The average price is NIS 16.93, with a standard deviation of NIS 13.40.[6] For each observation, we have the regular price, as posted by the store. If the price was offered at a discount, we also have the discounted price.

Over our sample period, inflation was low. The average annual inflation rate was 0.3%, and the average annual food price inflation was 0.9%. In addition, during our sample period, the prices of 21 basic food products were capped by government regulators. This is unlikely to affect our results, however, because the affected products comprise only 0.8% of the 2,403 UPCs in our data.[7]

3. Price rigidity

A. Weekly data

To make our results comparable with the existing literature (which typically uses weekly data), we start by studying price rigidity at a weekly frequency. As in Karadi et al. (2022), we define the weekly price as the mode price of each week. If there was more than one mode price, we chose the one that appears first (Kehoe and Midrigan 2015).

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[5] ELIs or Entry Level Items are the most granular, complete, and mutually exclusive breakdown of CPI items. Examples of ELIs include fresh tomatoes, red wine, laundry detergents, etc. A UPC, or Universal Product Code is a unique product identifier. For example, different flavors of the same brand, or different package sizes of the same brand, have different UPCs.
[6] The average exchange rate during our sample period was NIS 3.49 for US $1.
[7] In appendix E, we show that dropping these UPCs has very little effect on the results.

This yields 16,676,881 observations.

Because missing observations can affect the measured price rigidity, we follow the literature (Chahrour 2011, Eichenbaum et al. 2011) by focusing on store-product combinations that have no more than 3 missing observations. This yields 3,910,261 observations on 1,506 products sold in 79 stores that belong to 10 chains.[8]

Figure 1 depicts the time series of regular and transaction prices of four products sold in Store 18 of the largest chain, Shufersal. The first product, red peppers, is an example of a product with a volatile regular price. We also observe temporary cuts in the transaction price ("sales").

The second product, Tapuchips Potato Chips, is an example of a product that 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.

The third product, Spring strawberry-banana flavored nectar, is another example of a product with stable regular prices. The transaction price is more volatile, with several temporary price cuts (sales).

The fourth product, Cremissimo ice cream, had a stable regular price in the first part of the data. In that period, the transaction price was more volatile, with some of the price cuts lasting relatively long periods. In the second part of the data, after September 2019, the regular price became more volatile.

A.1. Generated regular prices

For lack of direct observations on regular prices, the literature uses "sales filters" for generating regular prices. I.e., researchers have designed algorithms that use information on transaction prices to identify the corresponding regular prices. Below, we use our data to compare the rigidity of the actual regular price (i.e., regular prices as defined by the stores) with the rigidity of generated regular prices.

[8] Stores that are not included in the final list are stores that were either opened in the middle of the sample period or were closed either temporarily or permanently during the sample period. For example, one of the largest chains, Yenot-Bitan, and its subsidiary chain Mega, came close to bankruptcy during our sample period, forcing the chain to close some branches and sell some branches to other chains. We, therefore, exclude all the stores that belong to these chains. The final list includes 9 food retailers and one drugstore chain.

We use four sales filters: Nakamura and Steinsson's (2008) sales filter A, Eichenbaum et al.'s (2011), Chahrour's (2011), and Kehoe and Midrigan's (2015).[9] Nakamura and Steinsson's (2008) filter is a one-sided filter, designed to identify the regular price by removing V-shape price cut patterns. We run the filter assuming that the maximum length of both symmetrical and asymmetrical sales is 6 weeks. Eichenbaum et al.'s (2011) filter defines a reference price, computed as the mode price in each quarter (13 weeks).[10] Chahrour's (2011) and Kehoe and Midrigan's (2015) filters also focus on the modal price. Their filters, however, find the mode price for moving windows rather than for set time periods. They also use a second-stage procedure for smoothing the 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 procedure that 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 generated regular prices obtained using the sales filters. Consider first red peppers. Here we find that none of the filters identify the movements of the regular price correctly because the regular price is 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.

In the case of potato chips, we find the opposite. Because the transaction price stays at a lower level than 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 flavored nectar, all four filters identify well the movements in the

[9] Other sales filters found in the literature include Nakamura and Steinsson's (2008) sales filter B, A.C. Nielsen's filter (as implemented by Kehoe and Midrigan 2007), Dutta et al.'s (2002) moving average filter, 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 (2022) base price filter. The filters we chose to analyze in this paper are the ones that are used most often.

[10] 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.

regular price.[11] In the case of Cremissimo ice cream, the filters underestimate the price rigidity in the first part of the data, when 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 tend to overestimate the regular price rigidity.

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

A.2 Actual vs 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. We report the statistics for the regular and transaction prices, as reported by the stores, along with the statistics for the four generated regular price series using the sales filters. The table also reports 95% confidence intervals, derived 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 changed every 4–28 weeks, with the median price changing every 7 weeks.

The behavior of the actual regular prices offers two observations. First, the median price changes every 84 weeks. In other words, the median regular price, as defined by the stores, changes every 1.6 years.

Second, there is a large variation across categories. In some categories, the regular prices are quite flexible. Examples include fruits and vegetables, with a median price change every 4 weeks, and condiments, cooking oil, and ice cream, with a median price change every 12 weeks. In other categories, we find that the median regular price has

[11] Eichenbaum et al.'s (2011) filter generates a price series with a wrong timing of price changes because it allows for price changes only at the beginning of each quarter. The algorithm is correct, however, about the number of price changes.

changed only once in more than 3 years. Examples include baking goods, canned food, coffee & 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 tend to overestimate the price rigidity when the actual regular price is flexible and underestimate it when the actual regular price is rigid. As a result, the standard deviations of the implied durations are 51 weeks, 53 weeks, 52 weeks, and 49 weeks for Nakamura and Steinsson's (2008) filter, Eichenbaum et al.'s (2011) algorithm, Chahrour's (2011) algorithm, and Kehoe and Midrigan's (2015) algorithm, 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 four filters underestimate the rigidity of the median regular prices. The median price change according to Nakamura and Steinsson's (2008), Eichenbaum et al.'s (2011), Chahrour's (2011), and Kehoe and Midrigan's (2015) filters, occurred every 24, 55, 33 and 27 weeks, respectively.

Eichenbaum et al.'s (2011) filter performs better than the other filters both in terms of the variation in the rigidity of regular prices across products and in terms of the median duration between price changes. However, even Eichenbaum et al.'s (2011) filter underestimates both the median rigidity of the regular prices and the variation in the rigidity of the regular prices.

B. Daily data

Figure 3 illustrates the behavior of the time series of regular and transaction prices of the same 4 products as in Figure 1 when we use daily data. 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 the Cremissimo ice cream, in the fourth 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 3 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 compose between 10.3% and 32.2% of all price changes, with an average of 18.5%.

However, 62.6% of these price changes completely cancel each other out. In another 23.4% of the cases, the changes occur in opposite directions, 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% of the cases, both price changes are increases, and in 7.4% of the cases, both price changes are decreases.

Figure 4 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 taken 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.[12]

Because the 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 chips in the early 2021, and the 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 the 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 second quarter of 2020.

Tables 4 and 5 summarize the findings on price rigidity for daily data. When we use daily observations, the median duration between regular price changes decreases from

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

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 (2011), Chahrour (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 the Nakamura and Steinsson's (2008), Eichenbaum (2011), Chahrour (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.

4. Size of price changes

A. Weekly data

Consistent with Bonomo et al. (2022), the size of price changes, calculated as log differences, is relatively large. The mean absolute size of price changes (standard deviation) 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 non-zero log price changes at the store-category level. Figure 5 depicts the histograms of $z_{is,t}$ for the actual regular prices, for the generated regular prices using the four sales filters, and for the transaction prices. Table 6 reports key statistics of the distributions.[13]

Several features of the size of regular price changes stand out. First, the distribution is

[13] Following Bonomo et al. (2022), we exclude observations at the top 0.5% of the distribution. In appendix F, we show that including all observations only has a very modest effect on the results.

almost symmetric, with a skewness of 0.005. Second, the distribution is slightly leptokurtic, with a kurtosis of 3.791. 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 the 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 7 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%. In France, Beradi et al. (2015), report that 11.2% of all price changes are smaller than 1%, and 23.7% are smaller than 2%. For the US, Midrigan (2011) reports that in his supermarket price data, 10% of all price changes are smaller than 3%, and 25% are smaller than 5%. Klenow and Kryvstov (2008) and Vermeulen et al. (2012) find that 25% of all price changes are smaller than 2.5% and 1.5%, respectively.

The histogram of the 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 in our data could be partly 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 G we show that the lack of price changes in the range NIS 0.01–0.09 cannot fully account for this finding because price changes below 0.5 NIS are quite rare.

A more likely explanation is the quality of our data. Cavallo and Rigobon (2016) and Cavallo (2018) use scraped data, and, like us, find that small price changes are rare. They suggest that the share of small price changes in scanner datasets, such as 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 law requires that retailers post a price tag on every product. Consequently, the menu cost is higher in Israel than in the US (Levy et al. 1997, 1998, Dutta et al. 1999). In addition, Sayag et al. (2023) argue that small price changes can be profitable when the sales volume is sufficiently large. This suggests that in countries with small populations (and thus with smaller sales volumes), such as Israel, the likelihood of small price changes should be lower than in larger countries, such as the US.

A third possible explanation is that the number of products in a typical Israeli supermarket is smaller than in US supermarkets. Bonomo et al. (2022) report that an average Israeli supermarket offers 7,217 products. For a comparison, Levy et al. (1997) and Kackmeister (2007) report that a typical US supermarket carries about 25,000 products and Ray et al. (2023) report that some Canadian large supermarkets carry around 30,000 products. Alvarez et al. (2016) show that when stores sell a small number of products and face a low probability of costless price changes, the distribution of the size of price changes approximates the bimodal distributions of Golosov and Lucas (2007). Yet the kurtosis of our data, 3.791 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.

When we compare the results for the regular prices, as defined by the store, with the results for the price series generated by the sales filters, we find the following. First, except for Nakamura and Steinsson's (2008) filter which indicates a slightly positive skewness, all the other filters correctly generate regular price series with a skewness that is close to zero. The generated price distributions also capture the "bimodal" shape of the distribution of the actual regular prices. However, in the generated regular prices series of Nakamura and Steinsson (2008), Eichenbaum, et al. (2011), Chahrour (2011), and Kehoe and Midrigan (2015), we find that the share of price changes smaller than 25% of the average change is respectively 25%, 38%, 26%, and 22% higher than what we find in the actual data. In particular, in the 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 kurtosis, while Nakamura and Steinsson's filter leads to excessively leptokurtic kurtosis.

B. Daily data

In the daily data (Table 7), 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, 0.090. Consistent with this finding, Table 8 reports that the share of regular price changes smaller than 1%–5% are smaller 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 removes 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 6 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, 4.171, 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) filter generates a regular price series with slightly excessive kurtosis, 4.06. 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—3.295 and 3.437, respectively.

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 a large number of 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 statistic for the actual regular prices, for the transaction prices, and for the regular prices generated using the four sales filters. Figure 7 depicts the results for both the weekly data (LHS panel) and the daily data (RHS panel). The black lines in the figure denote 95% confidence intervals derived by bootstrapping 1,000 times.

For weekly data, we find that the predicted effect of a small monetary shock is significantly greater if we use the data for the regular prices than if we use the series generated using the filters of Eichenbaum et al. (2011), Chahrour (2011), or the Kehoe and Midrigan (2015). This is because the actual regular prices have both a bigger kurtosis and a smaller probability of price changes than we find in the generated series.

We cannot reject, however, the null hypothesis that the sufficient statistic of the actual regular prices is not different than the sufficient statistic of the price series generated by Nakamura and Steinsson's (2008) filter. This happens 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.

For daily data, we find that the sufficient statistic of the actual regular prices is almost unchanged relative to the weekly data. However, all four filters generate price series with sufficient statistics that are smaller than what we obtain when we use 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 prices.

6. Conclusion

We study regular and transaction price data using a unique dataset that contains both. 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 prices 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 regular prices generated using sales filters do not succeed in capturing many of the properties of the actual regular prices. First, the generated regular prices change too frequently. In weekly (daily) data, the median regular price changes every 24 (193), 55 (293), 33 (190), and 27 (146) weeks (days) according to sales filters of Nakamura and Steinsson (2008), Eichenbaum, et al. (2011), Chahrour (2011), and Kehoe and Midrigan (2011), respectively. These figures are significantly smaller than the corresponding figures for the actual regular prices.

The 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 actual regular prices.

These results are important for several reasons. First, our findings suggest that studying price rigidity at weekly and daily frequency yields very similar results. Second, Alvarez et al., (2016) show that in a large number of 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, 3.791 in weekly data and 3.756 in daily data. Combined with the 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) that 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 in CPI data. They argue that scanner data 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 rather than from 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 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 the 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, our results suggest that sales filters generate regular price series whose properties are quite different from those of the actual regular prices. In particular, sales filters generate frequent “spurious” regular price changes, and especially, small regular price changes. Thus, estimating the menu cost based on generated regular price series, likely leads to estimates that are biased downward. 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.

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. For such products, the actual regular prices are much more rigid than the corresponding generated prices.

Seventh, a possible explanation for the existence of long-lasting sales in our data is the nature of the menu costs that the retailers in Israel face. Israel has an item price law that obliges retailers to attach a price tag to every item that is offered for sale. When a regular price is changed, the retailer must replace the price tag on each item on the display shelves. In contrast, when an item goes on sale, the retailer only needs to post a shelf price tag showing the reduced price. It implies that in Israel, the cost of changing a sale price is much lower than the cost of changing a regular price (Bergen et al., 2008). To minimize the menu costs, retailers that are uncertain about future demand might prefer to change the sale price rather than the regular price.

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 therefore consider models with multi-product retailers, where menu costs lead to a low likelihood of price changes and a very low likelihood of small price changes yet offer a greater distribution of price changes 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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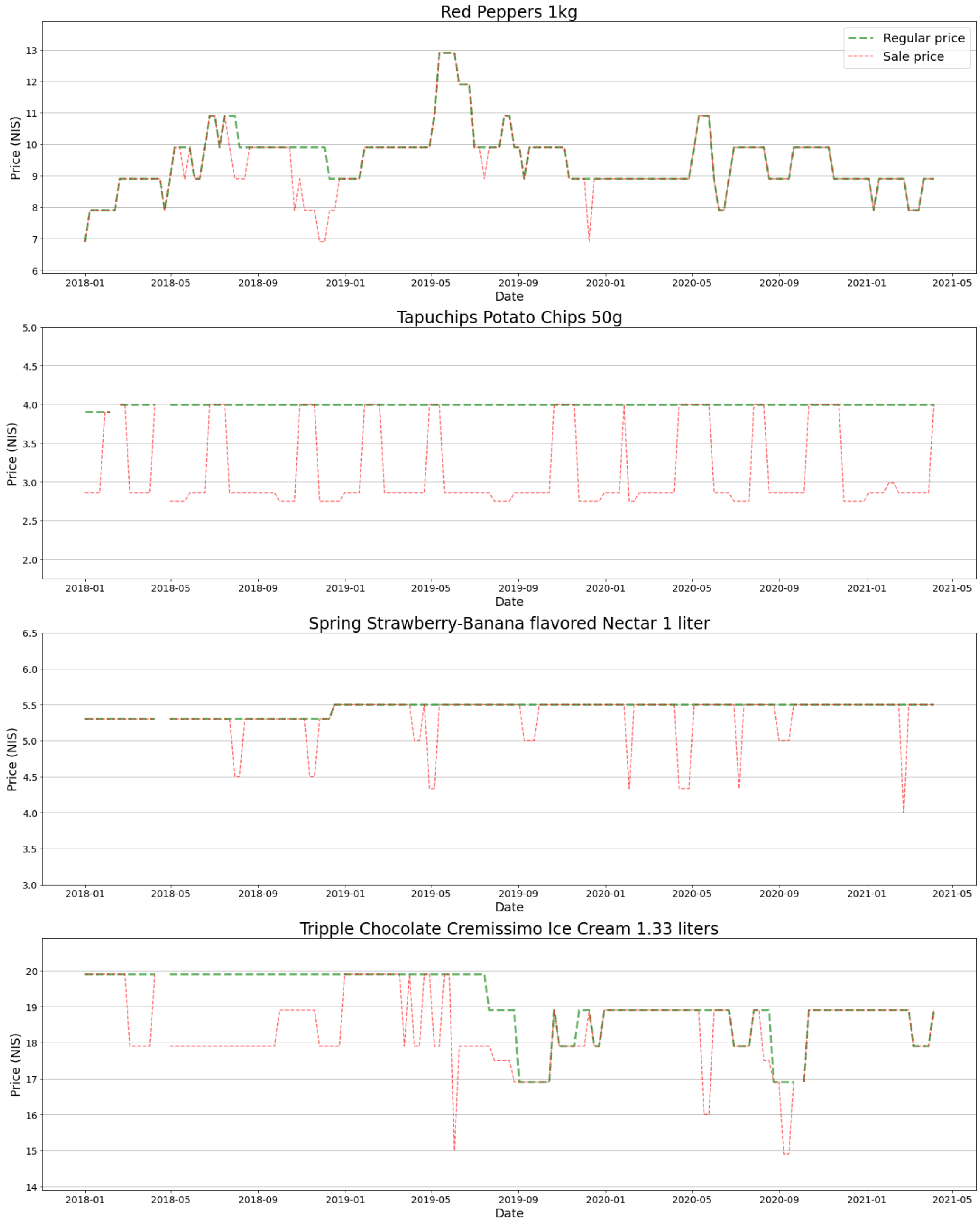
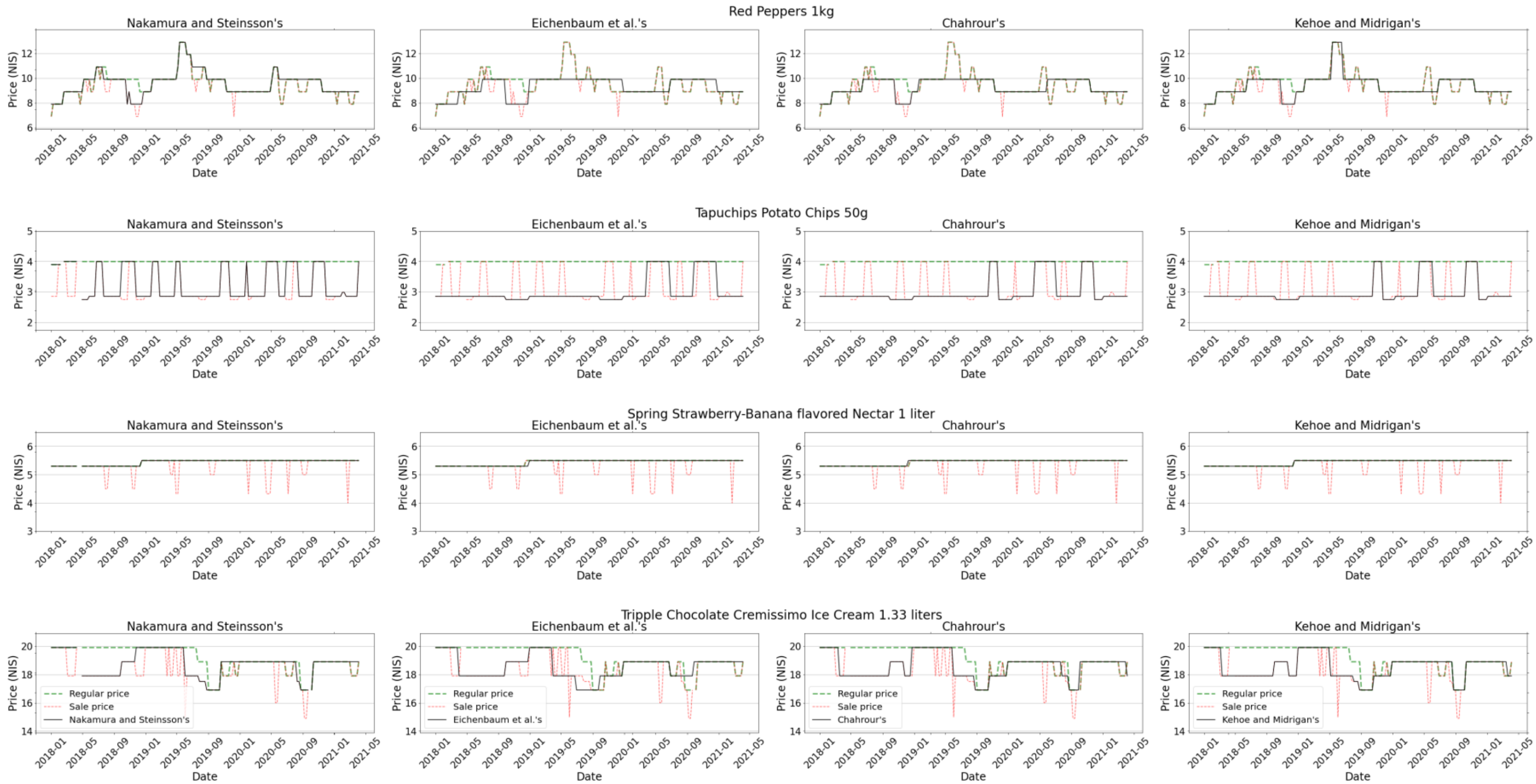
Figure 1. Regular and transaction prices of four products, weekly frequency



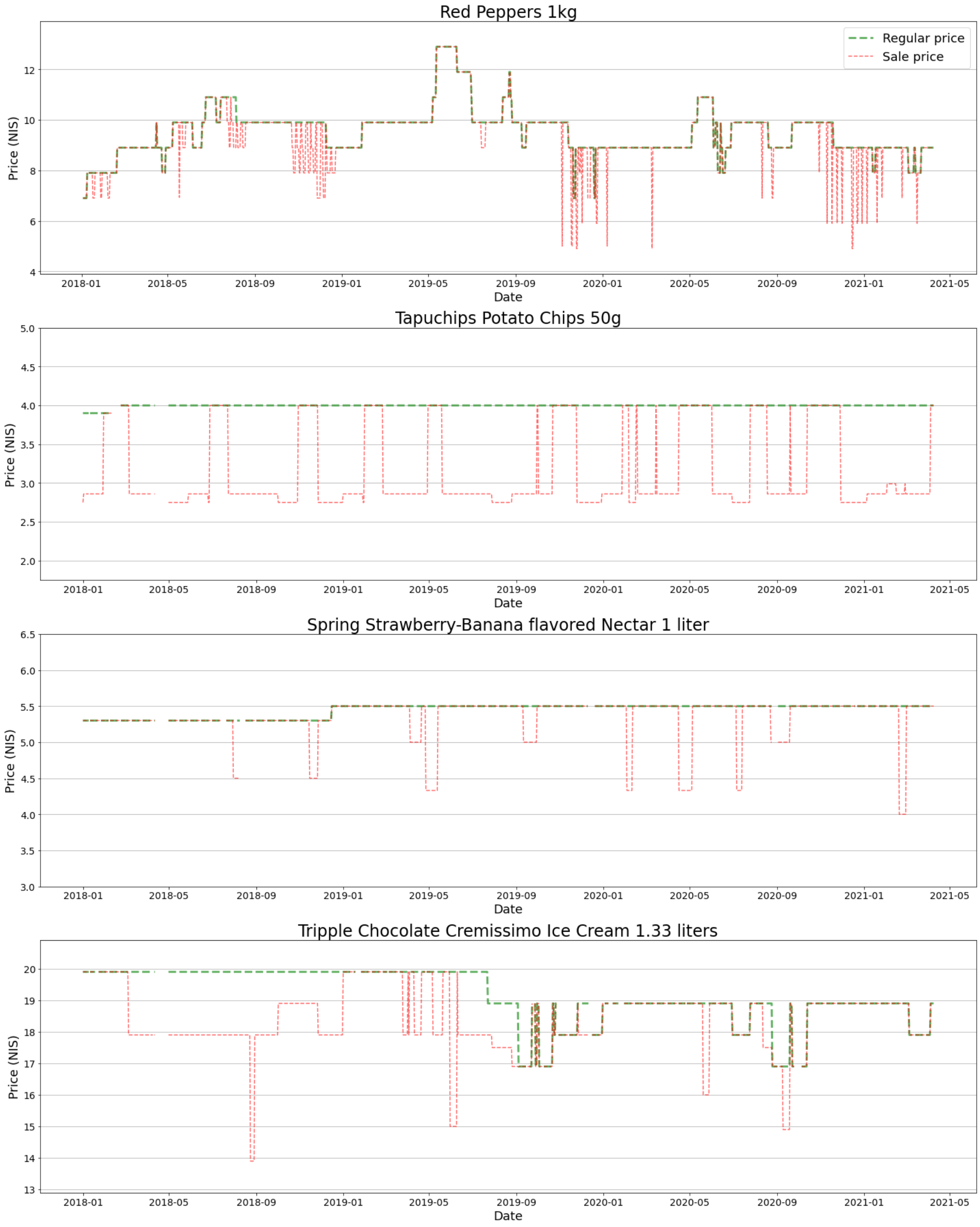
Notes: Weekly data from store 18 of Shufersal.

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



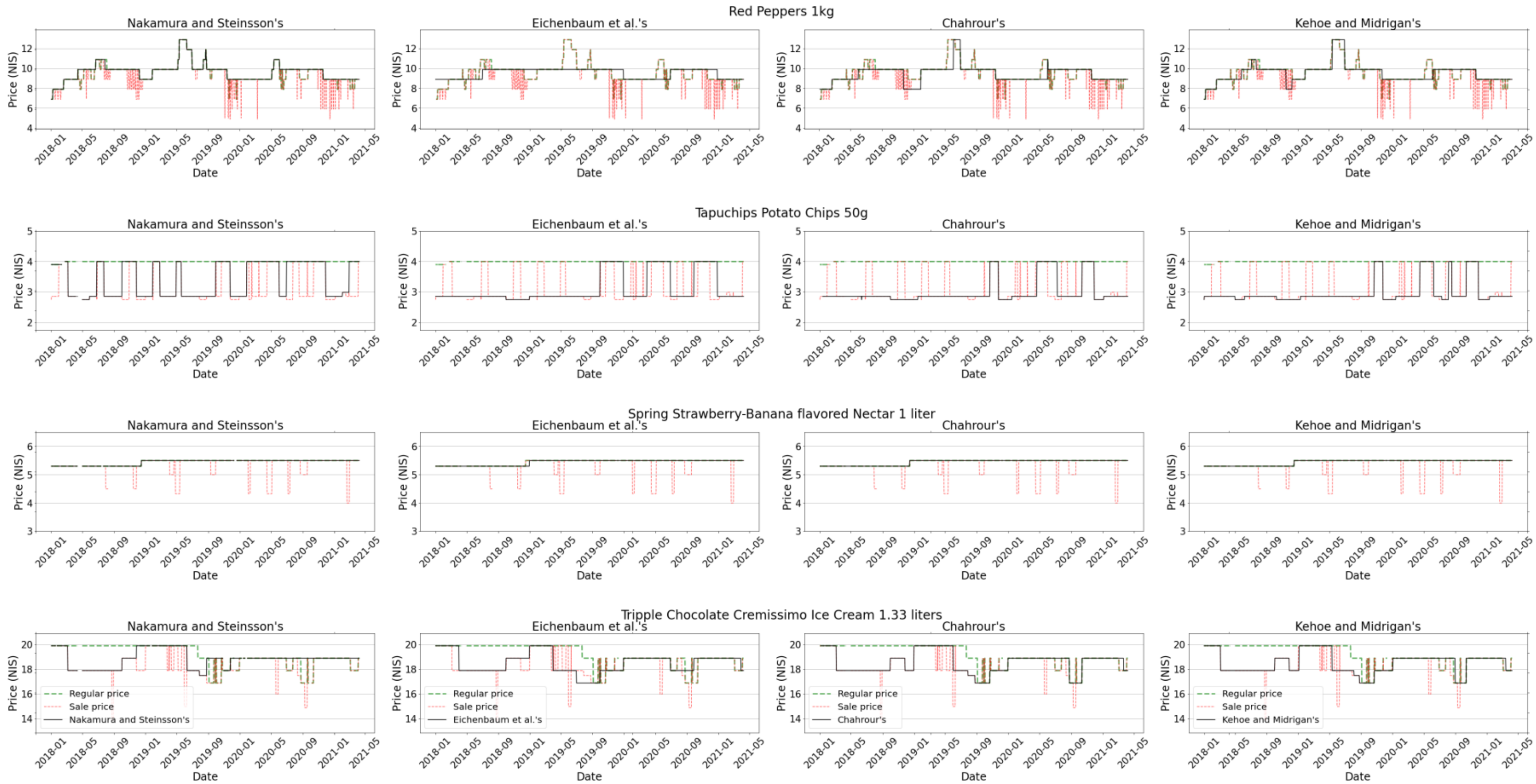
Notes: Weekly data from store 18 of Shufersal.

Figure 3. Regular and transaction prices of four products, daily frequency



Notes: Daily data from store 18 of Shufersal.

Figure 4. Actual regular prices vs. generated regular prices, daily frequency



Notes: Daily data from store 18 of Shufersal.

Figure 5. Histograms of the size of normalized price changes, weekly data

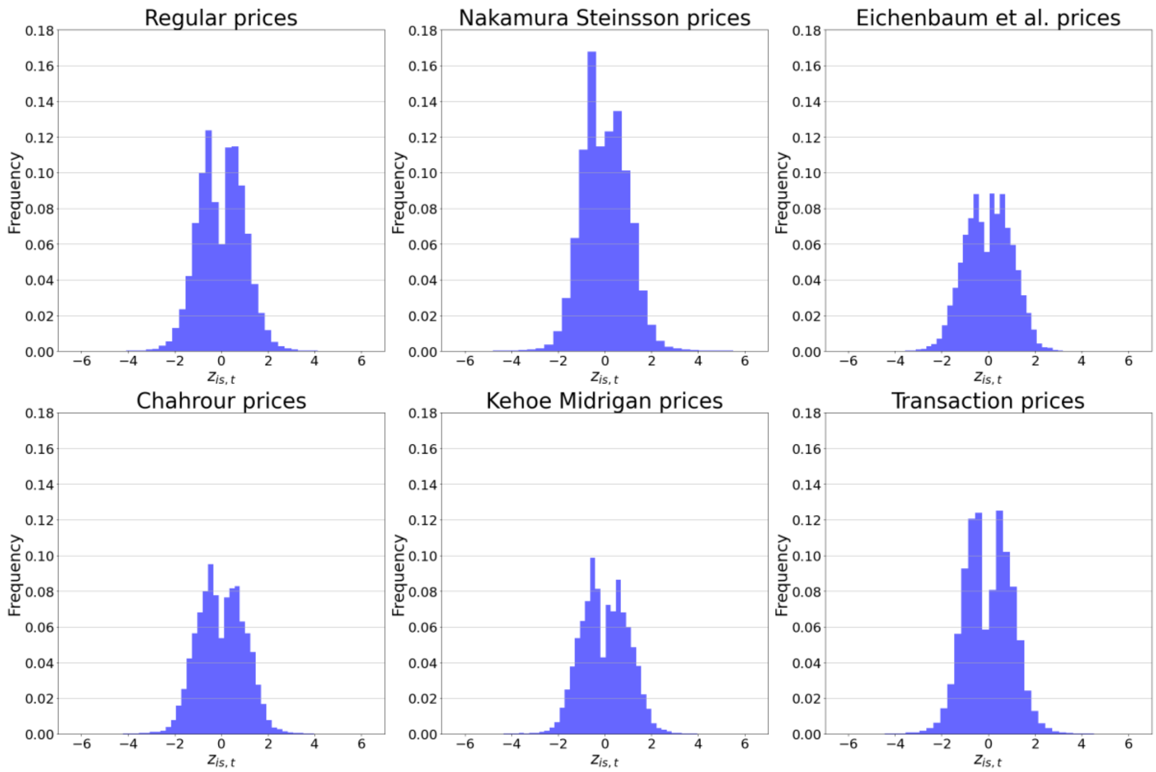


Figure 6. Histograms of the size of normalized price changes, daily data

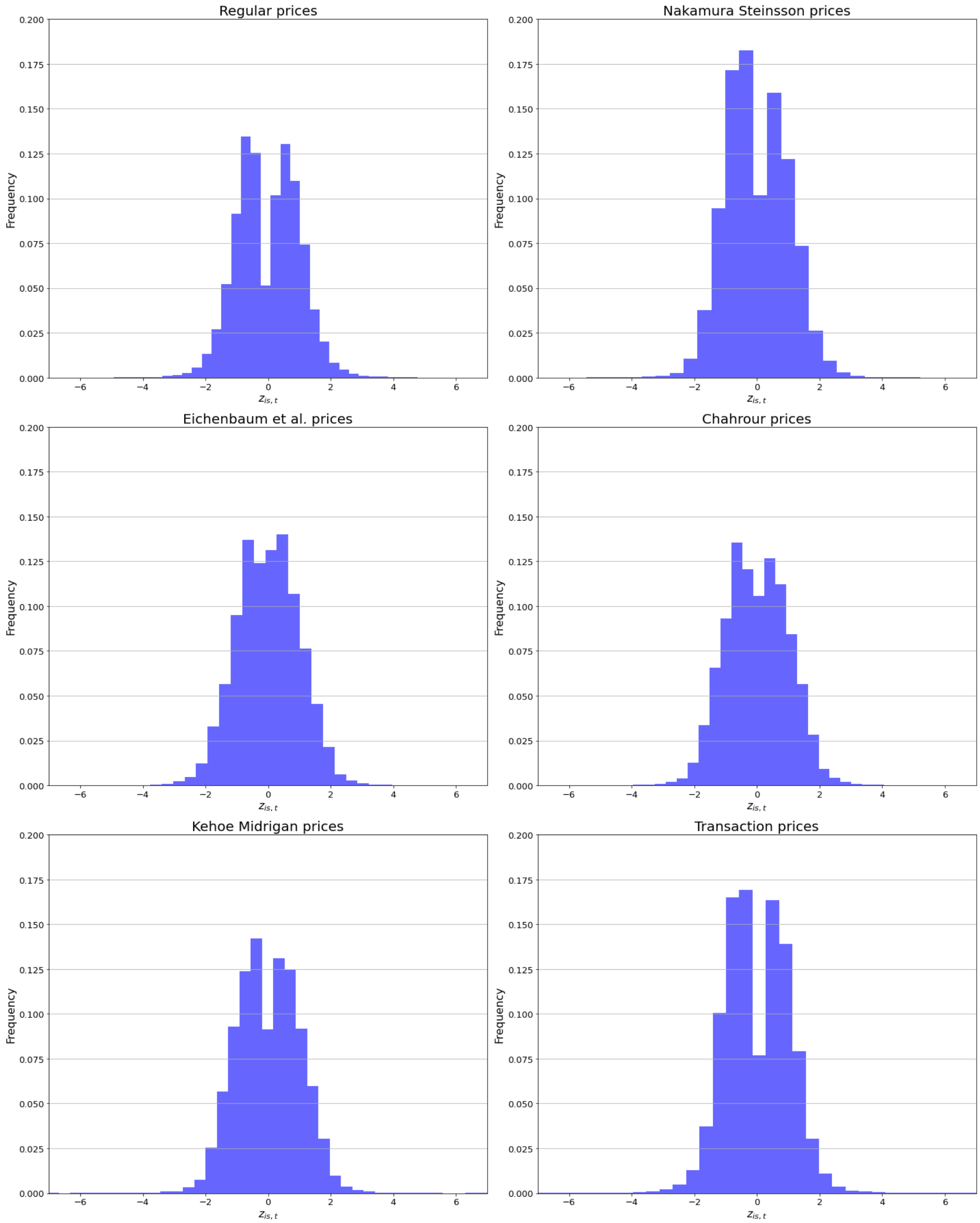
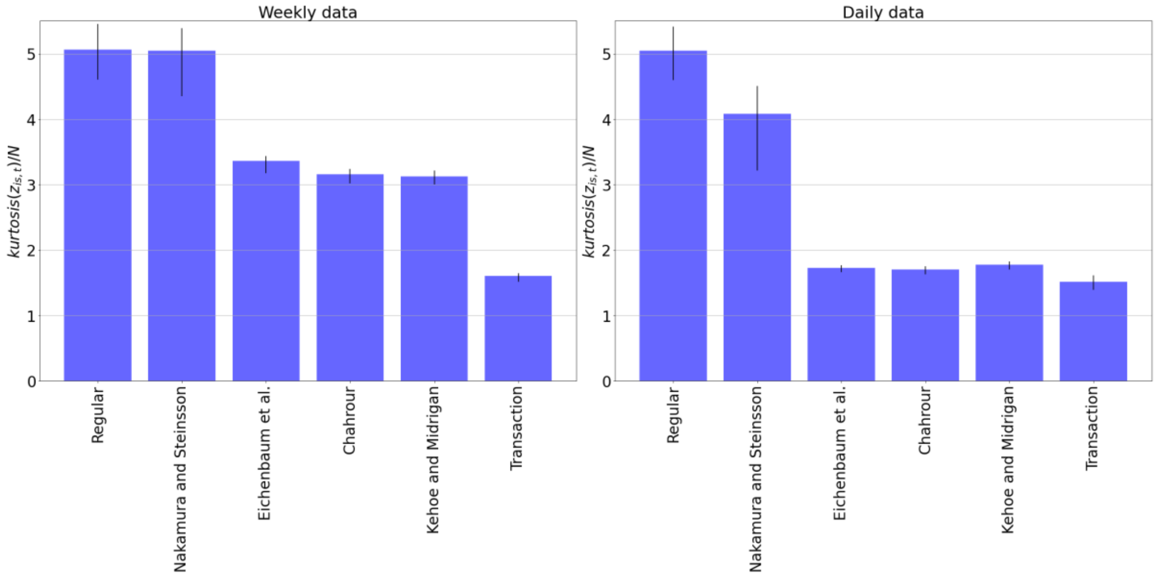


Figure 7. Sufficient statistics, weekly and daily data



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 – weekly observations

categories	Regular prices	Nakamura-Steinsson	Eichenbaum et al.	Chahrour	Kehoe and Midrigan	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 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 transaction prices. The observations are at a weekly frequency.

Table 2. The expected number of weeks between price changes

categories	Regular prices	Nakamura-Steinsson	Eichenbaum et al.	Chahrour	Kehoe and Midrigan	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. 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 4. Frequency of price changes, daily observations

categories	Regular prices	Nakamura-Steinsson	Eichenbaum et al.	Chahrour	Kehoe and Midrigan	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 transaction prices. The observations are at a daily frequency.

Table 5. The expected number of days between price changes

categories	Regular prices	Nakamura-Steinsson	Eichenbaum et al.	Chahrour	Kehoe and Midrigan	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 6. Summary statistics of the size of price changes, weekly data

	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× $\bar{z}_{is,t}$
Regular prices	0.005	3.791	0.687	0.244	0.090
Nakamura and Steinsson	0.216	5.137	0.742	0.264	0.113
Eichenbaum et al.	-0.061	2.810	0.683	0.263	0.124
Chahrour	0.011	2.938	0.675	0.255	0.114
Kehoe Midrigan	0.022	2.956	0.671	0.249	0.110
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. $z_{is,t} = (\Delta p_{is,t} - \overline{\Delta p_{is}})/\sigma_{is}$, 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 7. Share of price changes smaller than 1%–5%, weekly data

	< 1%	< 2%	< 3%	< 4%	< 5%
Regular prices	0.012	0.036	0.063	0.108	0.135
Nakamura and Steinsson	0.026	0.050	0.076	0.123	0.150
Eichenbaum et al.	0.027	0.052	0.080	0.147	0.173
Chahrour	0.027	0.048	0.071	0.124	0.149
Kehoe Midrigan	0.026	0.046	0.069	0.120	0.145
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.

Table 8. Summary statistics of the size of price changes, daily data

	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× $\bar{z}_{is,t}$
Regular prices	0.036	3.756	0.669	0.228	0.086
Nakamura and Steinsson	0.158	4.171	0.674	0.240	0.095
Eichenbaum et al.	0.059	4.060	0.725	0.279	0.126
Chahrour	0.040	3.295	0.694	0.263	0.118
Kehoe Midrigan	0.062	3.437	0.687	0.257	0.115
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. $z_{is,t} = (\Delta p_{is,t} - \overline{\Delta p_{is}})/\sigma_{is}$, where $p_{is,t}$ is the price of product i in store s at week t, $\Delta p_{is,t}$, are log price chnages, $\overline{\Delta p_{is}}$ 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 9. Share of price changes smaller than 1%–5%, daily data

	< 1%	**< 2%**	**< 3%**	**< 4%**	**< 5%**
Regular prices	0.009	0.030	0.054	0.087	0.110
Nakamura and Steinsson	0.018	0.038	0.062	0.102	0.126
Eichenbaum et al.	0.030	0.057	0.092	0.164	0.194
Chahrour	0.028	0.050	0.077	0.135	0.162
Kehoe Midrigan	0.027	0.047	0.073	0.129	0.155
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.