Sales filters and regular price rigidity

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Once more unto the breach: rigidity of regular prices

- **Study the rigidity and size of regular price changes**

- **We use a unique dataset**

- **Daily data**
  - **Regular ("list") prices**
  - **Transaction ("sale") prices**

- **Prices are very sticky**
- **Price changes are large**

How rigid are prices?

- **Bils and Klenow (2004): Prices aren’t rigid**
  - **Median price changes every quarter**
- **Nakamura and Steinsson (2008): If you remove sales, prices are rigid**
  - **Median price changes every 8 months**
- **Eichenbaum et al. (2011): reference prices are very rigid**
  - **Median price changes every 12 months**

Why regular prices?

- **Nakamura and Steinsson (2008), Anderson et al. (2017):**
  - **Sales are set in advance**
  - **Regular prices respond to cost shocks**
  - **Sale prices respond in the opposite direction**
  - **Sales do not respond to shifts in macroeconomic conditions**

- **Eichenbaum et al. (2011)**
  - **Regular (“reference”) prices maintain a stable markup**
  - **Regular prices change when the markup falls**

Theory

- **Midrigan (2011), Kehoe and Midrigan (2015), Eichenbaum et al. (2011)**

- **Midrigan (2011):**
  - **Retailer sets regular prices**
  - **Temporarily sets “sale prices”**
    - **Low menu cost**
  - **Almost half the sales are at sale prices**
  - **The effect of a monetary shock is manifested through the regular price**
    - **Sale prices follow regular prices**

But what do regular prices look like?

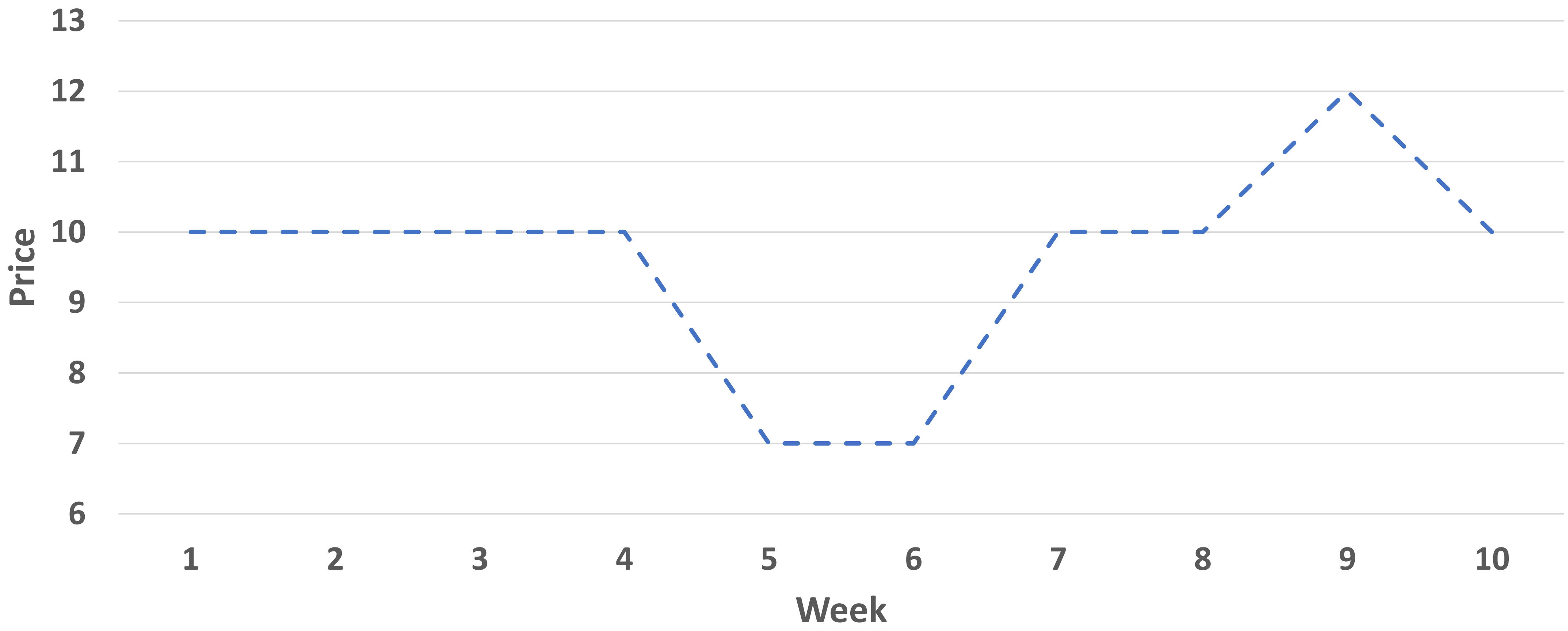
- **Most datasets contain information on transaction prices**

- **No direct observations on regular prices**

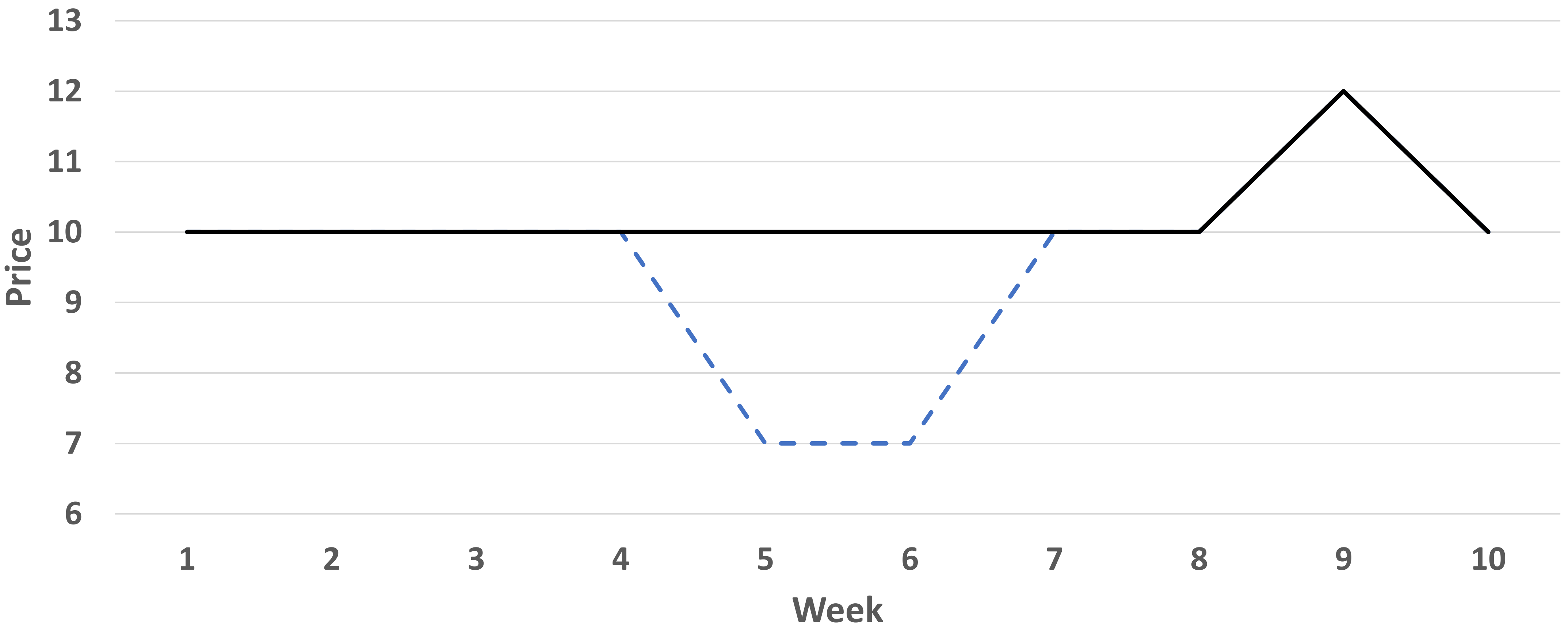
- **Data is usually based on scanner data**
  - **Measurement errors**

- **Identification of regular prices is usually based on “sales filters”**

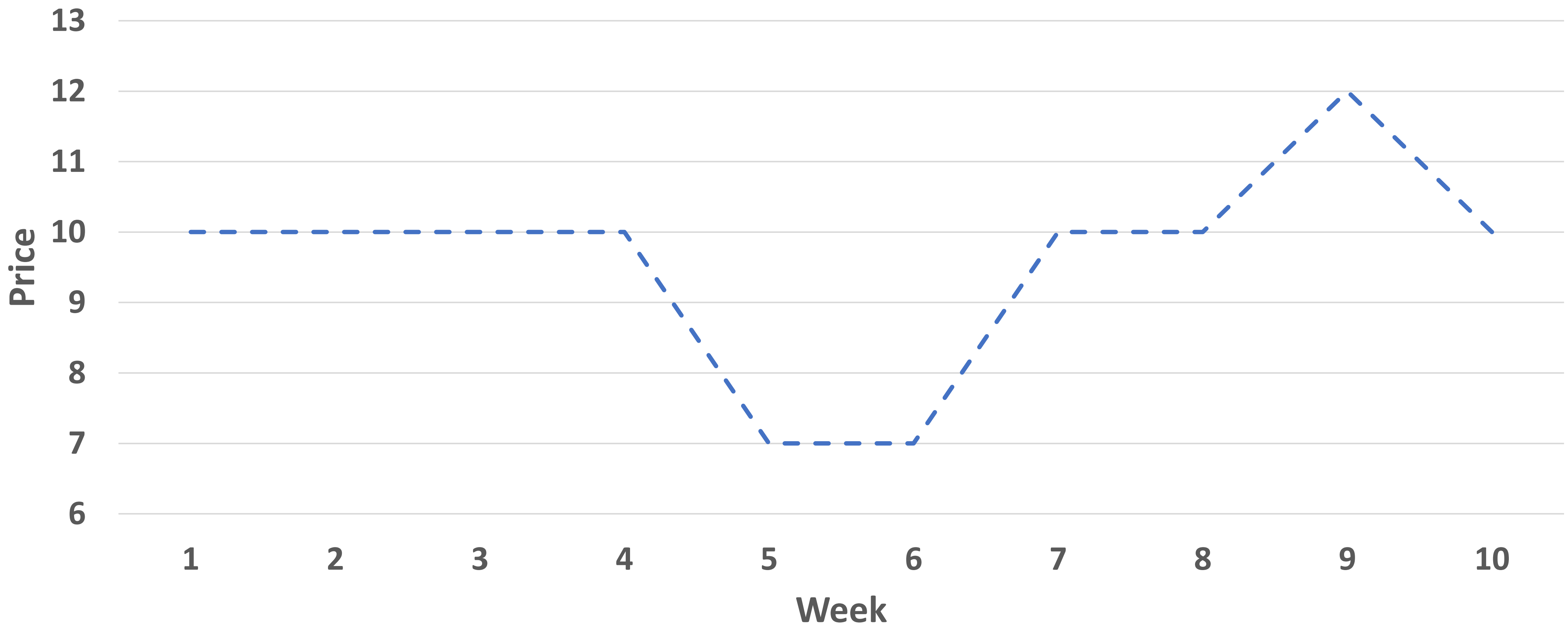
Two types of filters: (1) "V-shaped filters"



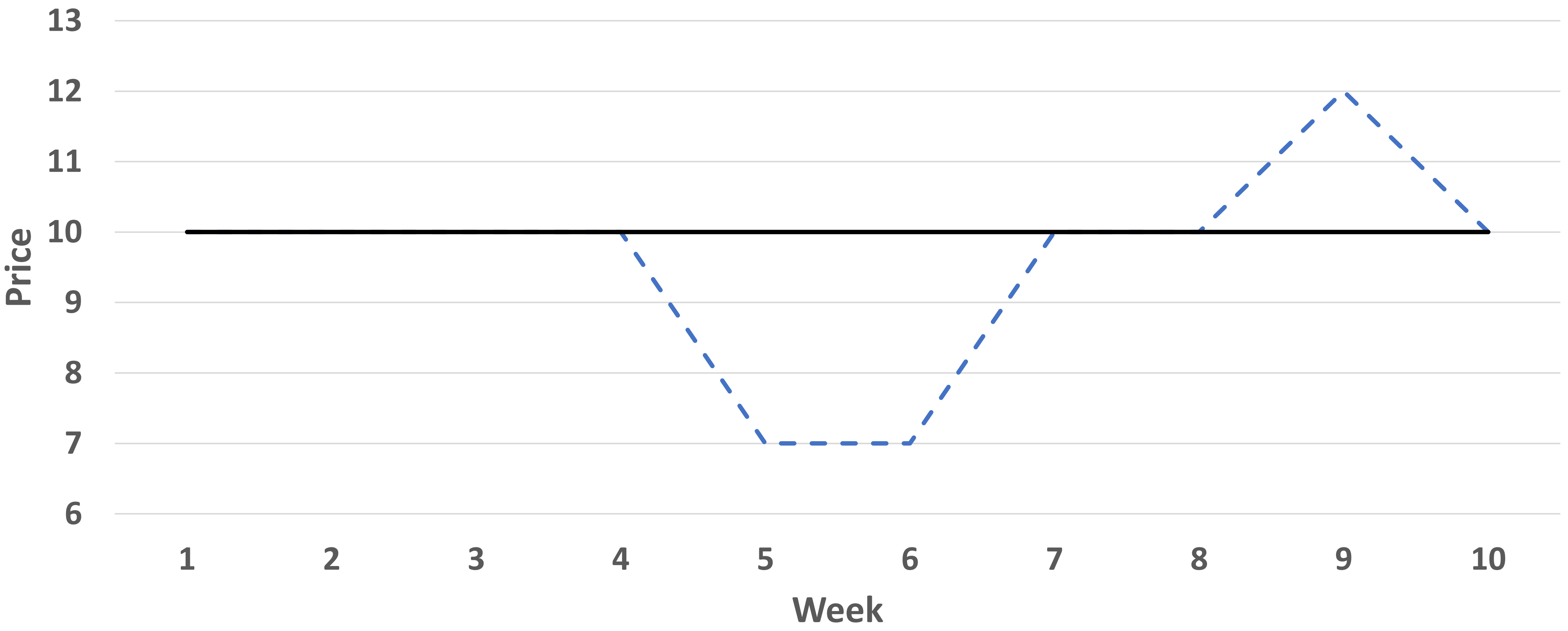
Two types of filters: “V-shaped filters”



Two types of filters:
(2) “reference prices”/“mode-based” prices



Two types of filters: "reference prices"/"mode-based" prices



Data

- “Price transparency law”
  - (Bonomo et al., 2022, Ater and Rigbi, 2023)

- Must post online the prices of all products in each store
  - Must be updated within 1 hour of the change

- May 2015: All large supermarket chains
- July 2017: All large drugstore chains

Data: General Info

- **January 1, 2018 – April 30, 2021**
- **2,403 products (UPCs)**
  - **Product groups that:**
    - **Have a large weight in CPI**
    - **Consumed by all income levels**
    - **Available all year**
- **106 stores**
  - **11 largest supermarket chains**
  - **Largest drugstore chain**
  - **Including online stores**
- **Stores drawn at random**
  - **According to the chain's market share**
- **107,743,561 observations**

Stores' locations

Product selection

- **Store-products with max 3 missing weeks**

- **27,648,264 observations**

- **10 chains**
- **79 stores**
- **1,350 products**
- **25 product categories**

- **Average regular price: NIS 14.34 (Std. dev.= 11.37)**
- **Average transaction price: NIS 13.43 (Std. dev.= 10.79)**

Analysis at weekly and daily frequencies

- **Most of the literature:**
  - Monthly
  - Weekly
- **We look at:**
- **Weekly frequency**
  - Taking the mode price in each week
- **Daily frequency**

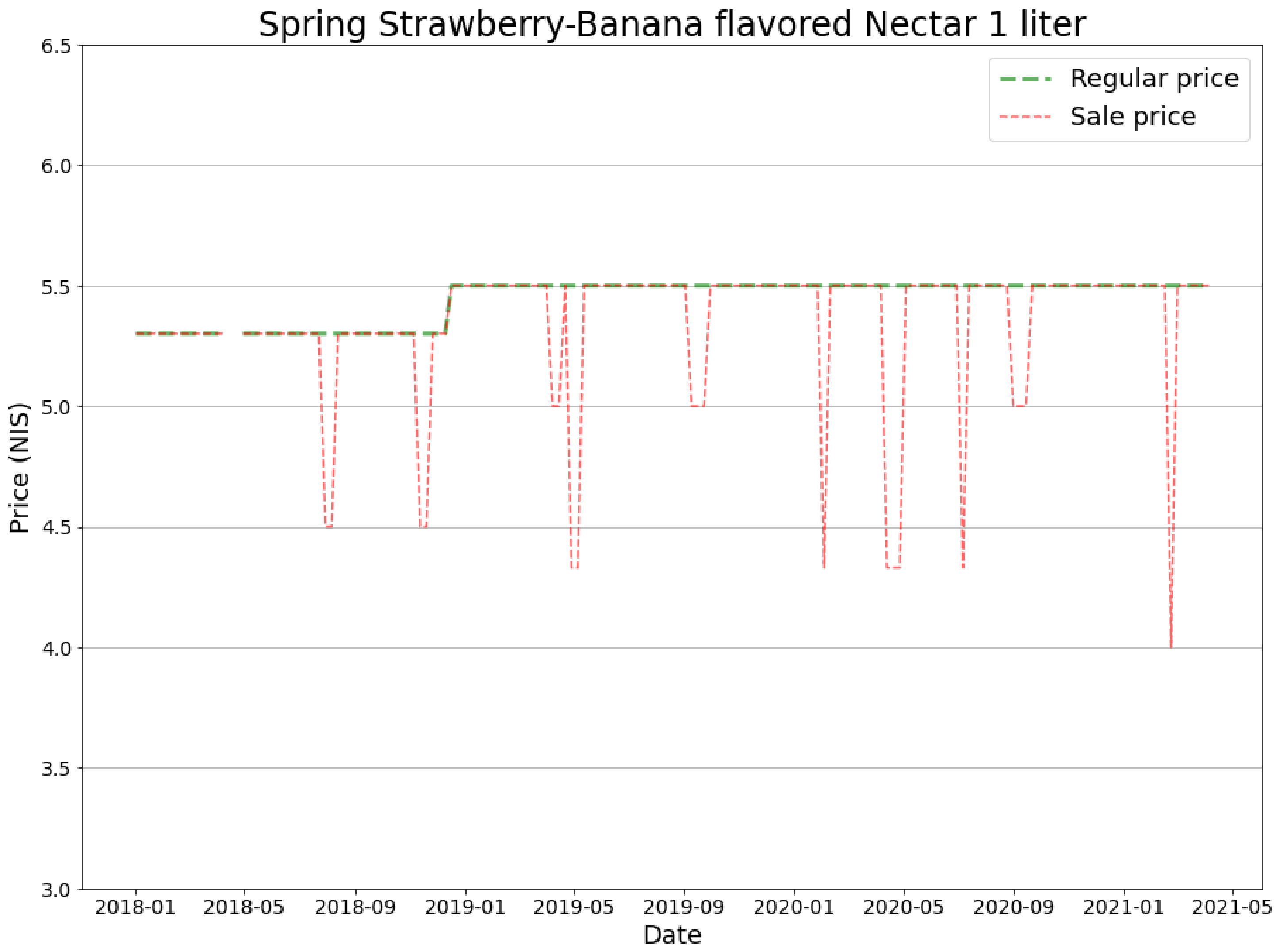
Our data and Midrigan's (2011) model

Menu Cost of changing:	Midrigan (2011)	Our data
Regular price	High	Item price law
Sale price	Low	Shelf sale sign

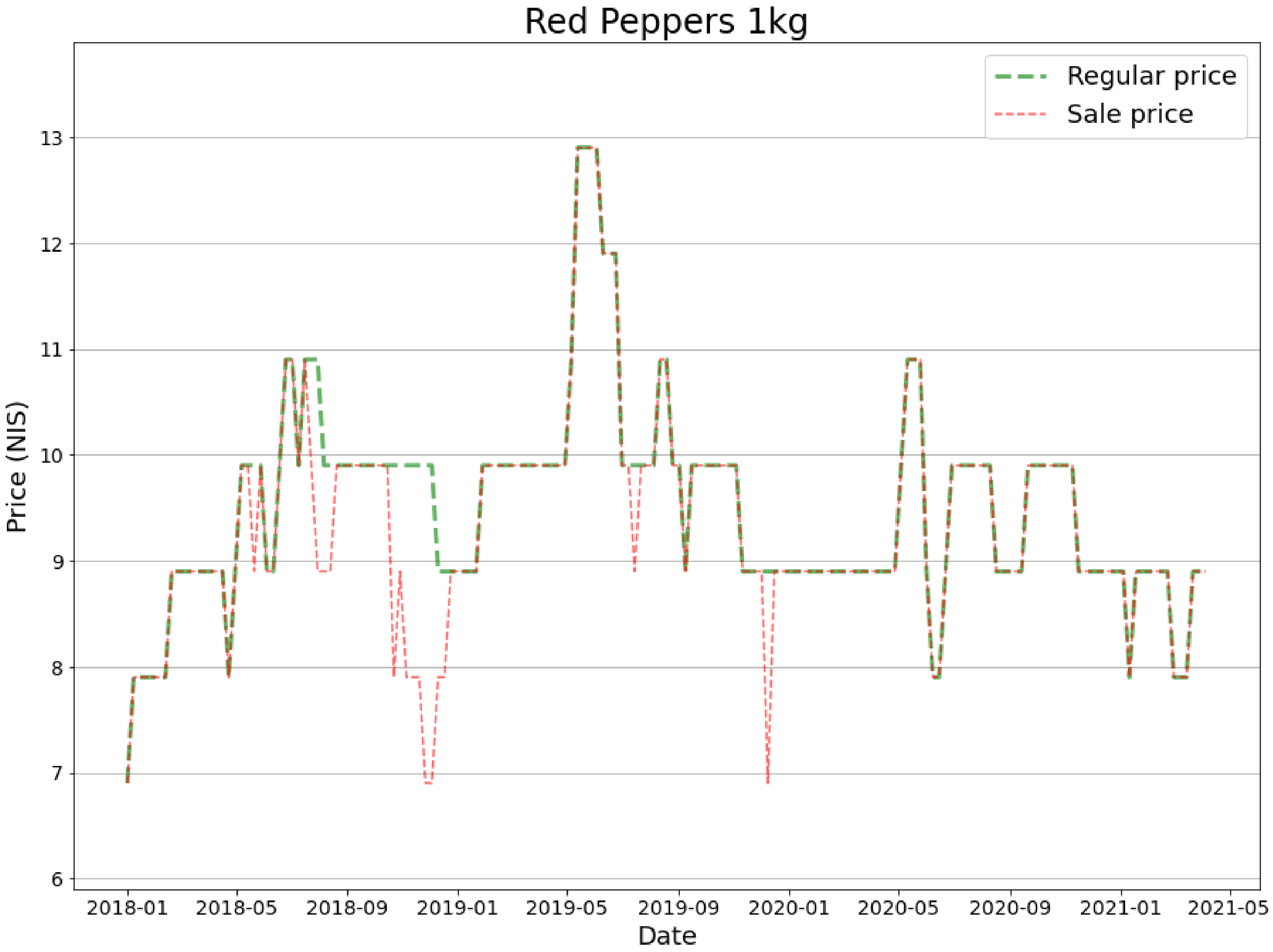
Regular price change

Sale price

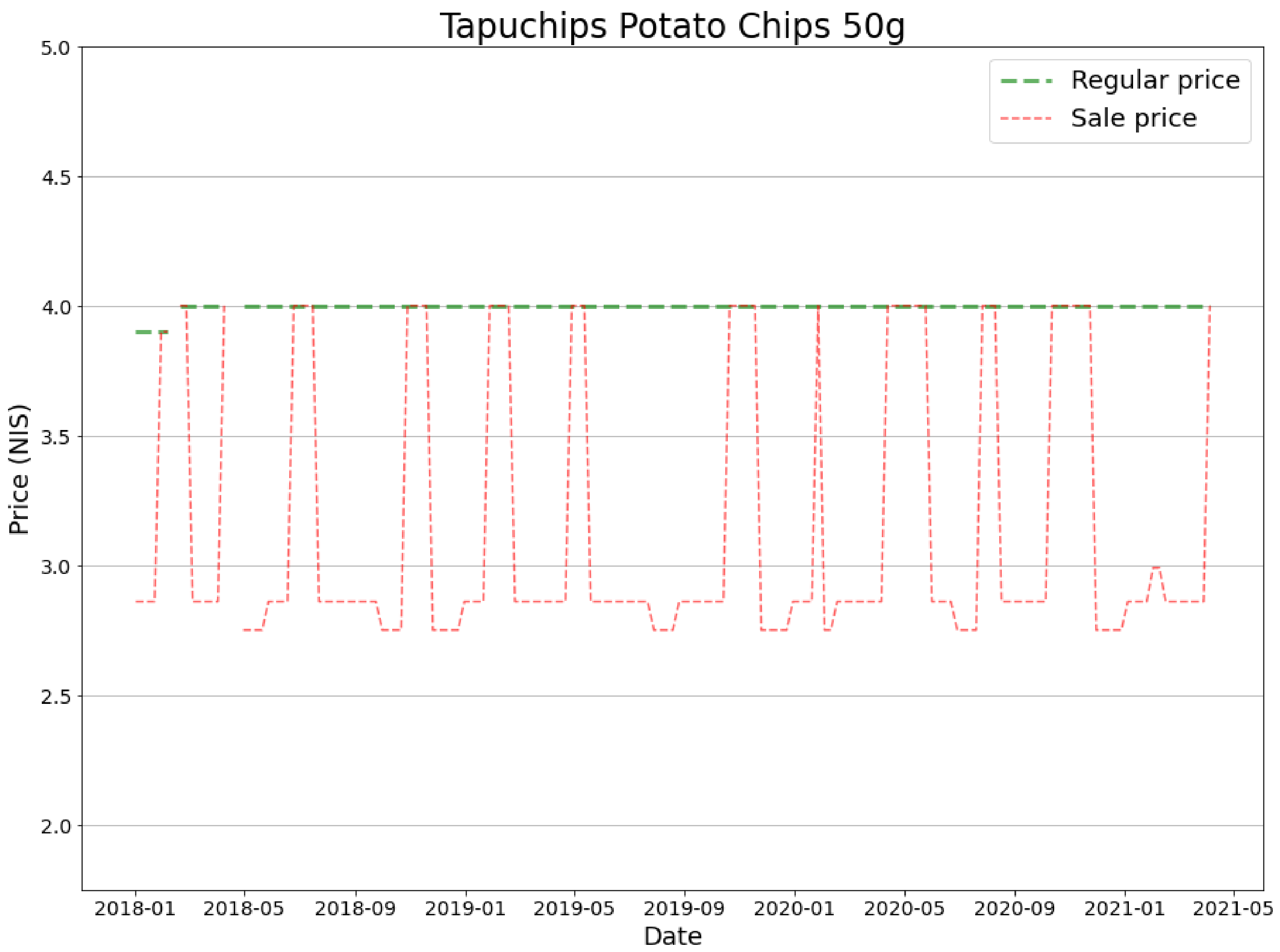
Example: Soft drinks



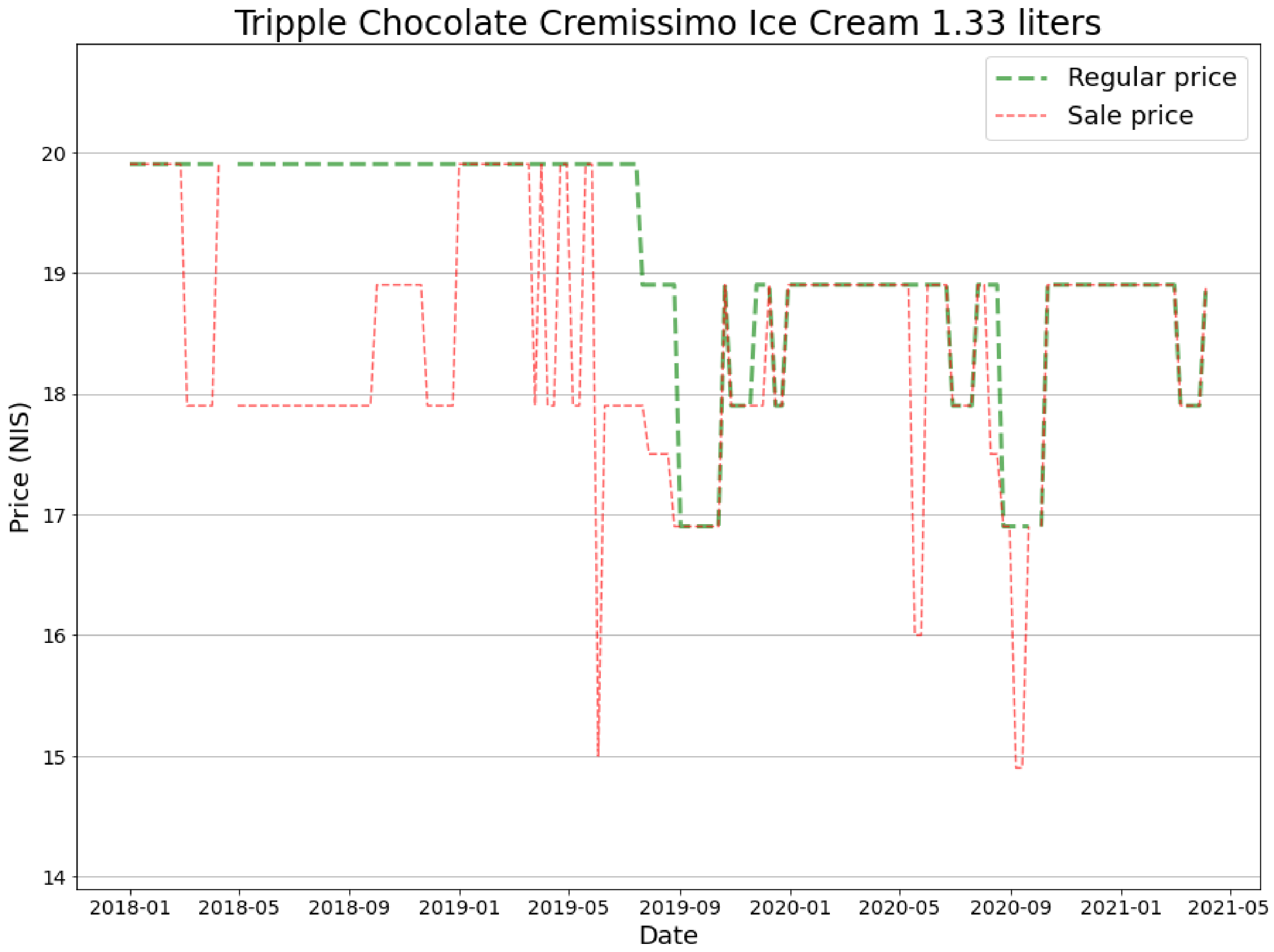
Example: Fruits and vegetables



Example: Snacks



Example: Ice cream

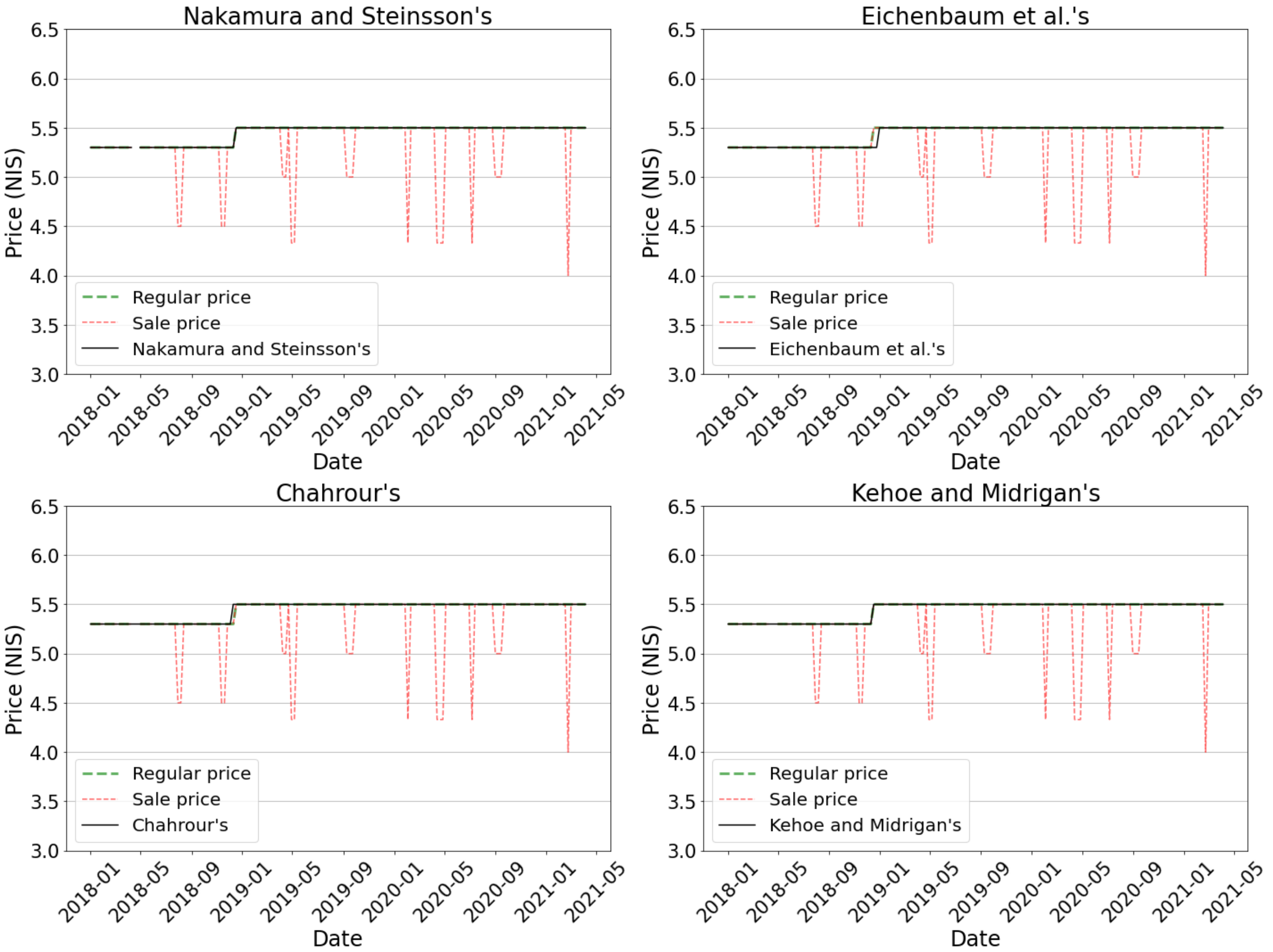


Can sales filters identify regular prices?

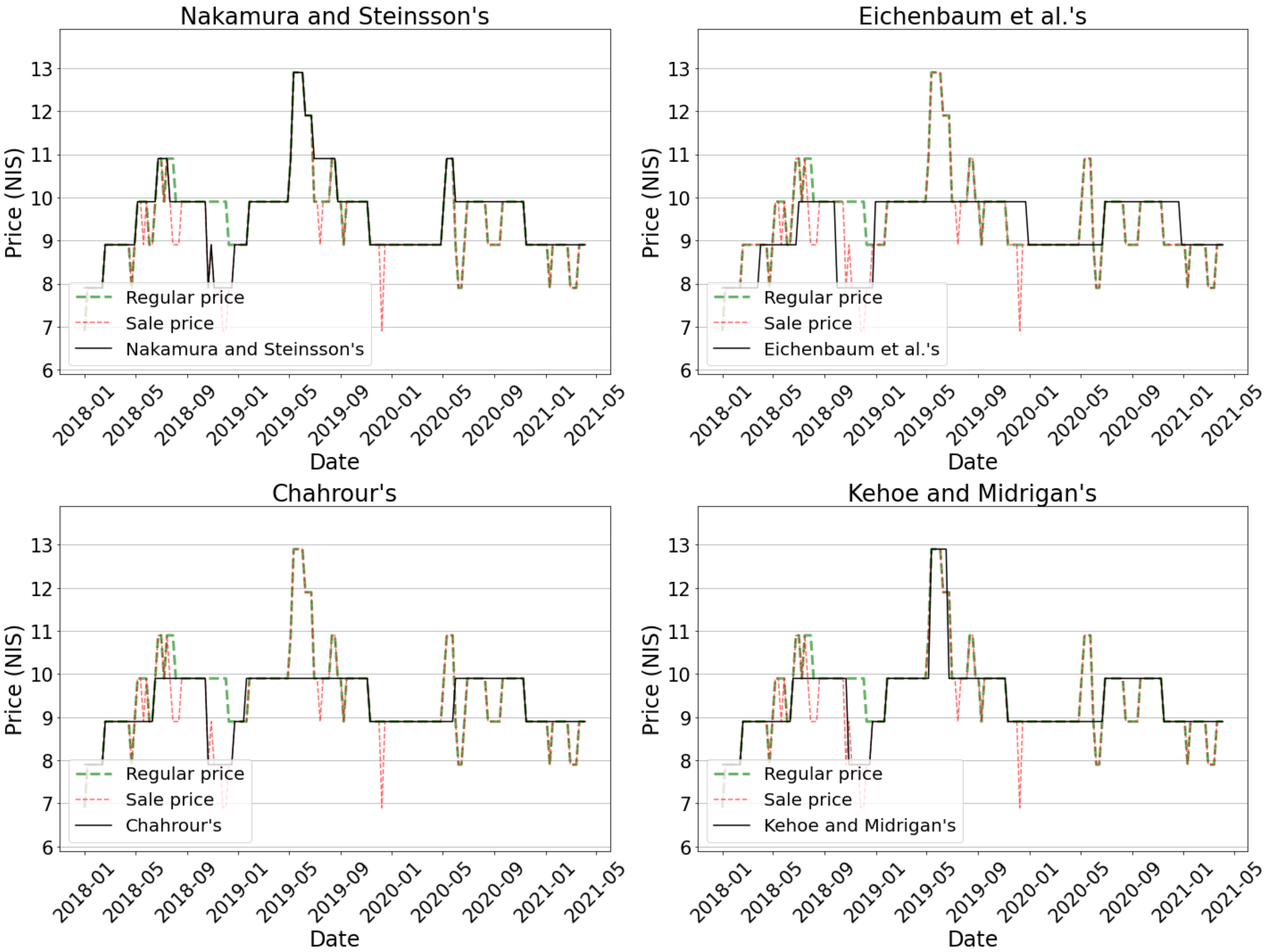
- **We look at four sales filters**
- **One V-shape filter**
  - **Nakamura and Steinsson's (2008) sales filter A**

- **Three "reference prices"/mode-based filters**
  - **Eichenbaum et al. (2011)**
  - **Chahrour (2011)**
  - **Kehoe and Midrigan (2011)**

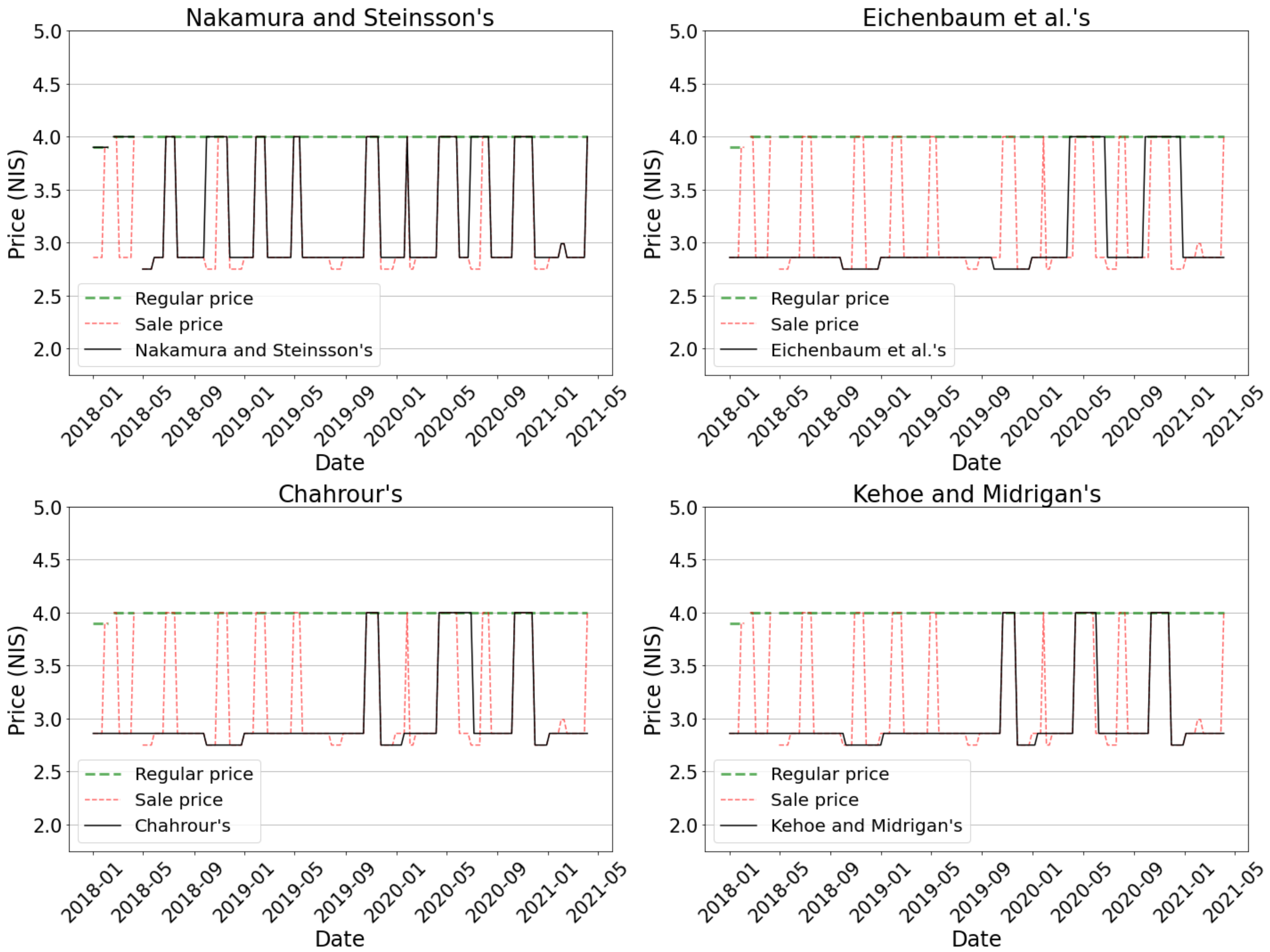
When it’s simple, they can: Soft drinks



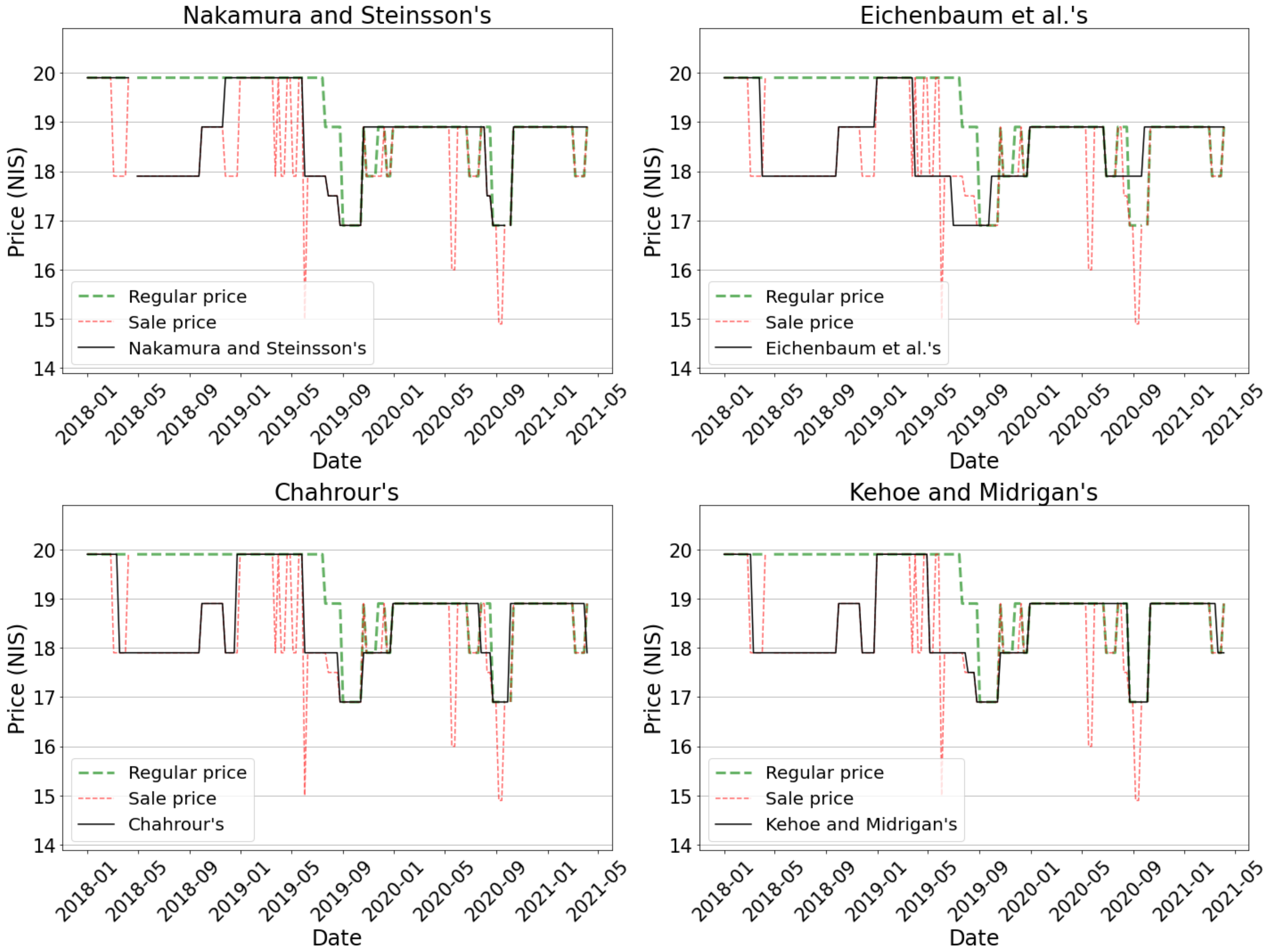
Filter generated prices too rigid: Red peppers



Filter generated prices too flexible: Snacks



Both too flexible and too rigid: Ice cream

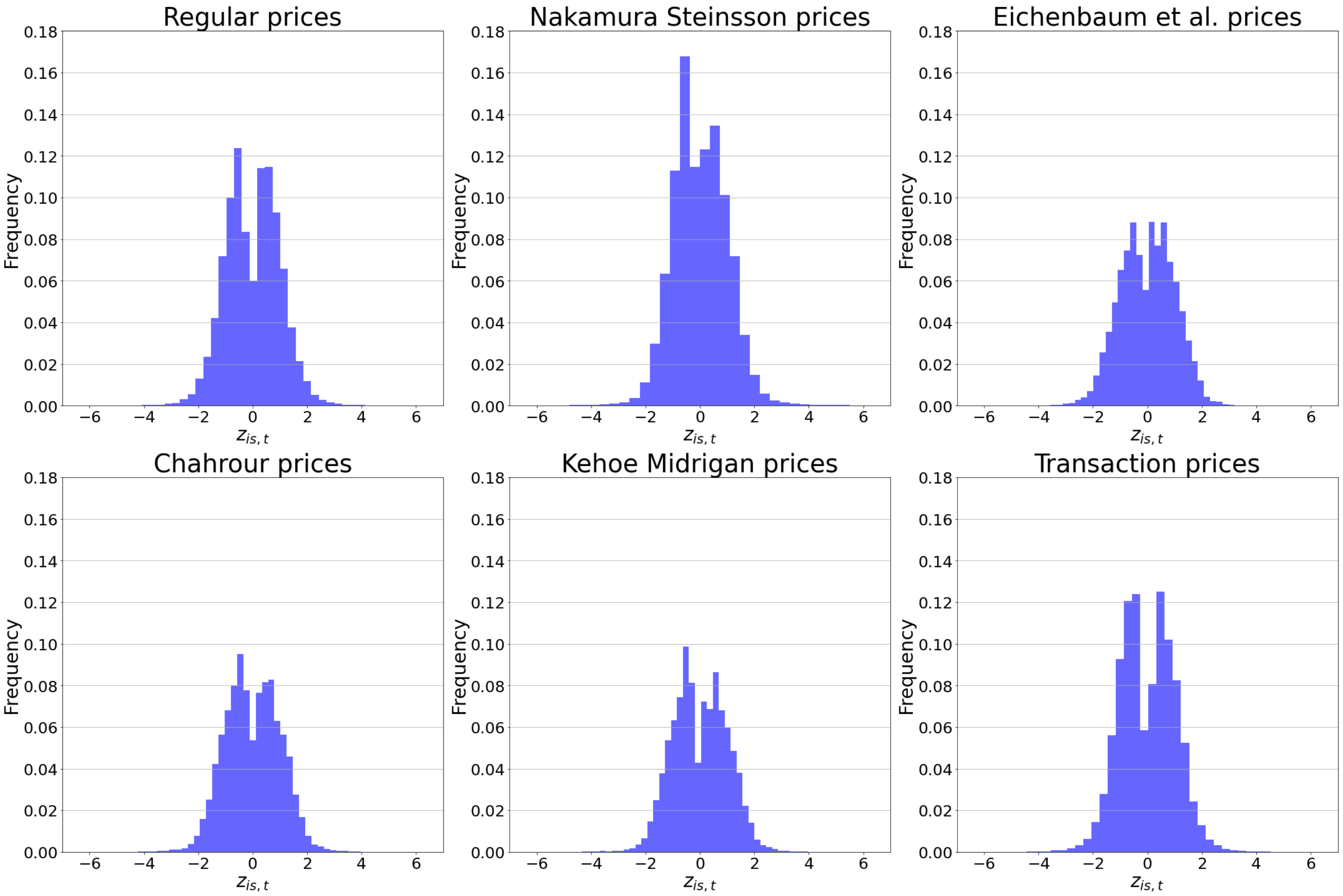


Price rigidity: Duration between price changes

	Weeks between price changes	Days between price changes
Regular price	**84**	**548**
Nakamura and Steinsson (2008)	**24**	**193**
Eichenbaum et al. (2011)	**55**	**293**
Chahrour (2011)	**33**	**190**
Kehoe and Midrigan (2011)	**27**	**146**
Transaction prices	**7**	**39**

Note: The table reports the median duration between price changes

Size of price changes: Weekly data



Summary statistics: Size of price changes, weekly data

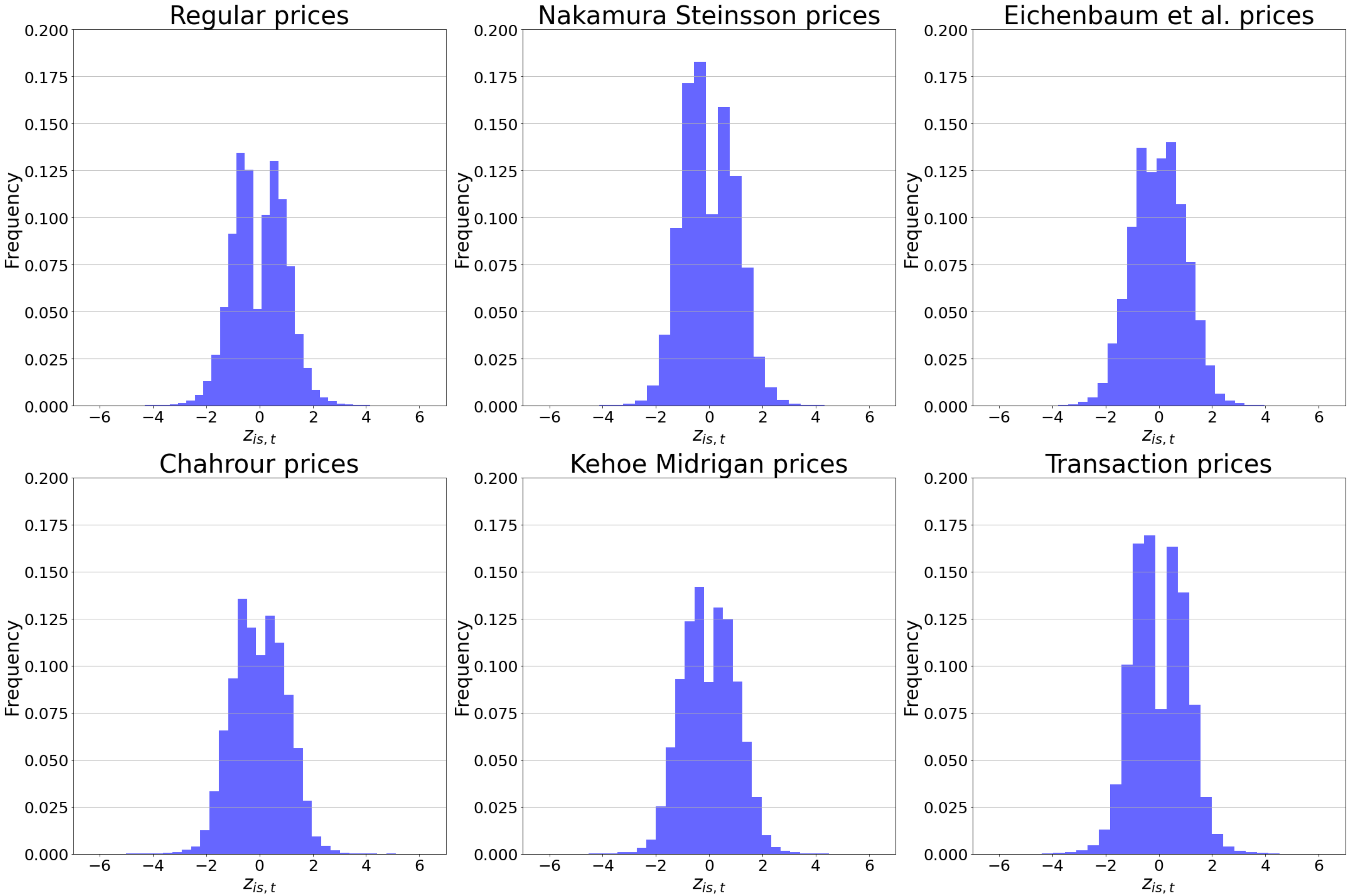
	Skewness	Kurtosis	$\sigma_{\lvert z_{is,t} \rvert} / \bar{z}_{is,t}$	$\lvert z_{is,t} \rvert < 0.5 \times \bar{z}_{is,t}$	$\lvert z_{is,t} \rvert < 0.25 \times \bar{z}_{is,t}$
Regular prices	0.001	3.816	0.688	0.244	0.090
Nakamura and Steinsson	0.221	5.267	0.744	0.265	0.113
Eichenbaum et al.	−0.063	2.823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

Distribution of small price changes, weekly data

	< 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

Klenow and Kryvstov (2008): 25% smaller than 2.5%
Beradi et al. (2015): 11.2% smaller than 1%, 23.7% smaller than 2%

Size of price changes: Daily data



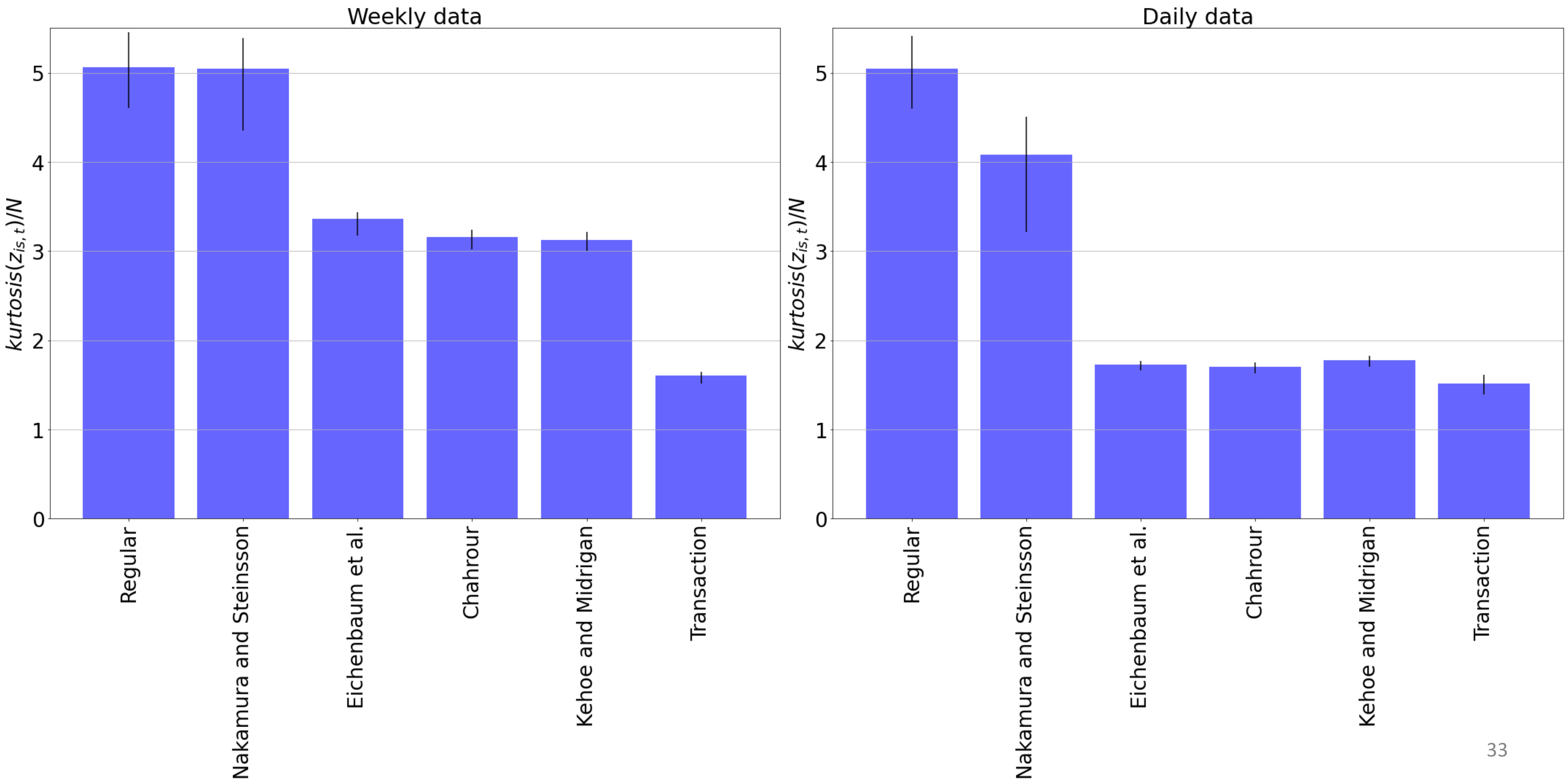
Summary statistics: Size of price changes, daily data

	Skewness	Kurtosis	$\sigma_{\lvert z_{is,t} \rvert} / \bar{z}_{is,t}$	$\lvert z_{is,t} \rvert < 0.5 \times \bar{z}_{is,t}$	$\lvert z_{is,t} \rvert < 0.25 \times \bar{z}_{is,t}$
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

Distribution of small price changes, 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 and Midrigan	0.027	0.047	0.073	0.129	0.155
Actual transaction prices	0.010	0.022	0.034	0.058	0.074

Effect of a monetary shock: Sufficient statistics



Conclusions

- **Regular prices are very rigid**
- **Price changes are large**
  - Golosov-Lucas (2007) type distribution
  - Alvarez et al. (2016) with one product and low probability of free price changes
  - Consistent with Cavallo and Rigobon (2016), Cavallo (2018) online data

- **Filters underestimate price rigidity**
- **Overestimate share of small price changes**
- **Underestimate the effect of monetary shock**
  - Nakamura and Steinsson (2008) and Eichenbaum et al. (2011) do a better job
  - Nakamura and Steinsson (2008) do a good job by making two mistakes

- **Results for regular prices are similar weekly/daily frequency**