Online Appendix to:
Scraped Data and Sticky Prices

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A Data

A.1 Database Details for US Retailers

The table below provides database details for all the retailers included in the U.S. database used in the paper. Each of these retailers is one of the largest by market share in the U.S. in their respective categories. USA1 is a supermarket. USA2 is a hypermarket/department store. USA3 is a drugstore/convenience retailer. USA5 is an electronics and appliance retailer.

Table A1: Database Description - US Retailers

	USA1	USA2	USA3	USA5
Total Observations (Millions)	9M	10M	4M	5M
Total Products	24K	94K	22K	30K
Initial Date	05/08	03/08	03/09	03/08
Final Date	07/10	07/10	07/10	07/10
Days	814	865	512	862
Categories	26	33	34	19
Urls	1471	6055	8085	1345

Notes: The number of observations does not include missing values within price series. The data contains missing values caused by items that go out of stock or failures in the scraping software that tend to last for a few days. Following Nakamura & Steinsson (2008), missing prices are replaced for the first five months of the price gap with the previous price available for each product. I also ignore all price changes exceeding +200% and -90%, which represent a negligible number but can significantly bias statistics related to the magnitude of price changes. See Section B.3 for details on data treatments.

B Additional Robustness Exercises

B.1 US Results by Price-Level Quintiles

Table A2 shows results in the U.S. for data at different price levels. I first took all price observations and calculated price level quintiles, shown in the second row of the Table. I then used these as thresholds to split the data, run the sampling simulations (weekly averages and cell-relative imputation), and compute durations and the size of price changes using the same methods applied in the paper.

Weekly averages and cell-relative (CR) imputation have the same effects identified in the paper: there is a reduction in durations and the size of price changes and the bias is stronger for weekly averages.

Table A2: US Price-Level Quintiles

Statistic	Quintile	Q1	Q2	Q3	Q4	Q5
	Price Level Cutoff	\$3.49	\$7.99	\$21.34	\$99.99	> \$100
Duration (months)	Monthly Online Data	2.59	3.79	7.62	11.05	13.03
	Weekly Average	1.5	1.73	4.01	3.22	2.5
	CR Imputation (Narrow)	2.94	2.8	7.06	8.86	10.49
Mean Abs. Size	Monthly Online Data	24.91	20.79	16.73	16.32	11.71
	Weekly Average	14.48	10.2	9.52	8.55	6.45
	CR Imputation (Narrow)	20.67	16.54	14.76	13.26	10.58

Notes: To obtain monthly implied durations, I first compute the monthly frequency per individual good by calculating the number of price changes over the number of total valid change observations for a particular product. Next, I calculate the *mean* frequency per good category, and finally, the *median* frequency across all categories. Finally, I compute implied durations using $-1/ln(1 - frequency)$, and convert them to monthly durations for comparisons across samples. The US results are weighted using BLS CPI category weights.

B.2 Calvo Model

The following table compares the U.S. results to those obtained from simulating a simple Calvo model. Results from the Calvo model were obtained by using the code and calibration parameters from Nakamura and Steinsson (2010).

Table A3: US and Calvo Simulation

Statistic	Source	USA	Calvo Simulation
Duration (months)	Monthly Online Data	4.7	4.35
	Weekly Average	1.69	1.08
	CR Imputation*	3.35	0.68
Mean Abs. Size	Monthly Online Data	20.82	10.64
	Weekly Average	11.06	5.59
	CR Imputation*	16.15	4.64

Notes: The Calvo model was parametrized to approximate daily online frequency of price change observed in the US online data. Simulated data was independently generated for 300 goods, each lasting 865 days to match the US online data. From the raw simulated data I randomly generated missing values to match the probability of observations with missing observations in the online data (37%), and then imputed those prices by carrying forward the last available price for a maximum of 5 months. This replicates the treatment in all the other datasets. The treatment of all the sampling simulations is identical to those applied in the online data, with the exception of the CPI imputation, which in this case uses the average price change of all other goods on the same day given that there are no categories of goods in the model.

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B.3 Treatment: Missing Values and Carry Forward

Missing values are treated using standard methods in the literature. Table A4 illustrates these treatment decisions using a hypothetical individual price series.

Table A4: Treatment of Price Spells - Sales and Missing Values

An Example of a Price Spell with Missing Data

Price Recorded	*\$2*	*\$1*	•	*\$2*	*\$1*	•	*\$3*
Sale Flag	*R*	*S*		*R*	*S*		*R*
Complete Including Sales	*\$2*	*\$1*	*\$1*	*\$2*	*\$1*	*\$1*	*\$3*
Complete Excluding Sales (v-shaped)	*\$ 2*	*\$ 2*	*\$ 2*	*\$2*	*\$1*	*\$1*	*\$3*
Complete Excluding Sales (Flag)	*\$ 2*	*\$ 2*	*\$ 2*	*\$2*	*\$2*	*\$2*	*\$3*

Notes: (•) represents a missing value. R is a regular price, S is a sale price identified with a “sales flag”.

Missing values are common within price series because products are either out of stock or not correctly recorded in the database on a particular day. Depending on the country, the percentage of these missing values is between 22% to 37%, as shown in Table 2 of the paper.[1] Given the high frequency of the data, and the fact that missing gaps do not typically extend for more than a few days, I complete missing values in the price series by carrying forward the last recorded price until a new price is available for a maximum of 5 months. This is the same method used in Nakamura and Steinsson (2008).

Sale events are sometimes identified explicitly by the retailers with a sales image or special html tags, and this information is recorded by the scraping program as a sales indicator or “flag” in the database. The share of prices identified with sales flags are 5.78% in Argentina, 2.94% in Brazil, and 6.26% in Colombia. Unfortunately the sales flag was not consistently scraped in the other countries, so for the main results of the paper I use a v-shaped sales algorithm used by Nakamura and Steinsson (2008) and others in the literature. The algorithm uses only the price information for each good. If the price of a good drops but later returns to exactly the same value within 30 days, then the non-sale price series will have no variation at all. Identifying sales this way misses some sales that have different characteristics, such as those that end with higher prices, as shown in Figure A4. The advantage, however, is that I can use it for all retailers and countries.

A few price changes in each country seem implausibly large and are likely the result of a scraping mistakes. They are a negligible part of all observations, but they can affect statistics related to the magnitude of price change. Consequently, all daily price changes that exceed 200% or -70% are excluded.

B.3.1 No Carry - Forward (Consecutive Prices)

Table A5 shows results when I exclude prices that have been carried forward as described above. This means price changes are calculated only with consecutive or “adjacent” prices that have been observed (not imputed in any way).

In contrast with the results in Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008), I find that durations fall when using only contiguous observations. This is because the

[1] Klenow and Kryvtsov (2008) report 12% in monthly US CPI data.

main reason for missing values in online data is scraping errors that create short gaps in the raw data. Without a real stockout, the likelihood of a price change is low. So when a missing price is filled by carrying it forward, no price change takes place, increasing the observed durations. If we instead remove those observations, prices appear to be more flexible.

This also explains why the size of price changes does not fall, or does so only slightly. If most of the carried forward missing prices were associated with long stockouts, we could expect that including them would lead to higher observed prices changes. This is not what the data suggests. In Argentina, Brazil, Chile, and Colombia, the mean absolute size of price changes fall marginally when carried forward prices are dropped. In the U.S., it increases slightly.

Whether we use only consecutive prices or not does not change the main results in the paper about the effects of sampling simulations and measurement bias. Both weekly averaging and cell-relative imputations lead to lower durations and smaller price changes.

Table A5: Consecutive Prices - No Carry Forward

		USA	Arg.	Brazil	Chile	Col.
Obs. with Sales		4.68%	2.55%	3.04%	3.7%	2.97%
Duration	Monthly Online Data	4.7	3.43	2.03	4.38	2.29
(months)	Monthly Online Data (CC)	4.18	3.14	1.79	4.14	2
	Weekly Average(CC)	1.67	1.28	.8	1.64	1
	CR Imputation (CC)	3.23	2.03	1.77	3.47	1.51
Mean Abs.	Monthly Online Data	20.82	11.54	10.07	14.29	9.92
Size	Monthly Online Data (CC)	21.07	11.27	10	13.85	9.67
	Weekly Average (CC)	11.44	6.15	6.79	8.7	6.08
	CR Imputation (CC)	11.87	8.27	8.74	10.07	7.44

Notes: To obtain monthly implied durations, I first compute the monthly frequency per individual good by calculating the number of price changes over the number of total valid change observations for a particular product. Next, I calculate the *mean* frequency per good category, and then, the *median* frequency across all categories. Finally, I compute implied durations using $-1/ln(1 - frequency)$, and convert them to monthly durations for comparisons across samples.The US results are weighted using BLS CPI category weights.

C Cross-Country Evidence: Inflation, Frequency, and the Size of Price Changes

Table A6 shows additional statistics on frequencies and the size of price changes. In the cross-section of countries, inflation rates are clearly not correlated with the overall frequency or size of price changes. Instead, Table A6 suggests they are correlated with the *relative* frequency of increases over decreases, and to a lesser extent, the relative size of price increases over decreases.

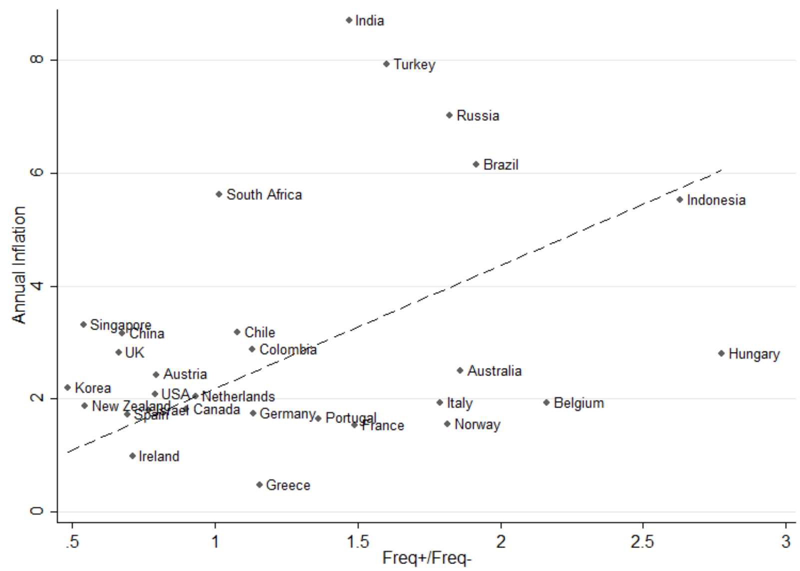
–Appendix–

Table A6: Duration and Size of Changes - Retailer Averages by Country

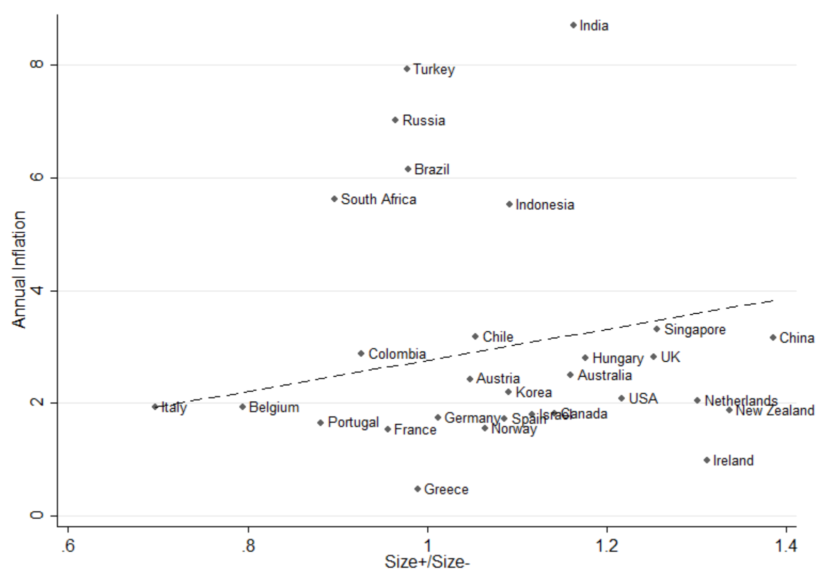
Country	(1) Retailers	(2) Inflation (%)	(3) Month Freq	(4) Mean Abs. Size	(5) Mean Size +	(6) Mean Size -	(7) Ratio Freq +/-	(8) Ratio Size +/-
Argentina	14	17.1	.298	13.8	14	-12.6	7.8	1.1
Australia	5	2.5	.201	25	26.9	-23.7	1.9	1.2
Austria	2	2.4	.357	11.9	13.3	-11	.8	1
Belgium	4	1.9	.109	9.3	8.2	-11.2	2.2	.8
Brazil	5	6.1	.314	12.9	12.8	-13.9	1.9	1
Canada	7	1.8	.168	21.3	23.9	-20.2	.9	1.1
Chile	5	3.2	.162	18	18.6	-17.5	1.1	1.1
China	3	3.2	.056	17.2	20.6	-14.4	.7	1.4
Colombia	4	2.9	.2	16.7	16.5	-17.1	1.1	.9
France	2	1.5	.126	15.9	16.8	-16.1	1.5	1
Germany	6	1.7	.073	15	15.4	-15.3	1.1	1
Greece	6	.5	.233	15.8	15.6	-16.3	1.2	1
Hungary	3	2.8	.2	23.8	26.8	-21.4	2.8	1.2
India	3	8.7	.119	18.2	19.2	-16.5	1.5	1.2
Indonesia	4	5.5	.115	12.3	12.8	-11.6	2.6	1.1
Ireland	6	1	.165	29.2	33.8	-25.9	.7	1.3
Israel	4	1.8	.25	23.2	25.9	-22.7	.8	1.1
Italy	4	1.9	.166	20.3	14.3	-21.9	1.8	.7
Korea	6	2.2	.128	17.5	18.1	-16.6	.5	1.1
Netherlands	2	2	.065	21.2	23.9	-19.5	.9	1.3
New Zealand	5	1.9	.288	27.4	32.5	-23.8	.5	1.3
Norway	4	1.5	.24	19.9	21.5	-20	1.8	1.1
Portugal	2	1.7	.071	15	12.9	-15.5	1.4	.9
Russia	5	7	.151	13.1	12.9	-13.2	1.8	1
Singapore	7	3.3	.067	17.4	19.8	-16.1	.5	1.3
South Africa	5	5.6	.118	19.8	17	-21.7	1	.9
Spain	9	1.7	.233	12	12.9	-11.4	.7	1.1
Turkey	7	7.9	.202	17.6	17.3	-19.2	1.6	1
UK	11	2.8	.219	26.2	29.7	-23.5	.7	1.3
USA	29	2.1	.2	24.8	27.5	-22.6	.8	1.2
Venezuela	2	37.5	.096	23.6	26.8	-18.4	1.7	1.5
Mean	6	4.6	.174	18.6	19.6	-17.8	1.5	1.1
Median	5	2.4	.166	17.6	18.1	-17.1	1.1	1.1

Note: I use monthly-sampled data collected from a sample of 183 large multi-channel retailers in 31 countries selling food, groceries, electronics, apparel, furniture, household products and related goods. Prices were collected on between 2007 and 2014, with different start dates for each retailer. Each statistics is calculated at the retailer level and then averaged within countries. The average gives the same importance to each retailer within a country. The simple mean and median over all countries is reported on the last two rows. Average annual inflation rates for the period 2008-2014 from the IMF World Economic Indicators database. Argentina's inflation from Cavallo (2013). The column labeled 'Ratio Freq+/-' is the monthly frequency of price increases divided by the monthly frequency of price decreases. The column labeled 'Ratio Size+/-' is the size of price increaes divided by the size of price decreases

The same information is plotted below in the scatter plots of Figure A1. When considered separately, both the relative frequency and the relative size of price changes appear to be correlated with inflation.



(a) Frequency of Increases / Frequency of Decreases



(b) Size of Increases / Size of Decreases

Figure A1: Inflation, Frequencies, and Size of Price Changes

Notes: Dashed line are linear fitted values. Argentina and Venezuela excluded.

If we run a simple regression with both variables, the relative frequency seems to be the main driver of inflation across countries, as can be seen in Table A7, column (2).

Interestingly, these results change if we separate countries with inflation rates below and

Table A7: Cross-Country Evidence on Inflation, Frequency, and the Size of Price Changes

	(1) Inflation	(2) Inflation	(3) Inflation < 5%	(4) Inflation > 5%	(5) Inflation > 5% Excluding Venezuela
Frequency	0.279				
	(14.44)				
Mean Abs Size	0.234				
	(0.143)				
Freq+/Freq-		1.772**	0.221	0.0476	1.493***
		(0.843)	(0.213)	(1.701)	(0.317)
Size+/Size-		2.163	1.678***	11.96*	4.274***
		(1.505)	(0.245)	(5.000)	(1.041)
Observations	31	31	23	8	7
R-squared	0.304	0.448	0.910	0.709	0.974

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

above 5%. If we focus only low inflation countries, as shown in column (3), the relative size of price changes explains most of their differences in inflation rates. The same thing happens if we focus only on high inflation countries, although this results is driven by Venezuela, which is an outlier in terms of relative frequency. If we exclude Venezuela, both the relative frequency and the relative size of price changes are correlated with inflation rates above 5%.

The link between frequency and inflation has been studied before using time-series for a single country. Examples include Nakamura and Steinsson (2008), who in the US CPI data find that the frequency of price increases is correlated with inflation, but no the frequency of price decreases. Gagnon (2009) uses a time series of CPI data in Mexico and finds that, at levels of inflation below 15%, the overall frequency of price changes is not correlated with inflation because there frequency of increases rises with inflation but it is offset by a similar fall in the frequency of price decreases. A similar result is present in Alvarez et al. (2015), a paper that uses Argentine CPI data from 1988 to 1997 and shows that inflation is strongly correlated with the difference between the frequency of increases and decreases at all levels of inflation. In a rare example with cross-country evidence, Dhyne et al. (2006) find that inflation is positively correlated with the frequency of price increases and negatively correlated with the frequency of decreases.

C.1 Daily Data - Cross Country

As mentioned in Section 4.3 of the paper, changes to the sampling interval affect the number and size of price changes observed in the data. In the main results of the paper I use monthly-sampled data to be able to compare with the rest of the literature, Table A8 below provides duration and size statistics for daily data.

Table A8: Duration and Size of Changes - Retailer Averages by Country

Country	(1) Retailers	(2) Inflation (%)	(3) Duration (months)	(4) Duration Ex-Sales (months)	(5) Size < |1%|	(6) Size < |5%|	(7) Mean Abs. Size	(8) Kurt.
Argentina	14	17.1	2.3	2.8	3.2	23.5	13.1	6.9
Australia	5	2.5	2.6	5	4	12.4	29.1	3
Austria	3	2.4	3.5	8	28.5	52.8	11.4	3.9
Belgium	4	1.9	5.9	8.8	8.4	45.8	10.3	6.6
Brazil	5	6.1	2.4	2.9	2.6	25.5	12.9	5.5
Canada	7	1.8	5.6	32	2	12.9	22.9	3.4
Chile	5	3.2	2.9	4.5	3	18.1	18.3	4.5
China	2	3.2	4.6	6.9	6.1	29.3	16.9	6.9
Colombia	4	2.9	4.9	6.7	2.4	16.3	20.3	4.2
France	2	1.5	4.6	6.4	9.7	31.3	17.5	4.3
Germany	6	1.7	5.2	7.7	7	34	15.2	7.9
Greece	6	.5	2.5	3.9	13	28.7	17	5
Hungary	3	2.8	4.8	6.8	3.5	11.4	26.1	3.1
India	3	8.7	5.1	7.9	3.2	22.2	16.7	5.3
Indonesia	4	5.5	4.4	7.6	4.6	29.3	12.5	7.2
Ireland	6	1	3.8	7.3	1.2	7.4	30.9	3
Israel	4	1.8	3.8	5.6	1.9	7.2	23.5	3.7
Italy	4	1.9	6.1	8.7	10	25.1	20.6	4.2
Korea	6	2.2	6	8.6	2.3	17.4	17.2	4.3
Netherlands	3	2	10.7	15	10.5	22.6	25.3	4.5
New Zealand	5	1.9	1.6	3.7	1.2	4.3	31.7	2.4
Norway	4	1.5	1.9	3.2	10.3	24.5	20.9	5
Portugal	2	1.7	7	12.1	6.4	27.2	13.1	6
Russia	5	7	3.8	4.4	16.1	39.1	12.4	6.2
Singapore	7	3.3	11.2	17.1	1.2	10.6	18.7	3.6
South Africa	5	5.6	4.7		5.4	11.6	20.3	4.8
Spain	9	1.7	3.8	5.9	11	35.5	12	5.2
Turkey	7	7.9	2.7	6	1.7	19.8	19.9	3.6
UK	12	2.8	3.5	5.5	5.8	15.4	25.8	4.5
USA	29	2.1	3.7	4.3	3	10.1	25.9	4.1
Venezuela	2	37.5	11.1		5.3	23.2	22.5	3.6
Mean	6	4.6	4.7	7.8	6.3	22.4	19.4	4.7
Median	5	2.4	4.4	6.7	4.6	22.6	18.7	4.5

Note: I use daily data collected from a sample of 183 large multi-channel retailers in 31 countries selling food, groceries, electronics, apparel, furniture, household products and related goods. Prices were collected on between 2007 and 2014, with different start dates for each retailer. Each statistics is calculated at the retailer level and then averaged within countries. The average gives the same importance to each retailer within a country. The simple mean and median over all countries is reported on the last two rows. The column labelled 'Literature' shows the implied monthly durations computed from the mean monthly frequencies reported in Table 1 of Klenow and Malin (2010). See that paper for original sources, including Alvarez (2008). Average annual inflation rates for the period 2008-2014 from the IMF World Economic Indicators

Table A9: Duration and Size of Changes - Retailer Averages by Country

Country	(1) Retailers	(2) Inflation (%)	(3) Month Freq	(4) Mean Abs. Size	(5) Mean Size +	(6) Mean Size -	(7) Ratio Freq +/-	(8) Ratio Size +/-
Argentina	14	17.1	.016	13.1	13.3	-12.6	5	1.1
Australia	5	2.5	.018	29.1	33	-25.3	1.2	1.3
Austria	3	2.4	.033	11.4	12.9	-9.9	1.1	1.2
Belgium	4	1.9	.007	10.3	9.9	-11	1.7	.9
Brazil	5	6.1	.035	12.9	13	-13.6	1.6	1
Canada	7	1.8	.016	22.9	25.4	-20.7	1	1.2
Chile	5	3.2	.015	18.3	19.7	-17	.9	1.2
China	2	3.2	.012	16.9	20	-14.3	2.4	1.4
Colombia	4	2.9	.023	20.3	21.9	-18.9	1.1	1.1
France	2	1.5	.014	17.5	18.7	-16.9	1.3	1
Germany	6	1.7	.009	15.2	17	-13.7	1.2	1.2
Greece	6	.5	.018	17	18	-16	1.3	1.1
Hungary	3	2.8	.019	26.1	30.1	-22.5	2.1	1.3
India	3	8.7	.007	16.7	18.1	-14.9	1.3	1.2
Indonesia	4	5.5	.01	12.5	12.9	-12.1	2.1	1
Ireland	6	1	.011	30.9	35.8	-26.5	.9	1.3
Israel	4	1.8	.028	23.5	27.4	-22.4	.8	1.2
Italy	4	1.9	.008	20.6	14.7	-21.2	1.1	.8
Korea	6	2.2	.01	17.2	18.9	-15.7	.8	1.2
Netherlands	3	2	.007	25.3	30.5	-22.3	.5	1.4
New Zealand	5	1.9	.067	31.7	38.2	-25.9	1.1	1.4
Norway	4	1.5	.024	20.9	23.9	-19.6	2.6	1.2
Portugal	2	1.7	.005	13.1	12.2	-13.4	1.2	.9
Russia	5	7	.014	12.4	12.7	-12.2	1.8	1
Singapore	7	3.3	.004	18.7	20.8	-16.9	.6	1.2
South Africa	5	5.6	.011	20.3	18.4	-21.3	1.2	1
Spain	9	1.7	.056	12	13.1	-11.1	1.1	1.1
Turkey	7	7.9	.02	19.9	21.5	-18.6	1.7	1.2
UK	12	2.8	.02	25.8	30	-22	.9	1.4
USA	29	2.1	.018	25.9	29.7	-22.8	.9	1.3
Venezuela	2	37.5	.004	22.5	25.2	-18.2	1.6	1.4
Mean	6	4.6	.018	19.4	21.2	-17.7	1.4	1.2
Median	5	2.4	.015	18.7	19.7	-17	1.2	1.2

Note: I use daily sampled data collected from a sample of 183 large multi-channel retailers in 31 countries selling food, groceries, electronics, apparel, furniture, household products and related goods. Prices were collected on between 2007 and 2014, with different start dates for each retailer. Each statistics is calculated at the retailer level and then averaged within countries. The average gives the same importance to each retailer within a country. The simple mean and median over all countries is reported on the last two rows. Average annual inflation rates for the period 2008-2014 from the IMF World Economic Indicators database. Argentina's inflation from Cavallo (2013). The column labeled 'Ratio Freq+/-' is the monthly frequency of price increases divided by the monthly frequency of price decreases. The column labeled 'Ratio Size+/-' is the size of price increaes divided by the size of price decreases

D Hump-Shaped Hazards and Survival Bias

A stylized fact that has also received some attention in the literature is the shape of the hazard function. The hazard is the instantaneous probability of price change at time t, conditional on the price not changing until that point in time.

In Calvo (1983)'s TDP model, the hazard function is flat because the probability of price change is fixed and exogenously determined. In Taylor (1980)'s model, the hazard is equal to one at the time when all price changes take place (eg. a month). With heterogeneity across goods, this can be generalized to have hazards with "spikes" at given frequencies.

By contrast, in SDP models hazard functions tend to be upward-sloping. The intuition is that inflation (or deflation) increases deviations from the optimal price over time, so as the price gets "older", the conditional probability of a price change also rises. Upward-sloping hazards are intuitively appealing, but there is no evidence for them in the current empirical literature. Nakamura and Steinsson (2008) found evidence of downward sloping hazards in US CPI prices, while Klenow and Kryvtsov (2008) found mostly flat hazard functions in similar data.

Scraped data has three advantages for the study of hazards rates. First, it is free from price imputations, as discussed in the paper. Second, we can see how the probability of change varies on a daily basis, which is important when most goods adjust within a few months. Third, we can compute hazard functions in countries with higher inflation rates. In contexts where aggregate shocks are strong and persistent, it should be easier to find evidence of upward-sloping hazards.

I measure hazard rates using standard Survival Analysis, which looks at the time elapsed from the "onset of risk" until the occurrence of a "failure" event. In a price-setting context, we are interested in the time between the firm's optimal price adjustments. The set of constant prices between these two dates is called a "price spell" and the duration (measured in days) is the length of the spell. Formally, if T is a random variable measuring the duration of the price spell, with density function $f(t)$ and cumulative density $F(t)$, the hazard $h(t)$ is the limiting probability that a price change occurs at time t, conditional on the price not changing up to that point in time:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t < T < t + \Delta t | t < T)}{\Delta t} \tag{A1}$$

The hazard measures the instantaneous "risk" of a price change, conditional on survival. We can add all hazard rates over time and obtain the total risk of price change accumulated up to time t. This is the Cumulative Hazard Function, H(t):

$$H(t) = \int_0^t h(u)du \tag{A2}$$

H(t) is an increasing, unbounded function of t, that accumulates the conditional probability of price changes over time. In the context of repeated "failures" (price changes), it can be interpreted as the expected number of price adjustments from 0 to t.

The Cumulative Hazard receives a lot of attention because it is easier to estimate than the hazard function itself. To estimate it, I use a non-parametric approach due to Nelson

(1972) and Aalen (1978), which does not require any distributional assumptions.[2] It provides a simple estimate of the cumulative hazard function $H(t)$, given by:

$$\widehat{H}(t) = \sum_{j|t_j \leqslant t} \frac{c_j}{n_j} \tag{A3}$$

where c_j is the number of price changes at time t_j and n_j is the number of price spells that can still change at time t_j. The incremental steps c_j/n_j are an estimate for the probability of price change at t_j, taking into account only those price spells that have survived until that point in time.

To obtain the smoothed hazard function $\widehat{h}(t)$, I take the discrete changes in $\widehat{H}(t)$ and weight them using a kernel function:

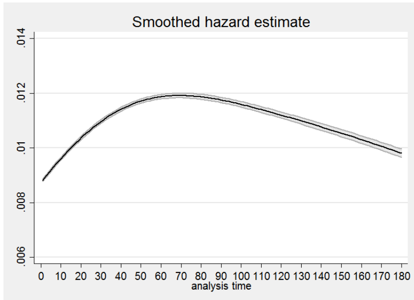
$$\widehat{h}(t) = \frac{1}{b} \sum_{j \in D} K\left(\frac{t - t_j}{b}\right) \Delta \widehat{H}(t_j) \tag{A4}$$

where K is a symmetric kernel density, b is the smoothing bandwidth, and D is the set of times with price changes. Following the literature, I implicitly assume that each price change restores the optimum price and treat all duration spells independently. I include right-censored spells, because we know for certain how old they are at each point in time, affecting n_j in equation A3. However, I exclude left-censored spells, for which the time since the last adjustment is unknown.

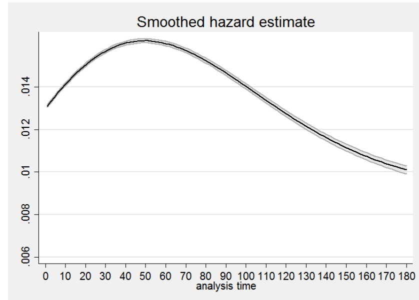
Figure A2 provide smoothed hazard rates in all countries. A common feature across countries is the hump-shaped pattern seen in Figure 2 of the paper. With peaks at different points in time, all hazard functions are initially upward sloping. The peaks in these hazard tend to coincide with the average implied durations estimated in the paper.[3]

[2] I choose this method because I want to study the *shape* of the hazard function $h(t)$, not the effects of any covariates. My results are robust to the use of a semi-parametric Cox model that can incorporate covariates and account for unobserved heterogeneity at the category level.

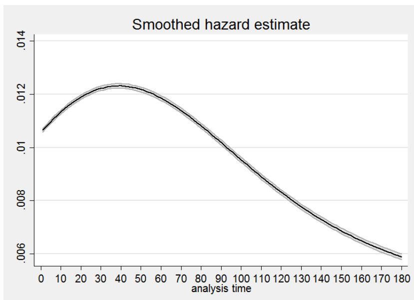
[3] These results imply that the assumption of flat hazard rates in those estimated duration numbers is not realistic (though it may be innocuous for certain purposes).



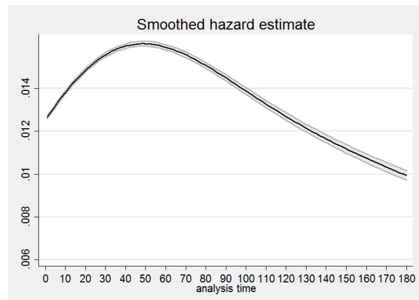
(a) Argentina



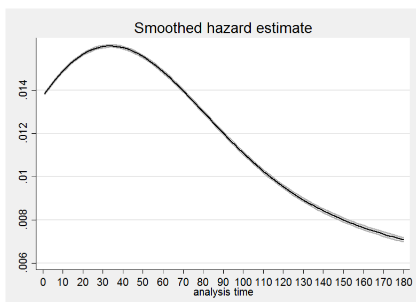
(b) Brazil



(c) Chile



(d) Colombia



(e) USA

Figure A2: Smoothed Hazard Functions

Notes: Initial 180 days shown. Left-censored spells are excluded.

These hump-shaped patterns do not fit standard TDP or SDP models. However, they could potentially be explained with TDP models if there are multiple firms adjusting at different times, with a majority of goods doing so at 40, 60, or 90 days. They could also be explained with SDP models when temporary shocks are relatively important, as Nakamura and Steinsson (2008) point out, because these shocks would cause a reversal of the adjustment within a short period of time. The evidence for SDP is reinforced by the fact that Argentina, with its high-inflation rates, has an upward-sloping hazard for a longer period of time. Even in standard SDP models, the higher the inflation rate, the more upward-sloping hazards become, because the deviation from the optimal price increases over time.

The differences with previous papers that found flat or downward sloping hazards is driven not only by the lack of time-averages or cell-relative imputations, but also by the fact that data are available in daily frequency and for a large and heterogeneous set of goods. The daily frequency provides the information needed to capture the initial rise in the hazard rates within the first month or two. The large set of goods provides a lot of price spells that can be used to better estimate hazard rates and try to control for problems like survival bias.

Detecting upward-sloping hazard functions is further complicated by the existence of a "survival" bias caused by heterogeneity across products in the shape of individual hazards. This bias, well known in the empirical literature, is illustrated in Figure A3 with a hypothetical example. Consider two types of goods with upward sloping hazards. One type changes prices more frequently, so it has higher hazard rates and will disappear from the sample faster. If we estimate the aggregate hazard for both goods, initially we would be using spells from both of them, but at some point in time we would start using only spells from goods with the lower hazard rates. This"survival" bias would tend to flatten the estimate, creating hump-shaped results. This is a well-know problem in survival analysis, for which there are not simple solutions.

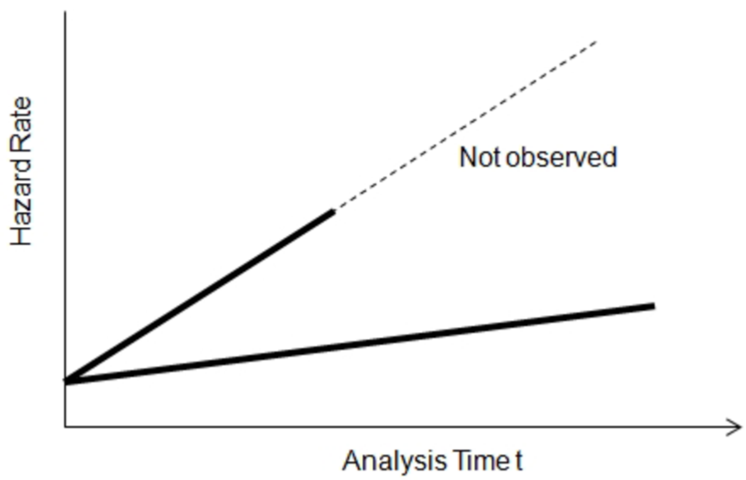
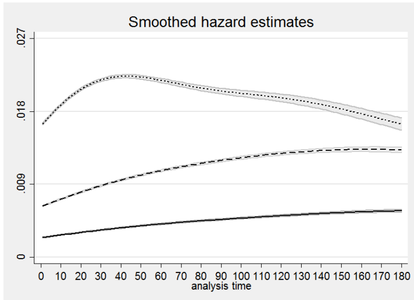


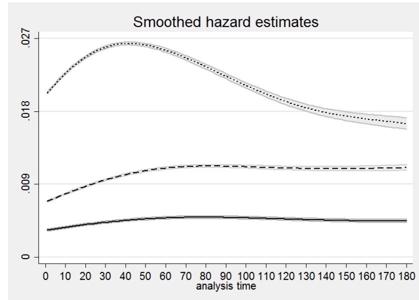
Figure A3: Heterogeneity and Survival Bias

Survival bias is a well-know problem in the estimation of smoothed hazard functions. Several papers in the literature have suggested this is one of the main reasons most estimated hazards are downward sloping.[4] Using the granularity of scraped data, I am able to find evidence of the existence of survival bias in Figure A4, where I separate goods in terms of their average durations and re-estimated their hazard functions. The dotted line represents goods that have average durations of less than 50 days, the dashed line is for goods with average durations of 50 to 100 days, and the solid line represent stickier goods with average durations over 100 days.

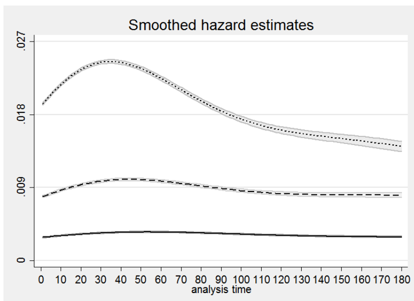
[4]See lvarez et al. (2005), **?**, Nakamura and Steinsson (2008), and Campbell and Eden (2014) among others.



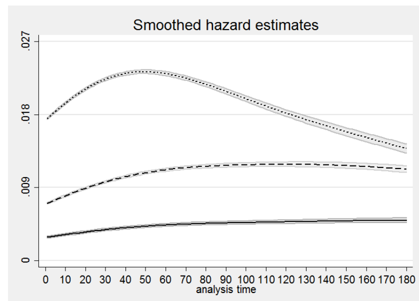
(a) Argentina



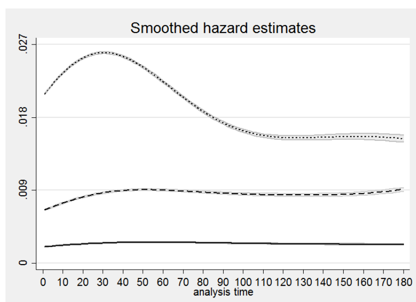
(b) Brazil



(c) Chile



(d) Colombia



(e) USA

Figure A4: Hazards for Different Duration Groups

Notes: Left-censored spells are excluded. Initial 180 days shown.

As I separate goods into different categories, each one of these hazards became more upward sloping. The hump-shaped patterns does not disappear completely because each one of these three hazards is itself constructed by aggregating across many goods, and therefore they are still affected by survivor bias.

Overall, my results suggest that the underlying hazard rates are more upward sloping than what the aggregate estimates tend to reflect.

E Additional Tables and Figures

Table A10: Duration and Size by COICOP Level 3 - USA

COICOP	Description	CPI Weight	Unique Products	Monthly Obs.	Mean Abs. Size	Mean Size Increases	Mean Size Decreases	Size < |1%|	Mean Daily Frequency	Implied Duration (months)
01.1.1	Bread and cereals	11.41	4431	74064	26.13	29.26	-22.6	1.84	.379	2.1
01.1.2	Meat	14.56	810	14639	25.78	28.92	-22.23	1.22	.428	1.79
01.1.3	Fish and seafood	2.81	243	4186	22.73	25.48	-19.76	.89	.439	1.73
01.1.4	Milk, cheese and eggs	9.82	858	14677	17.95	20.28	-15.59	2.14	.3	2.8
01.1.5	Oils and fats	2.45	195	4187	22.33	25.2	-19.33	1.17	.369	2.17
01.1.6	Fruit	7.12	516	8306	27.81	31.43	-23.75	1.65	.305	2.75
01.1.7	Vegetables	6.34	1460	27467	23.05	25.22	-20.37	1.33	.339	2.41
01.1.8	Sugar, jam, honey, chocolate and confectionery	2.98	2006	33371	23.71	27.09	-20.14	2.96	.352	2.31
01.1.9	Food products n.e.c.	14.85	3934	72908	23.81	26.93	-20.45	1.51	.377	2.11
01.2.1	Coffee, tea and cocoa	2.52	766	13340	22.02	24.43	-19.58	.23	.392	2.01
01.2.2	Mineral waters, soft drinks, fruit and vegetable juices	7.03	1687	28433	25.91	29.21	-22.17	1.54	.402	1.94
02.1.1	Spirits	.73	16	138	18.27	19.73	-14.13	0	.188	4.81
02.1.2	Wine	2.5	442	3502	14.68	16.32	-13.11	7.67	.393	2.01
02.1.3	Beer	2.74	212	1865	16.14	17.7	-14.11	.52	.343	2.38
05.1.1	Furniture and furnishings	10.62	15181	117008	14.25	14.5	-14.02	4.24	.085	11.25
05.1.2	Carpets and other floor coverings	.47	381	3519	15.5	13.02	-17.99	2.33	.123	7.64
05.3.1	Major household appliances whether electric or not and small electric household appliances	2.88	10964	109806	11.02	11.47	-10.5	1.14	.261	3.31
05.4.0	Glassware, tableware and household utensils	1.22	717	9684	19.37	20.05	-18.35	.48	.188	4.81
05.5.1	Major tools and equipment		614	4590	13.65	10.91	-15.78	8.09	.072	13.43
05.5.2	Small tools and miscellaneous accessories		2001	20800	19.97	21.88	-17.55	1.79	.094	10.08
05.6.1	Non-durable household goods	8.6	1925	28182	23.15	25.45	-20.42	.68	.308	2.71
08.2.0	Telephone and telefax equipment	.76	3096	22012	20.39	20.54	-20.28	2.15	.111	8.53
09.1.1	Equipment for the reception, recording and reproduction of sound and picture	17.28	13854	111231	15.02	15.78	-14.56	2.19	.126	7.41
09.1.2	Photographic and cinematographic equipment and optical instruments	1.21	3323	28647	15.3	15.27	-15.31	3.2	.118	7.93
09.1.3	Information processing equipment	3.88	11416	88106	15.07	16.28	-14.27	1.68	.212	4.19
09.1.4	Recording media	1.39	560	5872	27.36	31.43	-24.78	1.49	.229	3.85
09.2.1	Major durables for indoor and outdoor recreation including musical instruments	.41	2221	12719	19.13	15.06	-21.38	7.64	.073	13.21
09.3.1	Games, toys and hobbies	2.98	9402	61246	19.26	17.43	-20.28	4.99	.1	9.48
09.3.2	Equipment for sport, camping and open-air recreation	2.3	6275	41937	17.95	18.99	-17.22	5.86	.108	8.77
09.3.3	Gardens, plants and flowers	1.09	83	564	18.81	16.38	-22.46	4	.063	15.31
09.3.4	Pets and related products; veterinary and other services for pets	10.56	2405	29810	17.72	19.15	-16	.58	.2	4.47
09.5.3	Miscellaneous printed matter; stationery and drawing materials	1.97	3907	28830	17.94	17.03	-19.31	3.19	.045	21.54
12.1.2	Electrical appliances for personal care; other appliances, articles and products for personal care	7.27	18124	223774	23.9	26.13	-21.65	.47	.218	4.06
12.3.1	Jewellery, clocks and watches	2.22	182	1357	14.49	13.57	-14.84	9.24	.123	7.6
12.3.2	Other personal effects	1.95	6096	25734	15.46	15.41	-15.52	1.47	.263	3.27

Results for monthly sampled online data. CPI weights are missing when the US BLS ELI could not be matched to a specific COICOP code.

Table A11: Price Changes by Day of the Week

Day of the Week	USA		Argentina		Brazil		Chile		Colombia	
	Percent of Changes	Mean Abs Size	Percent of Changes	Mean Abs Size	Percent of Changes	Mean Abs Size	Percent of Changes	Mean Abs Size	Percent of Changes	Mean Abs Size
Sunday	18.21	16.52	10.02	9.09	2.07	18.81	5.9	12.03	7.44	11.74
Monday	14.8	17.59	20.16	14.94	10.4	13.16	6.2	17.33	4.06	10.67
Tuesday	14.45	21.07	13.37	12.25	11.43	10.88	18.68	15.93	14.87	10.57
Wednesday	26.85	27.18	11.78	10.49	15.36	9.19	19.14	13.71	17.17	11.51
Thursday	9.1	20.66	9.95	9.83	29.37	15.08	17.72	12.9	18.76	10.6
Friday	10.21	24.28	18.36	11.63	18.13	11.63	18.25	12.11	21	11.53
Saturday	6.35	20.22	16.92	9.1	13.22	7.79	14.99	11.36	16.67	12.39

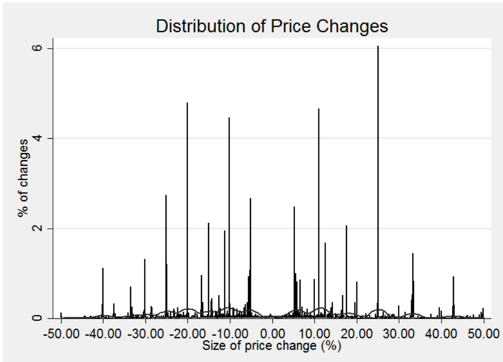
E.1 Scraping Failures

The following table shows some basic statistics on scrape job failures. Total failures are defined as the days where the scrape job fails to run and no data is collected. Partial failures are days when the number of products is less than one standard deviation under the maximum number of products recorded in the whole sample period.

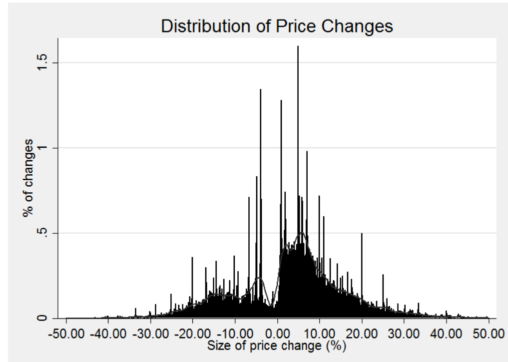
Table A12: Scraping Failures

Retailer	USA1	USA2	USA3	USA5	ARG.	BRAZIL	CHILE	COL.
Days	815	866	513	863	1042	1027	1025	993
Total Failures	40	135	137	125	99	149	186	55
% Total Failures	4.9	15.6	26.7	14.5	9.5	14.5	18.1	5.5
Mean Length TF (days)	1.7	3.9	6.0	3.4	1.9	4.0	2.0	1.4
Median Length TF (days)	1	1	1	1	1	2	1	1
Partial Failures	150	313	208	545	169	18	77	416
% Partial Failures	18.4	36.1	40.5	63.2	16.2	1.8	7.5	41.9

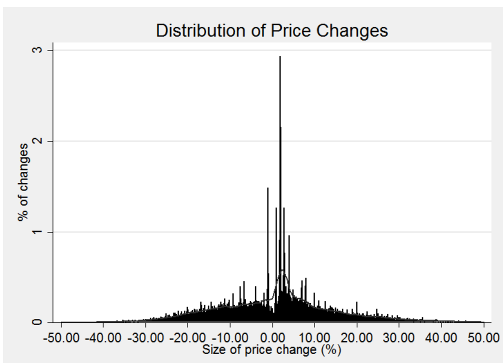
E.2 Distributions of the Size of Changes in Each Country



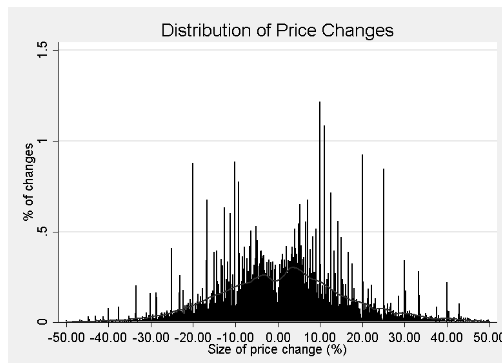
(a) USA



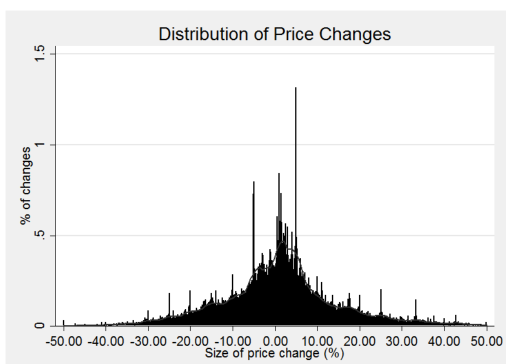
(b) Argentina



(c) Brazil



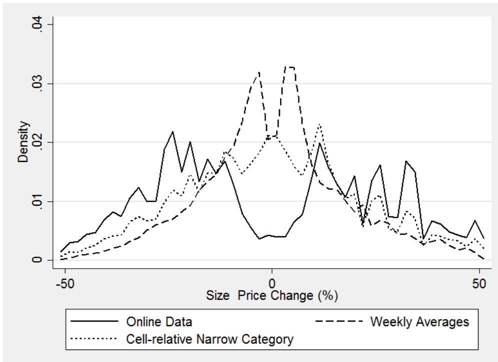
(d) Chile



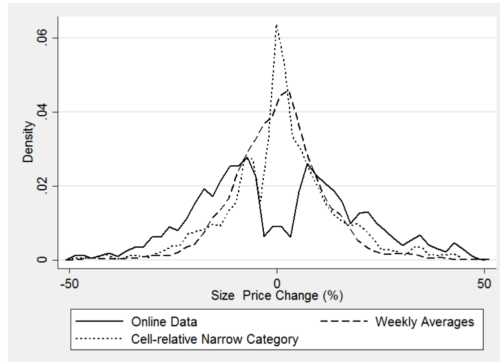
(e) Colombia

Figure A5: The Size of Price Changes

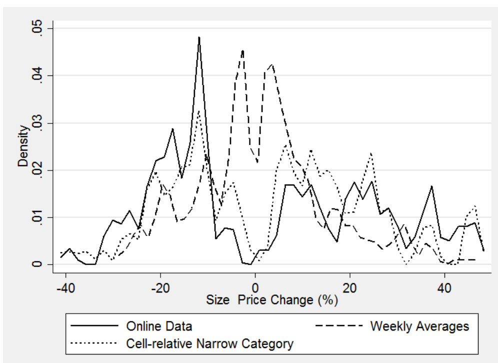
E.3 Distributions of the Size of Changes for each US Sector



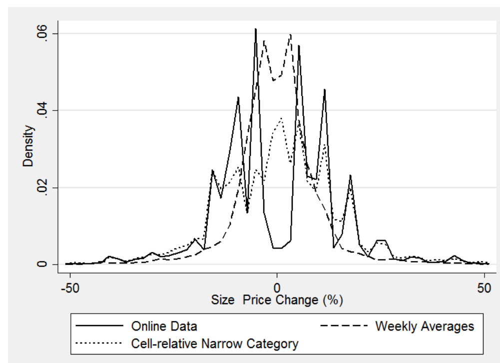
(a) Food and Bev - COICOP 100



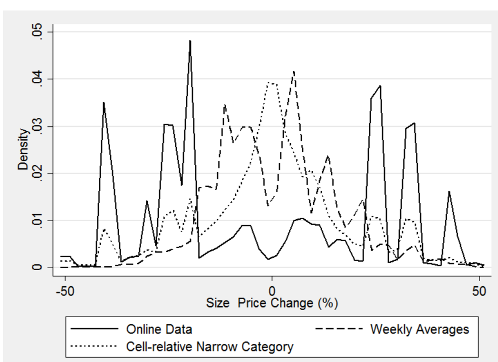
(b) Alcohol Bev - COICOP 200



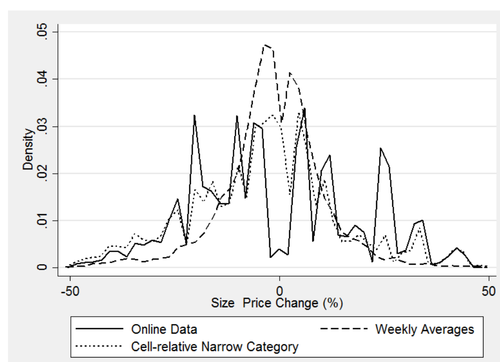
(c) Aparrel - COICOP 300



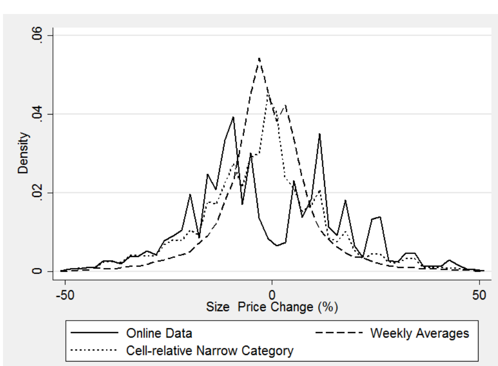
(d) Household Goods - COICOP 500



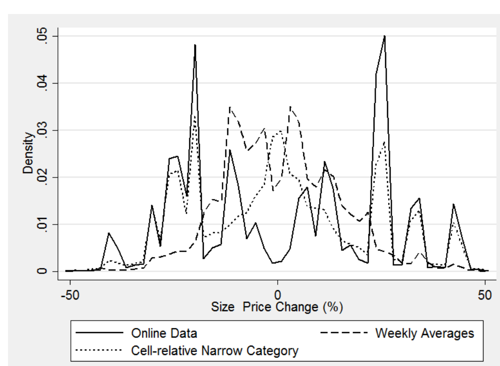
(e) Health - COICOP 600



(f) Communications - COICOP 800



(g) Electronics - COICOP 900



(h) Personal Care- COICOP 1200

Figure A6: Distribution Kernels at the Sector Level

E.4 Cumulative Density Functions in the US

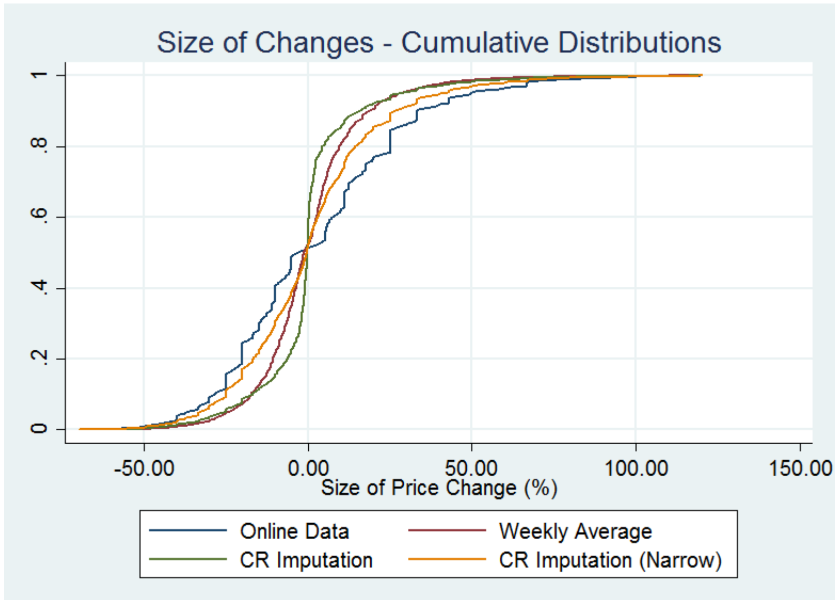


Figure A7: Cumulative Distribution Functions - USA

Note: "CR Imputation" stands for cell-relative imputation using the COICOP categories. "CR Imputations (Narrow)" uses the URL. See paper for details.

References

Alvarez, Fernando, Martin Gonzalez-Rozada, Andy Neumeyer, and Martin Beraja, "From hyperinflation to stable prices: Argentinas evidence on menu cost models," *SCID Working Paper 470*, 2015.

Calvo, Guillermo, "Staggered Prices in a Utility Maximizing Framework," *Journal of Monetary Economics*, 1983, *12*, 383–398.

Campbell, Jeffrey R and Benjamin Eden, "Rigid prices: evidence from U.S. scanner data ," *International Economic Review*, 2014, *55* (2), 423–442.

Cavallo, Alberto, "Online and official price indexes: Measuring Argentina's inflation," *Journal of Monetary Economics*, 2013, pp. 152–165.

Dhyne, Emmanuel, Luis J lvarez, Herv Le Bihan, Giovanni Veronese, Daniel Dias, Johannes Hoffmann, Nicole Jonker, Patrick Lnnemann, Fabio Rumler, and Jouko Vilmunen, "Price Changes in the Euro Area and the United States: Some Facts from Individual Consumer Price Data," *Journal of Economic Perspectives*, 2006, *20* (2), 171–192.

Gagnon, Etienne, "Price Setting During Low and High Inflation: Evidence from Mexico," *The Quarterly Journal of Economics*, 2009, *124* (3), 1221–1263.

Klenow, Peter J and Oleksiy Kryvtsov, "State-Dependent or Time-Dependent Pricing: Does it Matter for Recent US Inflation?," *The Quarterly Journal of Economics*, 2008, *73(3)*, 863–903.

lvarez, Luis J., Pablo Burriel, and Ignacio Hernando, "Do Decreasing Hazard Functions for Price Changes Make any Sense?," *Working Paper Series - European Central Bank*, March 2005, (461).

Nakamura, Emi and Jn Steinsson, "Monetary Non-neutrality in a Multisector Menu Cost Model," *The Quarterly Journal of Economics*, August 2010, *125* (3), 961–1013.

_ **and Jon Steinsson**, "Five Facts About Prices: A Reevaluation of Menu Cost Models," *Quarterly Journal of Economics*, 2008, *123(4)*, 1415–1464.

Taylor, John, "Aggregate Dynamics and Staggered Contracts," *Journal of Political Economy*, 1980, *88*, 1–23.