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Price Duration Using Daily Online Data: Time- or State-Dependent?*

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Abstract: Using daily retail prices gathered through web scraping in Mexico, we analyze if price changes can be characterized by time-dependent features, like the duration of the price spell, and/or by variables associated with the state of the economy. Through the lens of a duration model, we find evidence of both time- and state-dependency behavior. Favoring time-dependency, on the one hand, estimates indicate that price spells exhibit greater risk of ending every seven days relative to other days in between. Advocating for state-dependency, the probability of price changes seems to be affected by variations in the USD/MXN exchange rate, variations in real point of sales expenditures and the COVID-19 pandemic. Finally, leveraging data gathered via direct visits to brick-and-mortar stores, we also find time-dependency and state-dependency in the duration of price spells.

Keywords: Web scraped retail prices, Duration models, Nominal rigidities, COVID-19

JEL Classification: E31, C41, L16, C55

Resumen: Utilizando precios recopilados diariamente a través de *web scraping* en México, se analiza si los ajustes de precios se pueden explicar en función de características que dependen del tiempo, como la duración que permanece un precio sin cambio, y/o si dependen del estado de la economía. Mediante un modelo de duración, se encuentra evidencia de ambos, tiempo-dependientes y estado-dependientes. A favor de la tiempo-dependencia, los resultados muestran que los intervalos de precios presentan un mayor riesgo de concluir cuando sus duraciones son múltiplos de siete días. Con respecto a la estado-dependencia, la probabilidad de cambios de precios se ve afectada por variaciones en el tipo de cambio nominal USD/MXN y en el consumo real en terminales punto de venta, así como por la pandemia de COVID-19. Complementando el análisis con precios recopilados en tiendas físicas, la duración de estos parece también ser determinada por características tiempo-dependientes y estado-dependientes.

Palabras Clave: Precios minoristas por raspado web, Modelos de duración, Rigideces nominales, COVID-19

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1 Introduction

Price rigidities are a key element in workhorse New Keynesian frameworks. Predictions for real economic outcomes based on macroeconomic models can differ significantly depending whether time- or state-dependent price modelling is in place.

In this paper, we shed light on time- or state-dependent price stickiness by implementing duration models using daily retail prices in Mexico gathered through web scraping. In particular, we estimate the hazard function for the duration of price spells, which allows us to test whether time- or state-dependent features contribute to explain the probability of price changes. Our parametric specification is a proportional hazard model with a piece-wise constant baseline hazard and time varying covariates, as in Fougère et al. (2007) and Dias et al. (2007).¹ The time-varying covariates reflecting the changing conditions in the economy in our benchmark specification take the form of fixed-effects at yearly frequencies, which are then complemented with high frequency (daily) data like the exchange rate and consumer expenditure at point of sales.

The main dataset in this study comes from daily retail prices as advertised on retailers' websites. The price collection technique provides a census-like dataset of products and their prices. Whenever the price for a given product remains constant for a number of days, a spell is formed. We use prices between 2016 and the first half of 2022. These prices come from eight large multi-channel retailers with nationwide operations in Mexico. They are a mix of supermarkets, price clubs and departmental stores. All in all, this dataset encompasses over 184.1 million prices, from 1.7 million different products, leading to 10.3 million price spells. We also leverage data from the USD/MXN exchange rate and Point of Sales (PoS) terminals at daily frequencies. Finally, we use a second dataset of goods prices gathered at brick and

¹In a proportional hazard model, the hazard function is specified as the product of a baseline hazard function (i.e. the conditional probability of an event given the elapsed duration since the last event), which captures time-dependence; and of a multiplicative term depending on a set of time-varying covariates, which captures state-dependence. Intuitively, the hazard rate that a price spell will end after a certain number of periods is defined as the probability that the price spell will end after that number of periods given that it has survived to that point.

mortar stores by INEGI. Although smaller in size and with a lower frequency of observation as it provides only 1.8 million price spells, it offers data from a wider range of retailers than the web scraped dataset.

Our main results based on daily web scraped prices indicate that a purely time- or state-dependent pricing model would lack some features observed in the data. Favouring time-dependency, on the one hand, estimates indicate that price spells exhibit greater risk of ending every seven days relative to other days in between. This hazard shape would be implied in the Taylor (1980) pricing model. When looking at price hikes and price drops, we find that both are roughly equally likely to occur when the spells last multiples of seven days, and less likely otherwise. The web scraped dataset reporting prices at daily frequency allows us to uncover this feature. Advocating for state-dependency, on the other hand, results suggest that in 2017 prices were more likely to change than in 2016, 2018 and 2019; while 2020 and 2021 show greater hazard rates relative to 2017. Then, 2022 is the year with the greatest probability of observing price changes and, hence, shorter price spells.

When fitting our model by major product groups (i.e. more homogeneous goods), we also find evidence of time- and state-dependent pricing rules in web scraped data. First, the greater values in the baseline hazard function at focal points (every seven days in this case) prevails. Though, we observe that most Food, Medicines and Personal Care price spells end before their 21st duration day, while Apparel, Furniture and Recreation exhibit longer price spells as their baseline hazard decreases at a less rapid pace. Second, the model’s fixed effects associated to the state of the economy over the business cycle are normally statistically significant. For instance, Apparel, Furniture, Recreation and Personal Care price spells see a downward trend in their probability of price changes between 2016 and 2019, followed by a sharp increase since the start of the COVID-19 pandemic in 2020; Food price spells have shown increasing hazard rates of more frequent price changes over the years, specially price hikes in 2022; while the hazard rate for Medicines between 2016 and 2021 remains flat but spikes in 2022.

There is also evidence in favour of state-dependency pricing when we leverage high frequency covariates like the USD/MXN exchange rate (FX) and real expenditure at Point of Sales (PoS) in our empirical specification. Indeed, variations in the FX and PoS expenditure play a role as duration of price spells’ determinants.² Estimates suggest that Food and Medicines exhibit greater hazard rates of price changes and, thus, shorter price spells when the MXN peso depreciates relative to the US dollar. Indeed, it is more likely to see price hikes than price drops when the Mexican peso depreciates over the duration of the spell.³ Moreover, Apparel, Furniture, Recreation and Personal Care items are more likely to report shorter price spells, i.e. greater hazard rate of price changes, when there is a positive variation in real PoS expenditure over the duration of the spell.

Finally, we benchmark our estimates stemming from web scraped data with a second prices dataset gathered via direct visit to brick-and-mortar stores. This second dataset comes from price collected by INEGI for CPI computation purposes. While the comparison of results across sales channels (websites and brick and mortar stores) should be taken with caution due to compositional differences in goods and retailers in the sample, estimates from the proportional hazard model based on prices collected at brick and mortar stores are consistent with the ones found using web scraped data in general. First, the baseline hazard of the duration of price spells shows a similar shape in both online and offline datasets. It shows a rapid decrease in the first three months, then it stabilizes up to the run-up duration of the first year, period around which we observe a small hump at the 12th month across both sales channels.⁴ Second, the yearly fixed effects from 2016 to 2021 in both sales channels suggest similar hazard rates of price changes. It is in 2022 when the hazard rates have the

²We use an inflation-adjusted PoS series. In our context, a demand proxy should only include variations in quantities and not inflationary (price-driven) effects. As PoS expenditure is the product of prices and quantities, real PoS expenditure diminishes undesired nominal effects.

³These time-varying covariates are introduced in the model reflecting their cumulative variation since the start of each price spell.

⁴In terms of seasonal patterns, we document that both sales channels report increasing hazard rates of price changes over the first six calendar months of the year. In June, the hazard rate of price changes in web scraped prices continues increasing and the offline hazard of price changes decreases. During August, September and October both sales channels report similar hazard rates relative to their March values. Over November and December, the hazard of ending price spells increases by a larger margin online than offline.

largest deviation across datasets. This deviation, third, is mainly driven by Food items. That is, the length of Food’s price spells from web scraped data have increased over time, specially in 2022; in contrast, the hazard rate computed from offline prices increased only temporarily in 2020-2021 and has returned to its pre-pandemic values i.e. 2016 to 2019. Medicines have also displayed different patterns across sales channels. Furniture and Personal Care, and to a lesser extent Apparel and Recreation, are product groups that have exhibited similar hazard profiles over time across sales channels.

This paper speaks to two strands in the literature. The first strand in the literature is the studies using various observable proxies of disequilibrium between the current price level and the optimum price level. As menu-costs models predict, prices are more likely to change the further they are from their optimal level. To that end and using proportional hazard models with time-varying covariates similar to ours, Dias et al. (2007) look at industrial production activity as demand proxy, while Fougère et al. (2007) and Nakamura and Steinsson (2008) look at the inflation rate.⁵ We add to this literature the study of two high frequency macro variables: the USD/MXN exchange rate and PoS data. Contrary to other macro aggregates, these variables share the same daily frequency of observation as our price data. In addition, they can be seen as supply- and demand-side inflation drivers that may affect retail prices. Second, as most price-setting models have stark predictions for the shape of the hazard function of price changes, there is a large body of research documenting this stylized fact.⁶ In general, the literature has found either flat or downward-sloping hazard rates. Our results suggest that, even after estimating separate hazard functions for major product groups in order to account for a potential bias due to the cross-sectional heterogeneity of hazard rates,

⁵The aforementioned studies assess the effect of macroeconomic variables on (micro) price-setting. This is the approach we follow in this study. While not studying price duration, Borraz et al. (2022), Kryvtsov and Vincent (2021), among others, also look at the relationship between macro factors (unemployment) and micro price-setting (share of products on sale each month) in Uruguay and UK-US, respectively. Few studies have looked at firm level price determinants, like Campbell and Eden (2014) and Eichenbaum et al. (2011).

⁶Calvo’s (1983) price model predicts a flat hazard function; Taylor’s (1980) model generates a zero hazard, except at a single age where the hazard is one; menu-cost models can generate a variety of shapes: pervasive permanent shocks produce upward sloping hazard functions, while temporary shocks may yield flat or downward sloping hazard rates. See Klenow and Malin (2010) and Nakamura and Steinsson (2013) for a comprehensive review of studies estimating hazard functions.

the hazard functions are downward-sloping for the first few weeks and fairly flat thereafter. Finding a similar result to ours, Nakamura and Steinsson (2008) argue that temporary sales, bunching price adjustments together, may lead to downward sloping hazard functions. We also find a hump shape in the hazard function at the 12th month, as Álvarez et al. (2005) and Klenow and Kryvtsov (2008).

Our contribution is threefold. First, our study leverages PoS data as a price change driver. The daily observation frequency in both price and PoS datasets, as well as the COVID-19 context in which families reoriented part of their expenditure towards the goods market, make PoS data a suitable demand proxy candidate. To the best of our knowledge, this is the first paper using PoS data as an explanatory variable in duration models studying price changes. Second, we provide a comparison between hazard estimates computed using web-scraped prices and those employing CPI micro-data. Although with some quantitative differences, results stemming from these datasets align well in terms of the hazard of price changes at business cycle frequencies, despite differences of products, retailers and sales channels. Closest to this type of price-setting comparison are Cavallo (2017) and Solórzano (2023b). With their own particularities, these two studies do not estimate the hazard function for web scraped prices nor for prices observed at brick and mortar stores.⁷ Third, by using daily data, we are able to show that prices are more likely to change every seven days. As most of the literature studying price stickiness uses CPI micro-data, they are unable to uncover this feature (Luo and Villar, 2021; de Prince, 2018; Dhyne et al., 2009; Nakamura and Steinsson, 2008; Bils and Klenow, 2004, among others). Spikes at seven days interval in our estimated hazard functions is supportive evidence that some price adjustments follow a fixed schedule, as in Taylor (1980).

Thus, this paper provides evidence that price-setting models with only time- or state-dependent pricing rules may fail to represent some of the features found in the data. Uncovered due to the higher frequency of observation in web scraped data than in survey data,

⁷Cavallo (2017) and Solórzano (2023b) contrast the frequency and size of price changes, as well as price levels and reasons for online-offline pricing differences in retailers that sell both online and offline.

on the one hand, we show that à-la-Taylor pricing is still relevant for characterizing the behaviour of price-setters. On the other hand, our results suggest that price-setters also react to the state of the economy.⁸

The paper is organized as follows. Section 2 and Section 3 describe our data and empirical framework, respectively. Section 4 summarizes our results. Section 5 concludes.

2 Data

In this section, we describe the main data source in this study: retail prices gathered through web scraping techniques. We provide a description on the collection methods and construction of price spells, as well as few summary statistics. Additional data sets in this study, like the CPI micro-data or the PoS and FX series, are described in the Appendix for brevity.

2.1 Online Data

The main dataset in this study comes from prices as advertised on retailers' websites. The price revision, carried out by Banco de México, is executed by parsing out the website of eight large retailers with nationwide operations in Mexico. They are a mix of supermarkets, price clubs and departmental stores. In broad terms, the price revision consists in gathering prices from every product displayed on their websites. Per product, we observe the product's identifier, description and prices (normal and sales prices). We use sales prices when available. After the price revision is completed, goods are classified into "product categories" (lowest level of aggregation in the Mexican CPI).⁹

⁸Our analysis focuses on price stickiness. The complementary role of information stickiness or expectations in price-setting is out of the scope of this paper. For more, see Carrera and Ramírez-Rondán (2019) and references therein.

⁹They are known as "genéricos" by INEGI. One should interpret product categories as clusters of fairly homogeneous goods and similar to one further level of disaggregation from the UN's Classification of Individual Consumption by Purpose (COICOP) classes. Examples of product categories are Milk, Eggs, Women's Trousers, Men's Trousers, Fridges, Televisions, etc. Individual prices are mapped into these product categories by machine learning techniques. This process is out of the scope of this paper. Please contact the EconLab for further details.

We use prices from January 1st 2016 to June 30th 2022. Prices are mostly gathered on a daily basis.¹⁰ Table 1 provides an overview on the raw dataset at the Classification of Individual Consumption by Purpose (COICOP) Division level. Thus, before the construction of price spells, we have over 184.1 million prices stemming from 1.7 million different products. It is worth highlighting that the dataset includes items in 174 out of the 198 product categories in the goods sector encompassed in Mexico’s Core CPI.¹¹ In terms of CPI weights, the 174 product categories represent 32%, 42% and 80% of the CPI’s headline, core and goods consumption baskets, respectively.

Table 1: Price Dataset Gathered Through Web Scraping

COICOP Division		Prices (millions)	Products (thousands)	Categories
1	Food and Beverages	32	72	67
3	Apparel	54	1,020	24
5	Furnishings and Home Products	26	197	44
6	Medicines	17	64	15
9	Recreation	22	214	11
12	Personal Care	18	75	13

Note: Data from January 1st 2016 to June 30th 2022. It encompasses prices from 8 different retailers. The price revision considers data from every product displayed on the website. Per product, we observe the product’s identifier, description and price as presented on the website. COICOP Division 6 and 12 are called “Health” and “Other Goods” but substituted as “Medicines” and “Personal Care”, respectively, for illustration purposes. Source: Own calculations based on data gathered by Banco de México.

2.1.1 Price Spells

We briefly outline how the construction of price spells is carried out. As described above, a price spell is defined as an uninterrupted sequence of price reports associated with one individual product during which the price remains constant.¹²

¹⁰Solórzano (2023b) uses some version of this dataset and offers further details on the data collection and descriptive statistics.

¹¹Mexico’s CPI Base Ago 2018 = 100 considers 299 product categories, out of which 245 form Mexico’s Core CPI. Moreover, there are 198 product categories in the goods market and 47 in the service sector.

¹²We round all prices to their nearest cent (if they had more than 3 decimals). A price is said to be constant if in the uninterrupted sequence of price reports they are all exactly the same (to the nearest cent). In other words, we do not impose any minimum price variation (threshold) in order to be considered a price change. We believe that retailers’ price posts (on websites), in addition to our price collection technique (web scraping), measurement errors are less of a concern and, hence, do not establish any variation threshold

Bear in mind that the sequence of price reports can be interrupted because (i) it reaches the end of the observation period (June 30th 2022), (ii) an item is out-of-stock (temporally or permanently), or (iii) a technical issue. These instances can affect the length of price spells, shortening them most likely. For (i), the price spell is considered right censored.¹³ For (ii) and (iii), as they create a period with missing prices (i.e. a gap between observed prices), we assume that if the product’s price is the same to the left and to the right of the gap between observed prices and this gap lasts less or equal than 60 days, we impute such gap with the same observed price and allow the spell to continue.¹⁴ If observed prices are unequal at both ends of the gap between observed prices and/or the gap is greater than 60 days, we do not impute any price. In such cases, the price spell to the left of the gap is considered as a right-censored spell, while the price spell to the right of the gap is considered as a left-censored spell.

With that in mind, Table 2 breaks down the number of spells for each COICOP Division according to its spell type: (i) complete, (ii) right censored, (iii) interval right censored, (iv) left censored, (v) interval left censored, (vi) right and interval left censored, (vii) interval right and left censored, as well as (viii) interval right and interval left censored.^{15,16} As it is presented in Section 3, our empirical framework uses spells where the duration can be directly measured from the data (i.e. only complete, right censored and interval right censored price spells) and without having further assumptions on their starting dates and,

(as sometimes it is the case in self-reporting price or income surveys, for instance).

¹³See footnote 15 for more on the different spell types in the sample.

¹⁴Intuitively, suppose that we observe a sequence of prices for subject i such as p_{t-t_1} , p_t , p_{t+t_2} , $p_{t+t_2+t_3}$ with $t_1 < 60$, $t_2 \geq 60$, and $t_3 < 60$. Assume that the prices p_{t-t_1} , p_t , p_{t+t_2} , $p_{t+t_2+t_3}$ are the same, p^* . One might proceed in two different ways: (1) create a single complete spell k with duration $T_{i,k} = t_1 + t_2 + t_3$, $1 < k < K$; or (2) create two complete spells of duration $T_{i,k-1} = t_1$ and $T_{i,k} = t_2 + t_3$ with $k - 1 > 1$ and $k < K$ (the spells $k - 1$, and k for subject i are then right-censored and left-censored, respectively).

¹⁵ When the starting and ending date are well observed in a given spell, it is said that the spell is complete. If the starting date is observed but the ending date is not, then it said that the spell is interval right censored (e.g. temporal stockout). When the last observation of an interval right censored spell falls on the last day of the study, it is said that the spell is right censored. If the starting date is unknown for any given spell, then it is said the spell is interval left censored. If the first observation of an interval left censored spell falls into the first day of the analysis, then it is known as left censored. All combinations of (interval) left censoring and (interval) right censoring are possible.

¹⁶No right and left censored spells (simultaneously) were found in our data set.

hence, likely duration (e.g. left censored price spells). Thus, (i) the share of complete spells by COICOP Division ranges from 60.71% for Apparel to 76.82% for Food and Beverages, (ii) Right Censored (RC) spells are about 2% in all divisions, while (iii) the share of Interval Right-Censored (IRC) spells runs from 5.95% to 12.54% in Food and Apparel, respectively. The remaining spells are neglected from the empirical analysis in the next sections. Figure 1 complements this table by showing the number of observations (i.e. prices from individual products) depending on the type of spell they belong to across time.¹⁷

Table 2: Spell Type Distribution by COICOP Division

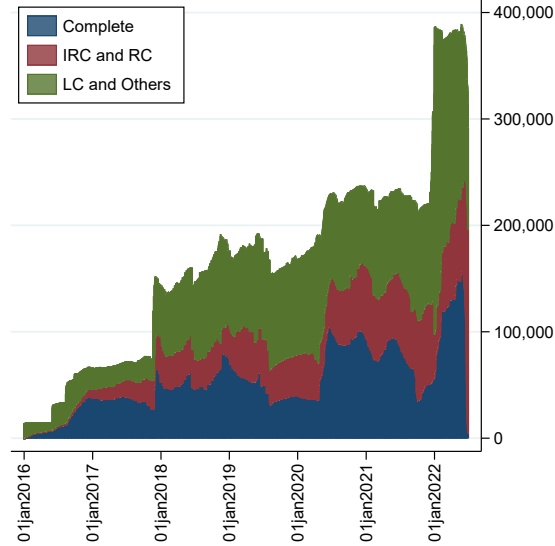
COICOP Division	Spells		Type of Spell (%)							
	Number	Share (%)	Complete	RC	IRC	LC	ILC	RC-ILC	IRC-LC	IRC-ILC
1 Food and Beverages	797	8	76.82	2.15	5.95	0.62	7.60	0.53	0.23	6.10
3 Apparel	5,296	51	60.71	1.75	12.54	0.00	14.36	0.77	0.00	9.88
5 Furnishings and Home Products	1,624	16	72.37	1.72	8.00	0.06	9.81	0.78	0.04	7.21
6 Medicines	545	5	70.82	1.87	9.37	0.47	10.83	0.81	0.11	5.72
9 Recreation	1,425	14	68.90	2.13	8.35	0.01	10.71	1.79	0.01	8.11
12 Personal Care	693	7	72.46	1.64	7.79	0.28	9.27	1.09	0.05	7.43

Note: This table summarizes all price spells that can be constructed in our data set. The column *Share* under the title *Spells* does not add up to 100 due to rounding. Rows under the title *Type of Spell* add up to one i.e. it provides a partition on the type of spells by COICOP Division. No RC-LC spells were found in our data set. Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

Moving on into the duration of price spells, Table 3 provides an overview on duration statistics for complete price spells by COICOP Division. In terms of the mean duration, COICOP Divisions can be roughly split into two. On the one hand, Food, Medicines and Personal Care report an average duration close to a month (30, 30 and 26 days, respectively). On the other hand, the mean duration of Apparel, Furniture and Recreation is close to a fortnight (16, 19 and 17 days, respectively). Taking a closer look at the distribution of the duration of price spells, this split is driven by the right tail of the duration distribution. For instance, the 90th percentile for Food is 76 days and for Medicines 78 days, while for Apparel and Recreation is 35 and 37 days, respectively. In contrast, COICOP Divisions are more homogeneous at the left tail of the duration distribution up to the median duration. That is,

¹⁷While complementary, bear in mind that Table 2 and Figure 1 summarize different things. In Table 2 each spell counts as one unit in computing the percentages. Therefore, short-length spells tend to be overrepresented (this is a form of length bias). Figure 1 does not suffer from a “visual” length bias as each price on a given day goes to one type of spell. A mismatch between Table 2 and Figure 1 would happen if censored spells report longer duration than complete spells. Indeed, Table 3 below shows that RC and IRC spells report longer duration than complete spells in general (LC or ILC spells’ duration are omitted for brevity as they are not used in the analysis).

Figure 1: Observations by Type of Price Spells



Note: Each observation (i.e. price from an individual product on a given day) belongs to one and only one spell. Then, we create a partition of spells depending on how they started and ended (see Table 2 for the complete spell partition by COICOP Division). Finally, we add the number of observations by spell type on a daily basis. Estimates in Section 4 employ observations from Complete (in blue), Interval Right Censored (IRC) and Right Censored (RC) (in maroon) spells only. Thus, the height in the figure represents the number of price spells in the data set on a given day. In the Appendix, Figure 10 breaks down the Left Censored (LC) and Others (in green) fraction of the spell partition. Data from January 1st 2016 to June 30th 2022. Source: Own calculations based on online data compiled by Banco de México.

about 10% of spells length is one or two days and about 25% of spells are equal or less than five days old. The median duration ranges from eight days (Food, Furniture and Recreation) to 10 days (Medicines). Finally, Table 3 also reports the share of spells by COICOP Division ending as a price hike or as a price drop. Given the positive inflation rates in Mexico, the fraction of spells ending as price hikes and price drops are somewhat balanced. The greatest difference is in Apparel (46.72% and 53.28% in favour of spells ending as price drops) and the smallest is observed in Recreation (50.09% and 49.91% favouring spells finishing as price hikes). Overall, Food, Medicines, Personal Care, as well as Recreation report more spells ending as hikes than as drops; Apparel and Furniture the opposite.

Thus, our dataset seems to exhibit a fair degree of heterogeneity in price-setting across different expenditure categories in CPI baskets.¹⁸ Interestingly, among the two groups of

¹⁸By using the frequency of price adjustment as a stylized fact of price-setting, and not through the lens of price spells, heterogeneity across consumption goods has been widely documented using survey data (e.g.

Table 3: Duration Distribution by COICOP Division

COICOP Division		Spells		Duration (Days)								Ending as (%)	
		Number (thousands)	Share (%)	Mean	P5	P10	P25	P50	P75	P90	P95	Price Hike	Price Drop
<i>A. Complete Spells only</i>													
1	Food and Beverages	612	9	30	1	1	2	8	28	76	138	53	47
3	Apparel	3,215	47	16	1	2	4	9	18	35	50	47	53
5	Furnishings and Home Prods.	1,175	17	19	1	2	5	8	21	41	63	50	50
6	Medicines	386	6	30	1	1	4	10	29	78	134	52	48
9	Recreation	982	14	17	1	2	4	8	19	37	57	50	50
12	Personal Care	502	7	26	1	1	4	9	26	63	105	51	49
<i>B. Complete, Interval Right Censored and Right Censored Spells</i>													
1	Food and Beverages	677	8	43	1	1	3	10	36	117	209	48	42
3	Apparel	3,972	49	21	1	1	4	9	20	42	80	38	43
5	Furnishings and Home Prods.	1,333	16	28	1	2	5	9	23	60	110	44	44
6	Medicines	447	6	41	1	1	4	11	37	118	185	45	41
9	Recreation	1,131	14	25	1	2	4	9	21	53	99	43	43
12	Personal Care	567	7	39	1	1	4	11	34	97	171	46	43

Note: This table summarizes the duration distribution of price spells by COICOP Division as computed from the web scraped data set. These are not fitted values from an econometric model. The column *Share* under the title *Spells* adds up to one. Moments in the duration distribution under the title *Duration* are computed by COICOP Division and reported in days. The rows under the title *Ending as* in panel B do not add up to 100 due to the interval right censored and right censored spells. Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

COICOP Divisions described in the previous paragraph, the ones with their mean duration closer to a month (Food, Medicines and Personal Care) include varieties that rarely disappear from the market (e.g. well-known varieties to Mexican households of tuna cans, paracetamol or body cream). In contrast, the ones with mean duration closer to a fortnight consider products with “life-cycles” (Apparel, Furniture and Recreation).¹⁹

Figure 2 complements Table 3 as it pools price spells across COICOP Divisions and depicts the duration distribution of complete spells.^{20,21} Notably, Figure 2 exhibits a bleep every seven days. In other words, there is a sizable share of price spells lasting multiples

Bils and Klenow (2004), Dhyne et al. (2009), Nakamura and Steinsson (2013) and Gautier, Conflitti, Faber, Fabo, Fadejeva, Jouvanceau, Menz, Messner, Petroulas, Roldan-Blanco, Rumler, Santoro, Wieland, and Zimmer (Gautier et al.)), and to a lesser extent using web scraped data but more recently (e.g. Cavallo (2018) and Solórzano (2023b)).

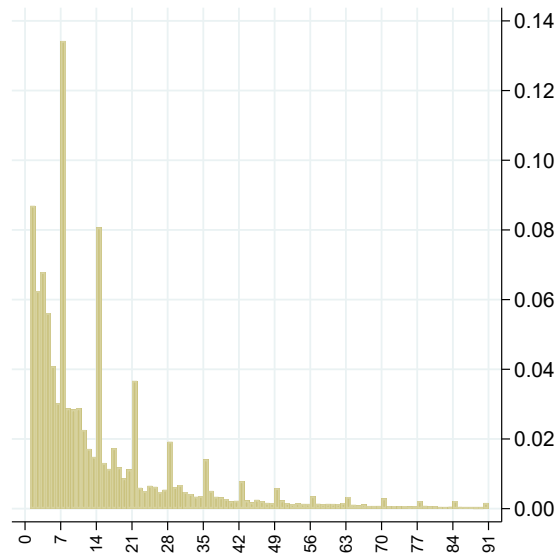
¹⁹That is, there is a continuous reshuffle of items as the new season, trend or technology arrives (e.g. swimwear, vintage sofas, smart TVs, toys or books). These type of items regularly enter the market with their highest prices as they are the *new(est)* model and, as new wave of models enter the market, they tend to experience price cuts rather than price increases. Some of these product categories are in fact subject to hedonic quality adjustments by Statistical Offices when measuring their inflation rates. See Ehrlich et al. (2021) and Bajari et al. (2021) for more on quality adjusted price indices using machine learning and AI.

²⁰For illustration purposes, Figure 2 shows complete spells lasting less or equal 91 days. As Table 3 reports, less than 10% of complete spells last more than 91 days. In the Appendix, Figure 10 illustrates the histogram with no length cap. Figure 11 depicts the duration histogram using complete, RC and IRC spells.

²¹In the Appendix, we report the duration distributions by COICOP Division as in Table 3 in Figure 12. Additionally, Figure 13 plots the duration distributions using complete, RC and IRC price spells.

of seven days. Though, the size of the distribution in first two or three weeks (21st day inclusive) is also non-negligible.

Figure 2: Fraction of Complete Price Spells by Days of Duration
Capped at 91 Days

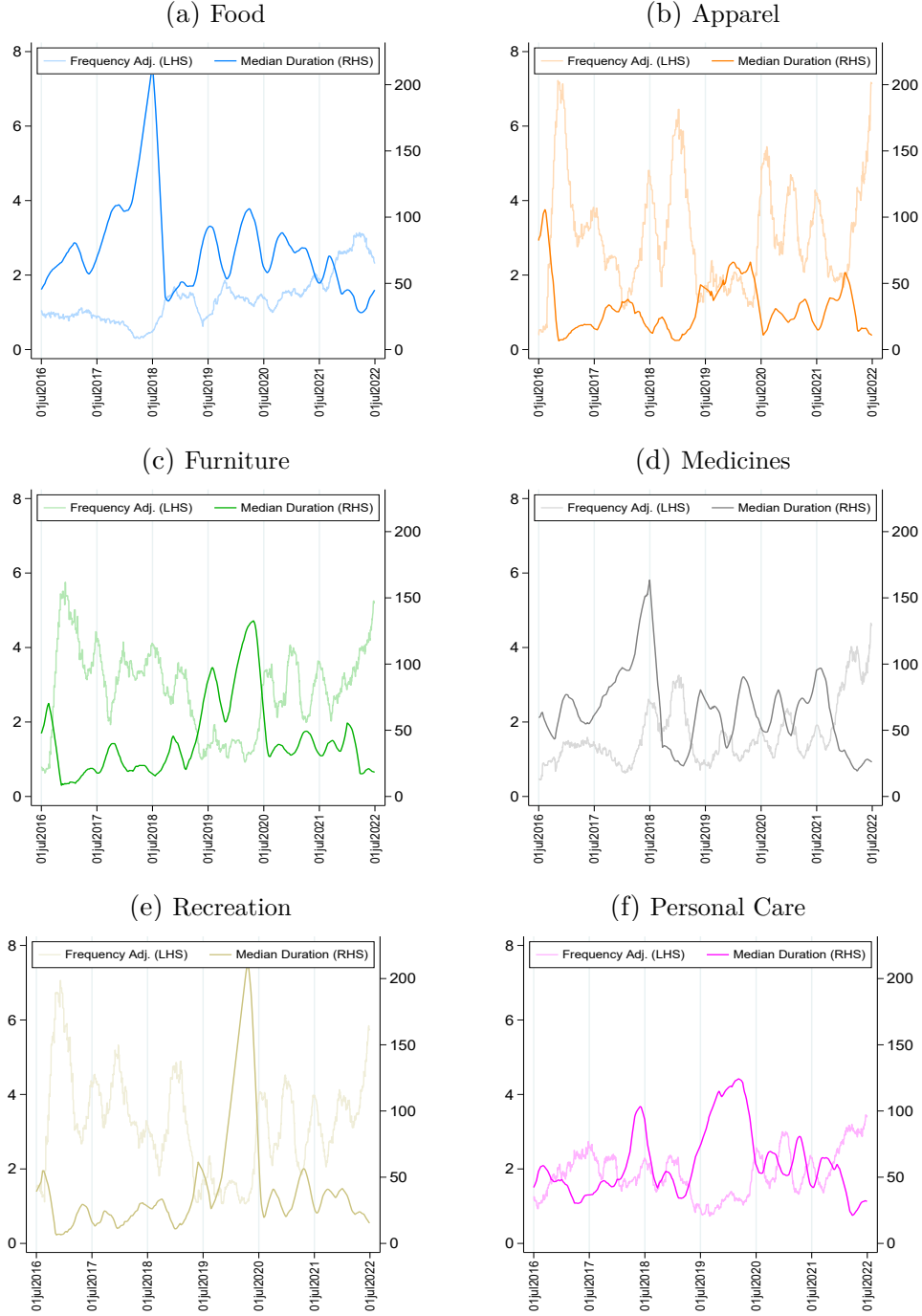


Note: This figure pools price spells across COICOP Divisions and depicts the duration distribution of complete spells lasting less or equal 91 days. As Table 3 reports, less than 10% of complete spells last more than 91 days. In the Appendix, Panel 10b illustrates the histogram with no length cap, while Figure 11 depicts the duration histogram using complete, RC and IRC spells. Also in the Appendix, we report the duration distributions of complete spells by COICOP Division (as in Table 3) in Figure 12 and in Figure 13 plots the duration distributions using complete, RC and IRC price spells. Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

Finally, as part of our analysis in Section 3 centres at associating duration dynamics to the business cycle, Figure 3 depicts the median duration, as well as the frequency of price changes by COICOP Division. It uses complete, RC and IRC price spells. Specifically, for every day in our sample we compute the on-going duration of the active spells; and the fraction of prices changing relative to its previous day.²² Although mechanically driven, it is reassuring to see that periods with greater frequency of price changes are associated to smaller median duration of price spells and vice versa.

²²It is worth mentioning that Figure 3 considers complete, RC and IRC price spells. In this case it is less of a problem to include RC and IRC price spells in the duration statistics since our aim here is to illustrate the on-going duration of active price spells (i.e. median sample age), as instead of computing the overall duration of price spells (i.e. life-expectancy).

Figure 3: Frequency of Price Adjustments in Percentages (LHS) & Median Duration in Days (RHS)
Quarterly Moving Average from Daily Data



Note: Daily series are smoothed using a three month moving average for illustration purposes. Monthly moving averages are reported in Figure 14 and Figure 15 in the Appendix. For every point in time we compute (i) the on-going duration of the active (complete, RC and IRC) spells at the time and (ii) the fraction of prices changing relative to its previous day. Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

3 Methodology

We outline the general methodology used in our analysis. In a proportional hazards framework each subject has the same (typically unknown) baseline hazard $\lambda_0(t)$ multiplied by a positive function of his vector of covariates, \mathbf{x}_i and the p -dimensional vector of coefficients, β . For subject i , his hazard function is formulated as

$$\lambda(t, \mathbf{x}_i) = \lambda_0(t) \exp(\mathbf{x}_i^\top \beta) . \quad (1)$$

The baseline hazard function is the hazard rate when all covariates are zero and common to all subjects in our dataset.

Based on Kiefer (1988), Kalbfleisch and Prentice (2011), and Fougère et al. (2007), we consider data only involving complete and right censored spells.²³ In such case, our likelihood function can be conveniently represented by pairs of random variables (t, δ) , where δ indicates whether the duration X is observed ($\delta = 1$) or not ($\delta = 0$); and $t = X$ if the duration is observed and $t = C_r$ if it is right-censored.²⁴ If we have a random sample of pairs (t_i, δ_i) where $i = 1, \dots, n$ represent products, then the loglikelihood function is

$$\begin{aligned} \log(\mathcal{L}) &= \log \left\{ \prod_{i=1}^n \Pr[t_i, \delta_i] \right\} = \log \left\{ \prod_{i=1}^n [f(t_i, \mathbf{x}_i)]^{\delta_i} [S(t_i, \mathbf{x}_i)]^{1-\delta_i} \right\} \\ &= \sum_{i \in n} [\delta_i \log f(t_i, \mathbf{x}_i) + (1 - \delta_i) \log S(t_i, \mathbf{x}_i)] . \end{aligned} \quad (2)$$

where f and S represent the density and survival function of the random variable t conditional on covariates \mathbf{x}_i . See Wooldridge (2010) for more.

²³ In addition to maximizing the number of spells in our analysis, the inclusion of right censored spells limits the potential upward bias in the hazard rate near the end of the analysis. Intuitively, if we had used complete spells only, then the closer we get to the study's end date the fewer spells there are (survivors) and, thus, affecting the denominator in the ratio of failures to survivals i.e. hazard rate. In contrast, by not restricting to complete spells only and including right censored spells, the denominator stays fairly steady closer to the study's end date.

²⁴ Our empirical approach is flexible enough to explicitly accommodate right censored spells in the likelihood function. As highlighted in footnote 23, right censored price spells are specially relevant for getting unbiased estimates of the hazard rate near the end of the study.

Fougère et al. (2007) further controls for individual heterogeneity assuming that this type of heterogeneity is randomly distributed. Moreover, Fougère et al. (2007) and Dias et al. (2007) consider a hazard model with unobserved individual heterogeneity (frailty). The size of the data set, on top of the non-linear problem at hand, prevent us from adding this term and it is left for future work.

After excluding the left-censored intervals, Dias et al. (2007) work with a single spell for each product randomly drawn from the set of spells available. The authors adopt this strategy in order to ameliorate the well-known length bias. We follow a different approach. We use all available price spells (complete, RC and IRC) and weight each product by the inverse of the number of spells the product provides to the sample. This strategy is followed in order to maximize the number of spells in our empirical framework. Dias et al. (2007) acknowledge these strategies are similar in spirit but theirs is less computational intensive than ours.

Moving on, for subject i , define τ_{it} as the elapsed duration since the start of the spell in period t and let T_i be the duration of the spell. Following Dias et al. (2007), using maximum likelihood estimation, we consider a parametric proportional hazard model with a piece-wise constant baseline hazard with time varying covariates. We exploit the nature of our data set by defining the piece-wise baseline hazard at a daily basis. Specifically, we allow for each day to report different values up to the 90th day since the beginning of the spell; from that point on, we cluster durations over fortnights up to six months, then in quarters, then in years i.e. $\lambda_{\tau_{ij}} = \lambda_j^*$, where $j = 1, 2, 3, 4, 5, \dots, 89, 90, (90,105], (105, 120], \dots(180,210], \dots(360,)$ days. The hazard function at τ_{it} is therefore given by

$$\lambda(\tau_{it}|Z_i, W_t, X_{it}, v_i) = \lambda_{\tau_{it}} \exp [f(Z_i, W_t, X_{it})] v_i, \quad (3)$$

where Z_i includes retailer and product category fixed effects; W_t considers day of the week, calendar day, month and year fixed effects. As a control for sales prices, X_{it} is the magnitude

of the last price change and enters the regression as X_{it}^a and X_{it}^- since some asymmetric effects are expected. X_{it}^a represents the absolute value of the magnitude of the last price change, whilst X_{it}^- is a dummy taking the value of one if the magnitude of the last price change is negative, zero otherwise. Intuitively, on the one hand, a price spell stemming from a price drop (potential sales price) may report shorter duration on average; on the other hand, as Dias et al. (2007) argue, firms might incur on negative reaction from customers following a price increase, leading to a longer price spell.²⁵ Lastly, v_i for item i assumed to be gamma distributed with mean 1 and variance σ^2 . Hence,

$$f(Z_i, W_t, X_{it}) = Z_i\beta_Z + W_t\beta_W + X_{it}^a\beta_{X^a} + X_{it}^-\beta_{X^-} . \quad (4)$$

4 Results

Regression coefficients are reported in exponentiated form. Given that our empirical model is a discrete time proportional hazards framework, the exponentiated coefficients can be interpreted as hazard ratios.²⁶ Qualitatively, a hazard ratio greater than one indicates a higher hazard rate for a price change to occur with all other covariates held fixed; a hazard ratio below one implies a lower hazard rate than otherwise. While hazard ratios can tell us whether the hazard increases or decreases, they do not tell us by how much quantitatively (e.g. in percentage points) due to the fact that our empirical framework is not linear.²⁷ Though, exponentiated coefficients keep an ordinal association between them i.e. an exponentiated coefficient greater than another exponentiated coefficient means a greater increase in the hazard rate of the former relative to the latter.

²⁵These variables are well defined for complete, interval right censored and right censored spells. For left censored spells, which are discarded from our analysis, these variables are undetermined.

²⁶Intuitively, a hazard ratio can be interpreted as the proportionate variation in the hazard rate given a change in a specific explanatory variable *ceteris paribus*. It is assumed that the change in the hazard rate, say, across duration periods is proportional.

²⁷The actual value of the hazard rate, and how it changes, depends on the values the explanatory variables take. This is carried out via the computation of marginal effects. The aim the paper is beyond these computations.

We first provide an overview of the results from the benchmark model pooling all observations together. Then, we separately fit the benchmark model for major product groups (more homogeneous goods) and summarize the results. Subsequently, the benchmark specification is enriched with data from the USD/MXN exchange rate and real PoS expenditure. Lastly, we compare the shape of the hazard function using web scraped retail prices to the hazard function stemming from CPI micro-data.

4.1 Benchmark Results

Figure 4 illustrates the baseline hazard, as well as year fixed effects included in Equation 3. Interestingly, Panel 4a shows that price spells exhibit greater risk of ending every seven days relative to other days in between. The daily frequency of observation in our sample allows us to uncover this feature.²⁸ Moreover, the baseline hazard of price spells exhibits a downward trend as days pass-by. Although at odds with the shape of hazard rates implied by theoretical pricing models (e.g. increasing, like in Golosov and Lucas (2007) menu costs models; or flat, as in Calvo (1983)), empirical studies like Álvarez et al. (2005) or de Prince (2018) have found similar results. Álvarez et al. (2005) shows that price spells’ downward baseline hazards might arise from aggregating heterogeneous price-setters. Indeed, in our sample there is a great degree of heterogeneity across types of goods and retailers which might lead to a decreasing aggregate baseline hazard. We come back to this theme when reporting results at more homogeneous groups of products.

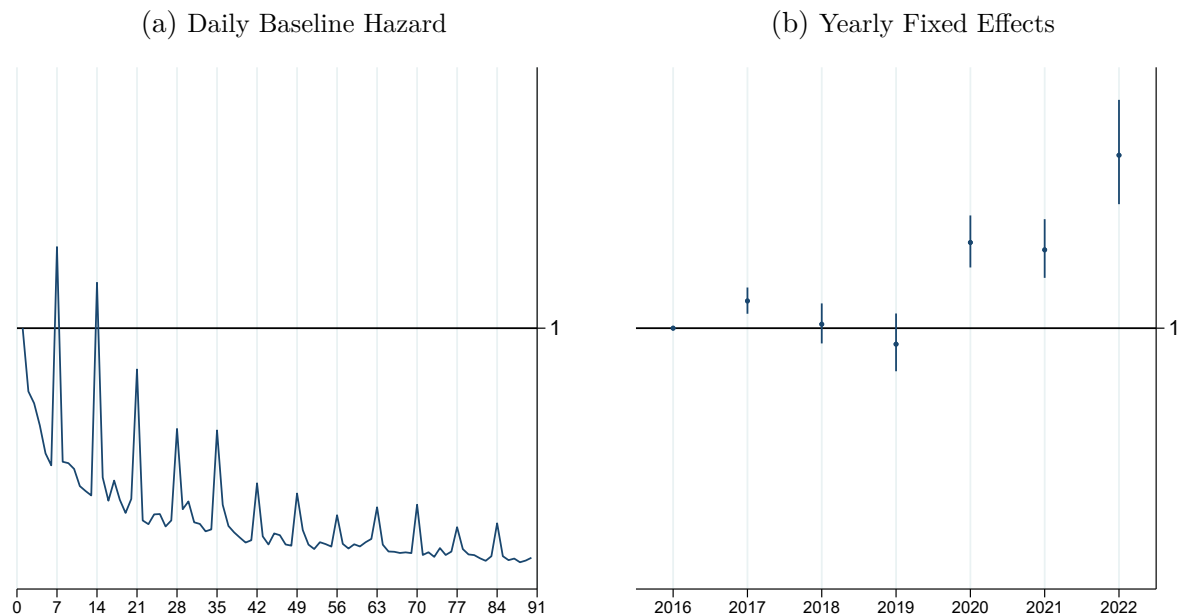
Panel 4b reports the hazard rates associated to the year fixed effects.²⁹ As described in Section 3, they are intended to reflect the hazard rates of price adjustments depending the state of the economy (i.e. deviations from the seasonal and product characteristics).

²⁸Most studies estimating proportional hazard models in the context of price spells use monthly price observations stemming from CPI surveys (e.g. Dias et al. (2007) and Fougère et al. (2007)), and thus are not able to calculate intra-month hazard rates. A notable exception is Cavallo (2018). The author also uses daily web scraped data and reports a baseline hazard rate exhibiting a bleep every seven days as well.

²⁹As discussed in footnote 23, the inclusion of right censored spells limits the potential upward bias in the hazard near the end of the analysis (affecting the coefficients associated to the year fixed effects). When including complete and right censored spells, the denominator in the ratio of failures to survivals (i.e. hazard rate) remains fairly steady closer to the study’s end date.

Our estimates suggest that prices gathered in 2017 exhibit greater risk of experiencing an adjustment than in 2016, 2018 and 2019. This pattern is in line with the uptick in the domestic headline inflation rate in 2017 due the liberalization of gasoline prices in Mexico, among other shocks. Then, affected by the onset of the COVID-19 pandemic, 2020 and 2021 show greater hazard rates relative to 2017. It is worth highlighting that, although headline inflation dipped in Mexico by the end of 2020 (3.15% in annual terms in December 2020), our data set encompasses prices from goods markets only (and not from services), which saw an increase in consumer demand as households reoriented their expenditure away from services. Finally, 2022 is the year with the greatest probability of observing price changes, and hence shorter duration of price spells.

Figure 4: Hazard Ratios from the Benchmark Model



Note: Panel 4a and Panel 4b depict the baseline hazard and year fixed effects coefficients, respectively, reported in exponentiated form. Bear in mind that exponentiated coefficients can be interpreted as hazard ratios since the cloglog model from Equation 3 is a discrete time proportional hazards framework. As hazard ratios do not tell us quantitatively by how much the hazard rate increases or decreases, the values in the y-axis are omitted but they share the same scale across panels. A hazard ratio greater than one indicates a higher hazard rate for a price change to occur with all other covariates held fixed; a hazard ratio below one implies a lower hazard rate than otherwise. Hazard ratios keep an ordinal association (e.g. greater values imply greater increase in the hazard rate). Regressions' results are reported in Tables 10-16 in the Appendix. The failure event at the end of (complete) spells is equal to one if $p_{i,t} \neq p_{i,t-1}$; zero otherwise. Estimates based on Complete, Interval Right Censored and Right Censored spells from all COICOP Divisions (pooled regression). Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

The empirical framework at hand can further decompose the benchmark model into price hikes and price drops, as illustrated in Figure 5.³⁰ Panel 5a shows that the overall shape of the baseline hazard does not change for price spells ending as a price hike or as a price drop. That is, both price hikes and price drops are more likely to occur when their spells length are multiples of seven days and lower otherwise.

Panel 5b reports that, while the difference between the hazard of price hikes and price drops is not statistically significant in all years, point estimates suggest greater chances to observe a price drop than a price hike (with the exception of 2017). We interpret this finding as a result of having in our sample a non-negligible share of spells from items subject to “life-cycles”.³¹ See Table 3 for more on the sample composition of price spells at the COICOP Division level.

4.2 Estimates by COICOP Division

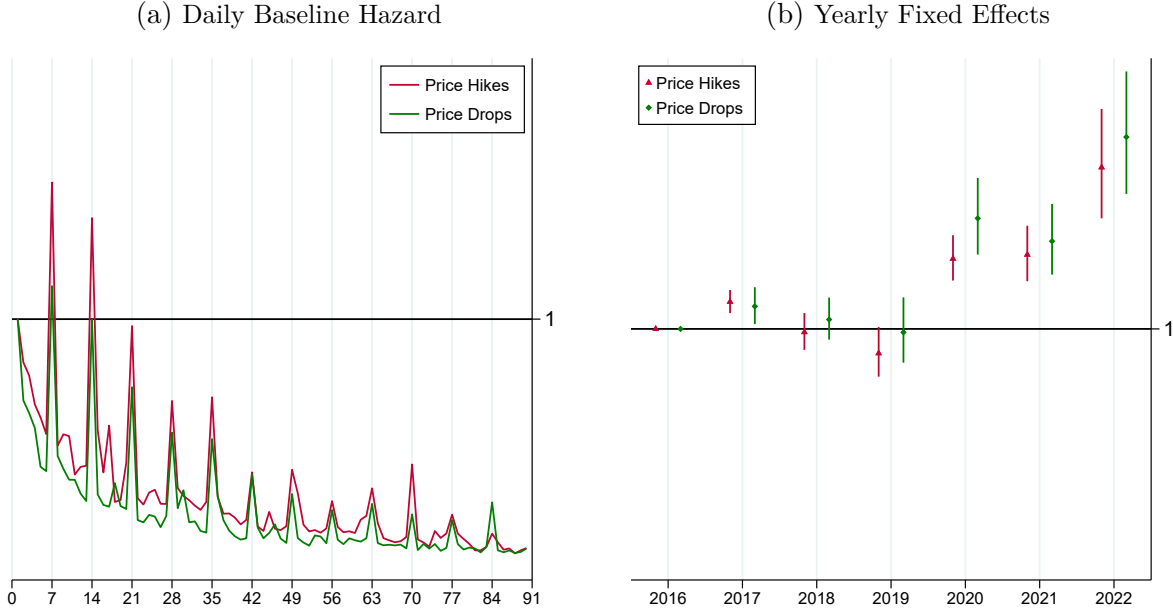
A regular feature in studies analyzing consumer prices using micro data is the great degree of heterogeneity in price-setting. See, for instance, Bils and Klenow (2004); Nakamura and Steinsson (2013). Although our benchmark specification includes controls at the product category level (i.e. lowest level of aggregation in the Mexican CPI), the shape of the baseline hazard, seasonal or year fixed affects do not vary across different types of goods. Thus, we proceed by estimating Equation 1 at the COICOP Division level.³²

³⁰It is worth highlighting that for the analysis of price hikes and price drops, we use the same empirical framework, as well as the same sample of complete, IRC and RC spells. However, the failure event at the end of (complete) spells is equal to one if $p_{i,t} > p_{i,t-1}$ and zero otherwise for price hikes; for price drops, the failure event at the end of (complete) spells is equal to one if $p_{i,t} < p_{i,t-1}$, zero otherwise. The failure event is zero along the spell for RC and IRC spells. Therefore, the regressions’ sample size are the same regardless if one looks at (i) all price changes, (ii) price hikes or (iii) price drops i.e. see regressions’ results from columns 1-3 in Tables 10-16 in the Appendix, for instance.

³¹In other words, items enter the market with their highest price and, as new models arrive, they tend to experience more price cuts than price hikes. For instance, Apparel, Furniture and Recreational Goods (like swimwear, minimalist dinner, books or toys). See Bajari et al. (2021) and Ehrlich et al. (2021) for a discussion on products life-cycles. In contrast, products in Food, Medicines or Personal Care categories (like butter, anti-flu or tooth paste) are more persistent over time, and thus subject to more price increases than price decreases.

³²Including interaction terms of the COICOP Division with the baseline hazard in Equation 1, for instance, would provide similar flexibility to study heterogeneity in our sample. We opted for a separate regression

Figure 5: Hazard Ratios from the Benchmark Model by Sign of Adjustment

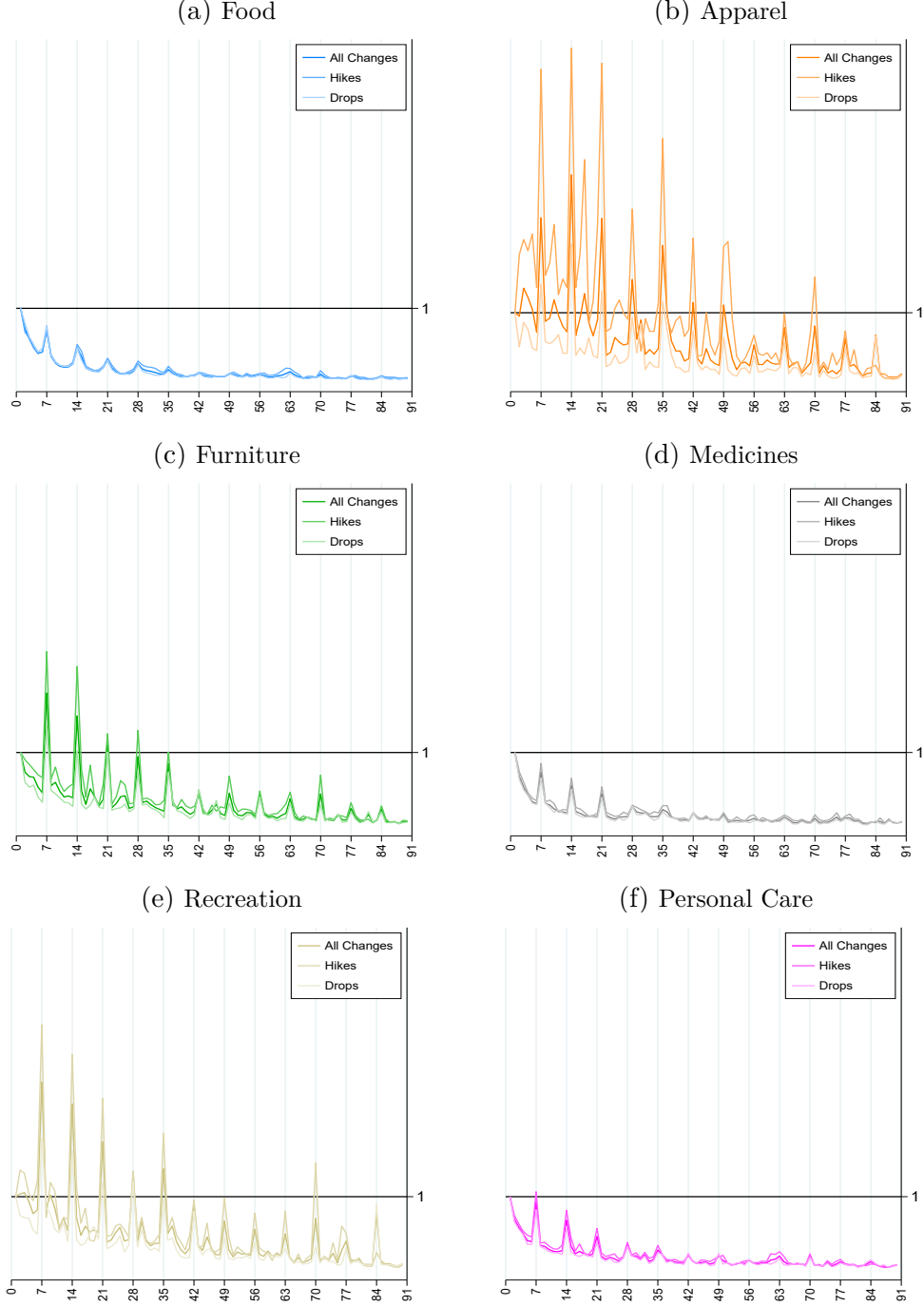


Note: Panel 5a and Panel 5b depict the baseline hazard and year fixed effects coefficients, respectively, reported in exponentiated form. Bear in mind that exponentiated coefficients can be interpreted as hazard ratios since the cloglog model from Equation 3 is a discrete time proportional hazards framework. As hazard ratios do not tell us quantitatively by how much the hazard rate increases or decreases, the values in the y-axis are omitted but they share the same scale across panels. A hazard ratio greater than one indicates a higher hazard rate for a price change to occur with all other covariates held fixed; a hazard ratio below one implies a lower hazard rate than otherwise. Hazard ratios keep an ordinal association (e.g. greater values imply greater increase in the hazard rate). Regressions' results are reported in Tables 10-16 in the Appendix. For red estimates, the failure event at the end of (complete) spells is equal to one if $p_{i,t} > p_{i,t-1}$, zero otherwise. For green estimates, the failure event is equal to one if $p_{i,t} < p_{i,t-1}$, zero otherwise. Estimates based on Complete, Interval Right Censored and Right Censored spells from all COICOP Divisions (pooled regression). Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

Figure 6 shows that indeed there is some heterogeneity on the baseline hazard of the duration of price spells across COICOP Divisions. For instance, Food, Medicines and Personal Care have a more rapid decrease in the first 21 days of the price spell, then the hazard rate plateaus. It implies that most spells end before their 21st day of duration (consistent with the summary statistics in Table 3). In contrast, Apparel, Furniture and Recreation exhibit less rapid decrease in their baseline hazard, which in turn translates into longer price spells. In fact, the hazard of price changes at the 70th day is about the same as in the first month of duration for Apparel and Furniture.

approach, however, since it is already a fairly saturated non-linear model with some computation challenges.

Figure 6: Hazard Ratios of the Baseline Hazard by COICOP Division



Note: Estimates using Complete, Interval Right and Right Censored spells. Failure events defined as in Figure 4 and Figure 5. Panels depict coefficients reported in exponentiated form, which can be interpreted as hazard ratios since we use a discrete time proportional hazards model. As hazard ratios do not tell us quantitatively by how much the hazard rate increases or decreases, the values in the y-axis are omitted but they share the same scale across panels. Values greater than one indicates a higher hazard rate for a price change to occur; a value below one implies a lower hazard rate than otherwise. Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

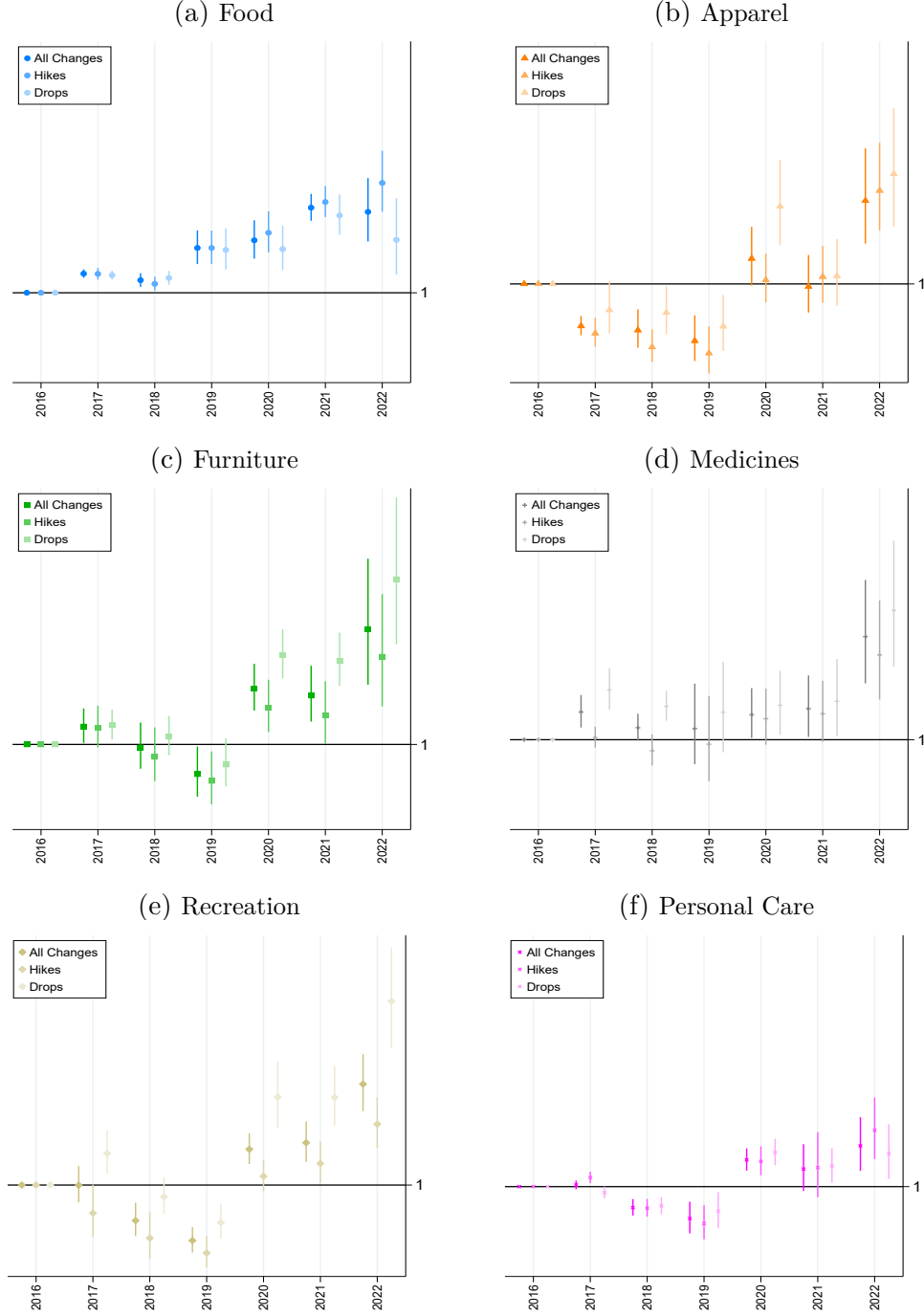
Figure 7 reports estimates for the year fixed effects by COICOP Division and sign of adjustment. There are a number of results to highlight. First, Food and Medicines deviates from the patterns found when pooling observations altogether. For Food, although with narrow confidence intervals in 2017 and 2018 relative to subsequent years, we observe the 2017 hump consistent with the uptick in the inflation rate in Mexico. However, the hazard of observing a price change has increased every year since then according to point estimates, with the exception of 2022. For Medicines, the hazard rate of price changes is fairly constant between 2016 and 2021, while in 2022 there is a notable increase. The remaining COICOP Divisions see a downward trend in their hazard rate between 2016 and 2019, followed by an increase since the start of the COVID-19 pandemic in 2020.

Second, looking at the hazard of price hikes and price drops, only Food reports greater point estimates of price hike hazard than price drop hazard in most years. In fact, it is in 2022 when we observe the greatest disparity between the hazard rate of price hikes and price drops for this COICOP Division. Furthermore, as mentioned earlier, Food, Medicines and Personal Care products are more likely to stay in the market for longer periods of time (less life-cycle effect). Hence, we see that the hazard rates of price hikes and price drops are generally not statistically different in a given year. In contrast, Apparel, Furniture and specially in Recreation products report that price drops are more likely than price hikes. For these three divisions, the greatest disparities between the hazard rates of price drops over price hikes are seen in 2020, the first year of the COVID-19 pandemic when vaccines were still unavailable.

4.3 FX and PoS as Determinants of Price Adjustments

We take a step further from our benchmark specification using yearly fixed effects as proxy for the state of the economy and we add time varying covariates to Equation 3. In particular, we add the bilateral USD/MXN exchange rate (FX) and inflation-adjusted Point of Sales (PoS) expenditure. We modify Equation 3 and Equation 4 and include the cumulative variation

Figure 7: Hazard Ratios of the Yearly Hazard by COICOP Division



Note: Estimates using Complete, Interval Right and Right Censored spells. Failure events defined as in Figure 4 and Figure 5. Panels depict coefficients reported in exponentiated form, which can be interpreted as hazard ratios since we use a discrete time proportional hazards model. As hazard ratios do not tell us quantitatively by how much the hazard rate increases or decreases, the values in the y-axis are omitted but they share the same scale across panels. Values greater than one indicates a higher hazard rate for a price change to occur; a value below one implies a lower hazard rate than otherwise. Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

in these covariates along the price spell as regressors.³³ The former has been associated as a supply-side inflation driver in small open economies as Mexico. The latter, a proxy of aggregate demand, gained attention after the loosening of COVID-19 restrictions. Note, we leave the year fixed effects that would capture macroeconomic factors other than the exchange rate and PoS expenditures.³⁴

First, Food and Medicines exhibit greater hazard rates of price changes and, thus, shorter price spells when the MXN peso depreciates (the point estimates for Medicines is greater than one but not statistically different from one though). In fact, when there is a depreciation over the duration of the spell there is an increased probability of spells ending as price hikes, while the probability of ending as price drop decreases. See columns (1) to (3) from Table 4 and Table 7 for Food and Medicines, respectively. For the remaining COICOP Divisions we see that the coefficients are less than one. We interpret this result as the rejection to the specification in place by the data e.g. perhaps the cumulative depreciation rate over longer periods of time, and not along the current price spell, is what matters.

Table 4: Hazard of Time Varying Covariates in Food Categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops
Size of Last Price Change (Abs Val, p.p.)	1.118*** [5.12]	1.090*** [3.37]	1.146*** [5.40]	1.118*** [5.14]	1.090*** [3.38]	1.146*** [5.40]	1.118*** [5.14]	1.090*** [3.38]	1.146*** [5.41]
Negative Last Price Change=1	1.056*** [2.94]	3.063*** [24.29]	0.315*** [-33.49]	1.056*** [2.96]	3.065*** [24.39]	0.315*** [-33.50]	1.056*** [2.96]	3.066*** [24.48]	0.315*** [-33.51]
FX Depreciation	1.482** [2.53]	1.782*** [3.08]	0.950 [-0.27]				0.917 [-0.43]	0.758 [-1.01]	0.793 [-1.17]
Real PoS Variation				0.166*** [-9.98]	0.053*** [-9.25]	0.546 [-1.63]	0.156*** [-7.48]	0.043*** [-6.70]	0.467* [-1.94]
AIC	341,075,570	207,157,765	199,614,460	341,041,091	207,104,745	199,612,515	341,040,891	207,103,646	199,611,833
Observations	29,109,518	29,109,518	29,109,518	29,109,518	29,109,518	29,109,518	29,109,518	29,109,518	29,109,518
Nonzero outcomes	612,169	326,558	285,611	612,169	326,558	285,611	612,169	326,558	285,611
Clusters	67	67	67	67	67	67	67	67	67

Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Standard errors clustered by product category.

Source: Authors' own calculations using daily online data.

³³For instance, for the observation associated to the first duration day from a given spell, the cumulative exchange rate (FX) variation relative to the first day is zero; for the observation associated to the second day, the cumulative FX variation is the log difference between the USD/MXN FX in day two relative to the USD/MXN FX in day one. For the PoS data, although available at daily frequency, we opt using the seasonally adjusted series, downloaded from Banco de México website. We first aggregate PoS expenditure at monthly frequencies and convert it into real terms. Then, the seasonally adjusted series is taken into a daily frequency using linear interpolation.

³⁴Industrial activity, energy prices, number of COVID-19 cases, freight costs, proxies for supply chain bottlenecks, among others, can be added to future work.

Table 5: Hazard of Time Varying Covariates in Apparel Categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops
Size of Last Price Change (Abs Val, p.p.)	1.070	0.447***	1.948***	1.074	0.446***	1.964***	1.070	0.446***	1.951***
	[0.82]	[-8.69]	[6.56]	[0.88]	[-8.77]	[6.79]	[0.83]	[-8.76]	[6.62]
Negative Last Price Change=1	0.990	5.820***	0.225***	0.991	5.846***	0.225***	0.990	5.842***	0.225***
	[-0.61]	[33.70]	[-19.54]	[-0.53]	[33.72]	[-19.73]	[-0.61]	[34.41]	[-19.66]
FX Depreciation	0.451**	0.439	0.453**				0.448*	0.679	0.312**
	[-2.04]	[-1.05]	[-2.23]				[-1.73]	[-0.42]	[-2.30]
Real PoS Variation				1.483	13.920***	0.465	0.968	11.540**	0.236
				[0.82]	[4.06]	[-1.09]	[-0.05]	[2.47]	[-1.57]
AIC	322,262,750	170,243,500	185,856,288	322,275,805	170,227,177	185,860,702	322,262,741	170,225,911	185,844,548
Observations	84,584,797	84,584,797	84,584,797	84,584,797	84,584,797	84,584,797	84,584,797	84,584,797	84,584,797
Nonzero outcomes	3,214,825	1,501,950	1,712,875	3,214,825	1,501,950	1,712,875	3,214,825	1,501,950	1,712,875
Clusters	24	24	24	24	24	24	24	24	24

Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Standard errors clustered by product category.
Source: Authors' own calculations using daily online data.

Table 6: Hazard of Time Varying Covariates in Furniture Categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops
Size of Last Price Change (Abs Val, p.p.)	1.191***	1.030	1.348***	1.193***	1.031	1.350***	1.191***	1.030	1.347***
	[3.06]	[0.37]	[3.26]	[3.07]	[0.38]	[3.28]	[3.06]	[0.37]	[3.25]
Negative Last Price Change=1	1.058**	3.820***	0.285***	1.058**	3.820***	0.285***	1.058**	3.820***	0.285***
	[2.08]	[21.45]	[-20.76]	[2.09]	[21.44]	[-20.79]	[2.09]	[21.44]	[-20.76]
FX Depreciation	0.437***	0.495	0.345***				0.504**	0.648	0.318***
	[-2.80]	[-1.18]	[-4.30]				[-2.24]	[-0.70]	[-4.06]
Real PoS Variation				2.754**	4.398*	1.407	1.872	3.455	0.719
				[2.32]	[1.89]	[0.83]	[1.39]	[1.54]	[-0.69]
AIC	301,245,490	172,820,517	174,649,720	301,252,025	172,816,595	174,663,939	301,242,173	172,814,752	174,649,199
Observations	37,631,114	37,631,114	37,631,114	37,631,114	37,631,114	37,631,114	37,631,114	37,631,114	37,631,114
Nonzero outcomes	1,175,315	584,733	590,582	1,175,315	584,733	590,582	1,175,315	584,733	590,582
Clusters	44	44	44	44	44	44	44	44	44

Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Standard errors clustered by product category.
Source: Authors' own calculations using daily online data.

Table 7: Hazard of Time Varying Covariates in Medicines Categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops
Size of Last Price Change (Abs Val, p.p.)	1.532***	1.459***	1.582***	1.531***	1.460***	1.580***	1.532***	1.460***	1.582***
	[11.33]	[8.36]	[15.47]	[11.22]	[8.20]	[15.52]	[11.22]	[8.26]	[15.49]
Negative Last Price Change=1	1.169***	3.605***	0.327***	1.167***	3.598***	0.327***	1.167***	3.599***	0.327***
	[5.08]	[7.42]	[-8.89]	[5.05]	[7.39]	[-8.91]	[5.04]	[7.40]	[-8.91]
FX Depreciation	1.144	2.028**	0.574***				0.670**	1.231	0.343***
	[0.53]	[2.11]	[-5.95]				[-2.34]	[0.88]	[-2.85]
Real PoS Variation				0.288**	0.227***	0.416	0.216***	0.265***	0.196
				[-2.38]	[-3.37]	[-1.17]	[-2.88]	[-4.08]	[-1.59]
AIC	91,418,173	54,442,835	50,674,892	91,408,807	54,438,504	50,674,506	91,407,308	54,438,290	50,669,548
Observations	18,465,526	18,465,526	18,465,526	18,465,526	18,465,526	18,465,526	18,465,526	18,465,526	18,465,526
Nonzero outcomes	385,848	202,029	183,819	385,848	202,029	183,819	385,848	202,029	183,819
Clusters	15	15	15	15	15	15	15	15	15

Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Standard errors clustered by product category.
Source: Authors' own calculations using daily online data.

Table 8: Hazard of Time Varying Covariates in Recreation Categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops
Size of Last Price Change (Abs Val, p.p.)	0.997	0.732	1.312	0.998	0.734	1.312	0.996	0.731	1.312
	[-0.02]	[-1.11]	[1.48]	[-0.02]	[-1.10]	[1.48]	[-0.03]	[-1.11]	[1.48]
Negative Last Price Change=1	1.194***	5.054***	0.288***	1.197***	5.071***	0.288***	1.197***	5.066***	0.288***
	[4.23]	[20.18]	[-9.64]	[4.23]	[19.73]	[-9.67]	[4.23]	[19.77]	[-9.68]
FX Depreciation	0.448***	0.210***	0.828				0.610	0.318***	0.855
	[-2.58]	[-3.38]	[-0.41]				[-1.51]	[-3.26]	[-0.30]
Real PoS Variation				7.092***	34.270**	1.257	5.659***	21.439**	1.160
				[3.28]	[2.26]	[0.59]	[2.66]	[1.98]	[0.30]
AIC	177,085,561	98,618,269	102,414,444	177,076,244	98,610,680	102,414,532	177,073,626	98,604,273	102,414,388
Observations	28,297,447	28,177,774	28,297,447	28,297,447	28,177,774	28,297,447	28,297,447	28,177,774	28,297,447
Nonzero outcomes	981,935	491,805	490,130	981,935	491,805	490,130	981,935	491,805	490,130
Clusters	11	11	11	11	11	11	11	11	11

Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Standard errors clustered by product category.
Source: Authors' own calculations using daily online data.

Table 9: Hazard of Time Varying Covariates in Personal Care Categories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops
Size of Last Price Change (Abs Val, p.p.)	1.281***	1.200***	1.309***	1.281***	1.200***	1.307***	1.281***	1.200***	1.309***
	[9.36]	[3.47]	[11.42]	[9.40]	[3.50]	[11.40]	[9.36]	[3.47]	[11.44]
Negative Last Price Change=1	1.021	2.967***	0.285***	1.020	2.962***	0.285***	1.021	2.967***	0.285***
	[0.60]	[20.33]	[-36.31]	[0.58]	[20.20]	[-36.35]	[0.60]	[20.33]	[-36.17]
FX Depreciation	0.326***	0.185***	0.407***				0.264***	0.186***	0.218***
	[-5.08]	[-4.43]	[-3.38]				[-4.63]	[-3.88]	[-5.51]
Real PoS Variation				1.062	3.031**	0.312***	0.432**	1.029	0.103***
				[0.25]	[2.29]	[-3.64]	[-2.22]	[0.05]	[-5.22]
AIC	161,275,888	94,931,978	93,366,666	161,296,410	94,951,013	93,368,574	161,272,266	94,931,976	93,352,220
Observations	22,233,647	22,233,647	22,233,647	22,233,647	22,233,647	22,233,647	22,233,647	22,233,647	22,233,647
Nonzero outcomes	501,862	258,389	243,473	501,862	258,389	243,473	501,862	258,389	243,473
Clusters	13	13	13	13	13	13	13	13	13

Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Standard errors clustered by product category.
Source: Authors' own calculations using daily online data.

Second, Apparel, Furniture, Recreation and Personal Care items are more likely to report shorter price spells, i.e. greater hazard rate of price changes, when there is a positive variation in real PoS expenditure. Moreover, for these COICOP Divisions, the cumulative variation of real PoS expenditures along price spells increases the hazard of price hikes. In contrast, the hazard rate of price drops is either less than one or statistically not different from one for these covariate as one might expect. See columns (4)-(6) in Table 5, Table 6, Table 8 and Table 9. Data from Food and Medicines seems to reject our covariate specification as the cumulative PoS expenditure lowers the hazard rate of price changes, specially price hikes.

When introducing both covariates at the time, it looks like the demand proxy (i.e. the variation in real PoS expenditure along the price spell) fits better the variation in the data.

The coefficients for the real PoS variation remain robust for most COICOP Divisions, while the exchange rate coefficients of Food and Medicines become less than or statistically insignificant from one.

In the Appendix, Table 17 to Table 22 report the same specification for time varying covariates as Dias et al. (2007) and Fougère et al. (2007). Specifically, each covariate enters in two different forms: (i) as the absolute value of the cumulative variation along the price spell and (ii) a dummy variable if the cumulative variation is negative. Our results hold qualitatively when using their specification.

4.4 Benchmark with Brick-and-Mortar Price Spells

In this subsection we contrast our estimates stemming from web scraped data with price data gathered via direct visit to retailers. This second price dataset, which comes from prices collected by INEGI for CPI computation purposes, has a number of features that are worth highlighting before jumping into the comparison of hazard rates.³⁵

4.4.1 Data Similarities and Differences Across Sales Channels

We start by describing some of the efforts to make the sample of price spells across sales channels (web scraped and brick and mortar stores) comparable. Then, we describe the prevailing differences between datasets.

First, the original price dataset gathered at brick and mortar stores encompasses some prices from product categories not included in the web scraped dataset (e.g. non-core component, like fresh fruit, energy prices and service sector prices). Hence, we narrow the sample in the former dataset to match the product categories in the latter dataset. Second, as there are numerous price informants in the price survey taking place at brick and mortar retailers, we report results from three different sets of price informants. They are (i) using

³⁵Solórzano (2023b) describes and compares different versions of these datasets: web scraped data compiled by Banco de México and INEGI's CPI micro-data. The author characterizes, among other price moments, the frequency of price changes as the fraction of goods adjusting prices in a given period. We deviate from Solórzano (2023b) by looking at the frequency of price changes through the lens of duration models.

all retailers in the offline sample, (ii) only using supermarkets, departmental stores and price clubs i.e. similar retail chains as in the web scraped dataset and (iii) same retail chains as in the web scraped dataset.³⁶ Third, we use the raw/actual price quotes as observed from the shelves (brick and mortar prices dataset) or websites (web scraped prices dataset), and not imputations nor average prices across different collection dates in the datasets.³⁷ Fourth, we narrow the sample of prices from brick and mortar stores from 2016 to June 2022, which is the same analysis period as in the web scraped prices. Fifth, since brick and mortar prices are reported at a fortnightly frequency, a fortnightly baseline hazard specification is adopted for the daily online data.³⁸ Specifically, using the same daily observations, we cluster daily baseline hazards into fortnightly baseline hazards in Equation 3. For instance, in the regression we include one dummy for [1 day - 15 day] durations, a different dummy for [16-31], and so on (the fortnightly dummies essentially average the daily dummies reported in Figure 4). For the brick and mortar price data, we use a piece-wise baseline hazard at a fortnightly frequency i.e. dummies for the fortnights the price survives.

We now pivot to the differences that persist amidst our efforts to make our sample of price spells comparable across sales channels. First, despite matching the product categories across datasets, the sample of products within product categories is different (even when narrowing the sample of retailers). The price survey at brick and mortar stores follows only a subset of products per retailer period by period; in contrast, the online gathering process

³⁶INEGI classifies price informants into types of retailers. Some are related to the ones in our web scraped data: supermarkets, departmental stores and price clubs. Note, however, there are more supermarket retail chains in the CPI price survey than in our web scraped data, for instance. Thus, we refer to point (ii) as “similar” retailers. For point (iii) we use all branches/stores of the retail chains included in our web scraped data. The validity of considering price spells in different stores of the same retail chains comes from the fact that, although price levels might be different across stores, price-setting dynamics are mainly dictated by corporate and less so by local store managers. In fact, using data from the US, Cavallo (2018) reports evidence of little price dispersion within stores of the same retailer, while DellaVigna and Gentzkow (2019) and Nakamura et al. (2011) document uniform prices across different branches of the same retailer. Additionally to the three already mentioned, INEGI’s other six types of retailers are: street markets, traditional market, specialized store, convenience store, grocery stores, and others.

³⁷Imputations or average prices lead to more frequent price changes and, thus, shorter price spells. Cavallo (2018) and Álvarez et al. (2005) show how averages and/or imputations bias the stylized-facts of price changes.

³⁸Some price categories, mainly food items, are priced on a weekly basis in the offline dataset. Without loss of generality, for weekly priced items we use the prices reported in the second week of every fortnight. All other non-food goods are priced once every fortnight.

considers all products displayed at time of collection. Second, sales channels are different: the web scraped data set comes from an online channel (prices as advertised on retailers' websites), while prices gathered via direct visit come from an offline channel (prices posted on retailers' shelves). It is not obvious to think that prices might reflect the same dynamics across sales channels.³⁹

Finally, it is worth noticing in April 2020 the price survey that would normally take part at brick and mortar stores took place partially online. Though, INEGI's CPI price collectors manually looked up for the products originally included in the survey. They did not gather prices in a census-like fashion nor use web scraping techniques for data collection.

4.4.2 Proportional Hazard in Brick-and-Mortar Price Spells

Figure 8 shows the results across sales channels, including estimates from the offline channel stemming from different subset of retailers. Notably, narrowing the composition of retailers in the brick and mortar sample has very little impact on the results i.e. it seems that the duration of price spells across retailers' types are characterized in a similar fashion by the covariates included in our econometric specification.

Panel 8a highlights the baseline hazard of the duration of price spells across sales channels. They exhibit similar trends. First, they have a rapid decrease in the first three months, implying that the majority of spells lasts no more than three months. Then, the baseline hazard stabilizes in both offline and online price samples up to the run-up duration of the first year. While we observe a small hump at the 12th month across both sales channels, these humps are not statistically different from adjacent months within sales channels. In

³⁹For instance, differences might arise if consumer demand is heterogeneous across sales channels. Solórzano (2023a) provides a good example in food away from home industry of heterogeneous price dynamics across sales channels, likely driven by mobility restrictions early in the pandemic. Moreover, one might think that price comparisons are easier online than offline, leading to more flexible price-setting, and/or space restrictions or local shocks might rise sales strategies in brick-and-mortar stores not seen on websites. Solórzano (2023b), using similar datasets to ours, reports that prices tend to change more frequently in physical stores than on their websites; but given a price change, the size of price changes are larger online than offline. In contrast, Cavallo (2018) reports that prices tend to change at similar frequencies across channels.

the second year of duration the baseline hazard further decreases in both price samples. In terms of magnitudes, the fact that the baseline hazard is greater for the brick and mortar estimates than for the web scraped results suggests that duration of price spells plays a lesser role in characterizing the probability of price changes in the offline dataset than in web scraped prices.

Panel 8b shows the year fixed effects intended to capture the state of the economy. For the years prior the pandemic, (i) the hazard rate of price changes is greater in the web scraped data than in the brick and mortar price survey in 2017 and 2018; and (ii) the hazard of ending price spells is about the same in 2019 across sales channels. As the pandemic started to unravel in 2020 and 2021, both sales channels exhibit a similar increase in their hazard rates. That is, it was more likely to observe price adjustments in such years than prior 2020 and the increased likelihood in both sales channels was about the same. It is in 2022 when the hazard rates deviate the greatest across datasets, mainly driven by Food items as we explain below.

Regarding seasonal patterns reported in Panel 8c, we observe that both sales channels report increasing hazard rates from February to May relative to their base category (January). Again, we see very little differences across estimates depending on the sample of retailers used in the brick and mortar dataset. Estimates differ across datasets in June as the hazard rate of web scraped prices continues increasing, while brick-and-mortar prices see a decrease in their hazard of price changes. It is only in July when a drop in the hazard rate appears for online prices. During August, September and October both sales channels report similar hazard rates relative their March values. Lastly, we observe a more drastic increase on the hazard of ending price spells in the online channel than in the offline in November and December.

When looking at the hazard rates over time for the different COICOP Divisions stemming from the brick and mortar dataset, as shown in Figure 9, it seems that the hazard rate from 2016 to 2019 remains either flat (Apparel, Furniture and Recreation) or slightly subdued (Food,

Medicines and Personal Care). Then, offline price changes from all COICOP Divisions spike in 2020. For this same data source, in 2021 the majority of hazard rates remain high but by a lower margin than in 2020. The exception is Medicines that, for some sub-samples of retailers, their 2021 estimates are not statistically different to pre-pandemic levels i.e. before 2020.

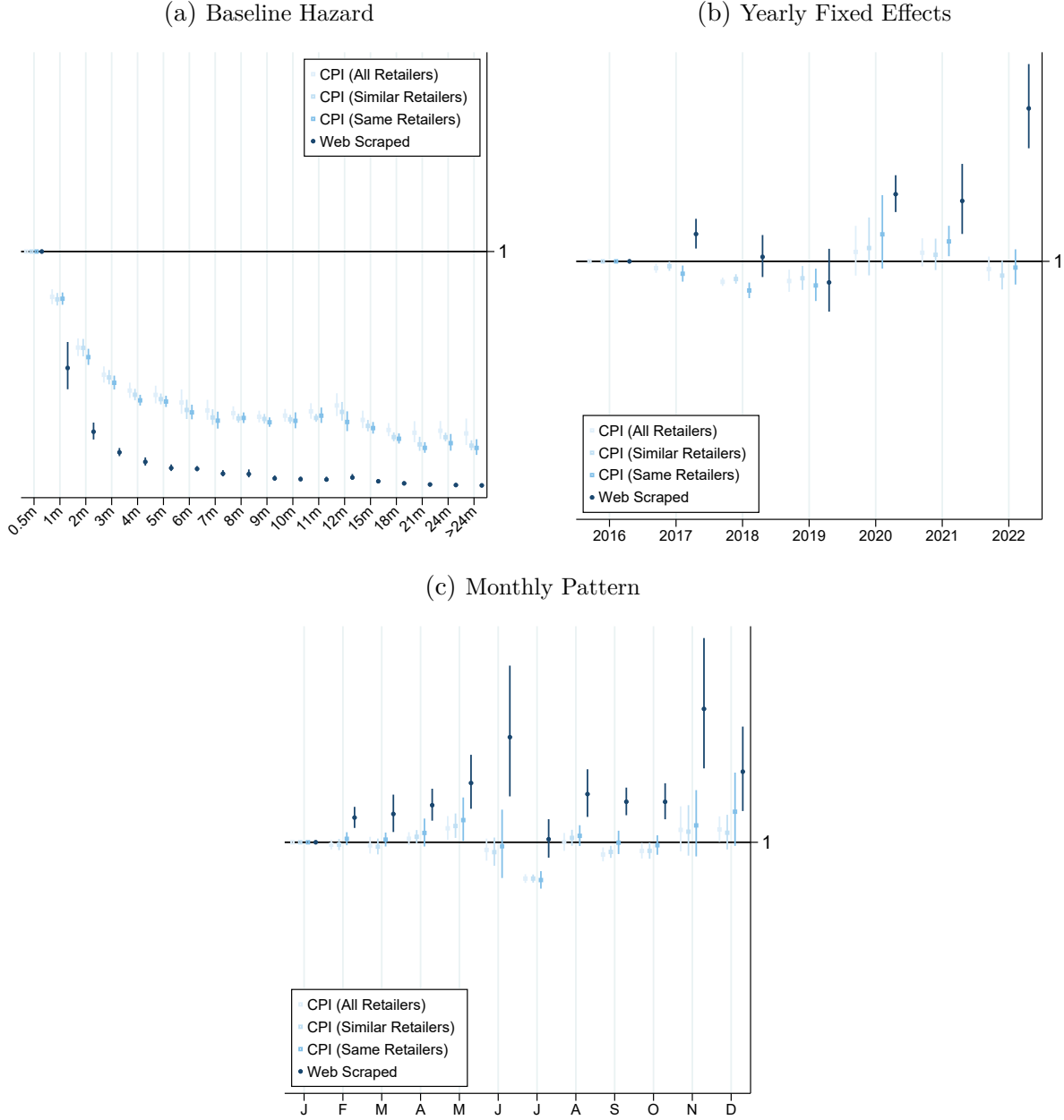
Across sales channels, Food is perhaps the COICOP Division with perhaps the starkest differences, as shown in Panel 9a. For the price spells built from web scraped data, the hazard rate looks like a step-function increasing over the years. That is, they seem to be changing ever more frequently. In contrast, the hazard rate computed using data from brick and mortar stores increased only temporarily in 2020 and 2021.⁴⁰ Medicines also display different patterns across sales channels. Excluding 2016, web scraped prices have shown a constant hazard rate, even during the onset of the COVID-19 pandemic, followed by an increase in 2022. In contrast, prices in brick-and-mortar stores have exhibited less of a constant hazard rate. In other words, they first decrease in 2018 and 2019, then they exhibit an increase in 2020, and finally they have returned to their 2016 and 2017 levels.

Furniture and Personal Care, depicted in Panel 9c and Panel 9f, respectively, are perhaps the COICOP Divisions that exhibit the closest hazard profile over time across sales channels. That is, decreasing trend between 2016 and 2019 and subsequent increase in 2020 and 2021. They are rather different in 2022 since the hazard rate calculated from online data is still high while offline hazards return to pre-2020 levels.

Apparel and Recreation, highlighted in Panel 9b and Panel 9d, respectively, show similar patterns across sales channels with the distinction that their 2020 and 2021 hazard rates for web scraped prices do not increase as dramatically (relative to their base category) as it does in the prices gathered via direct visit.

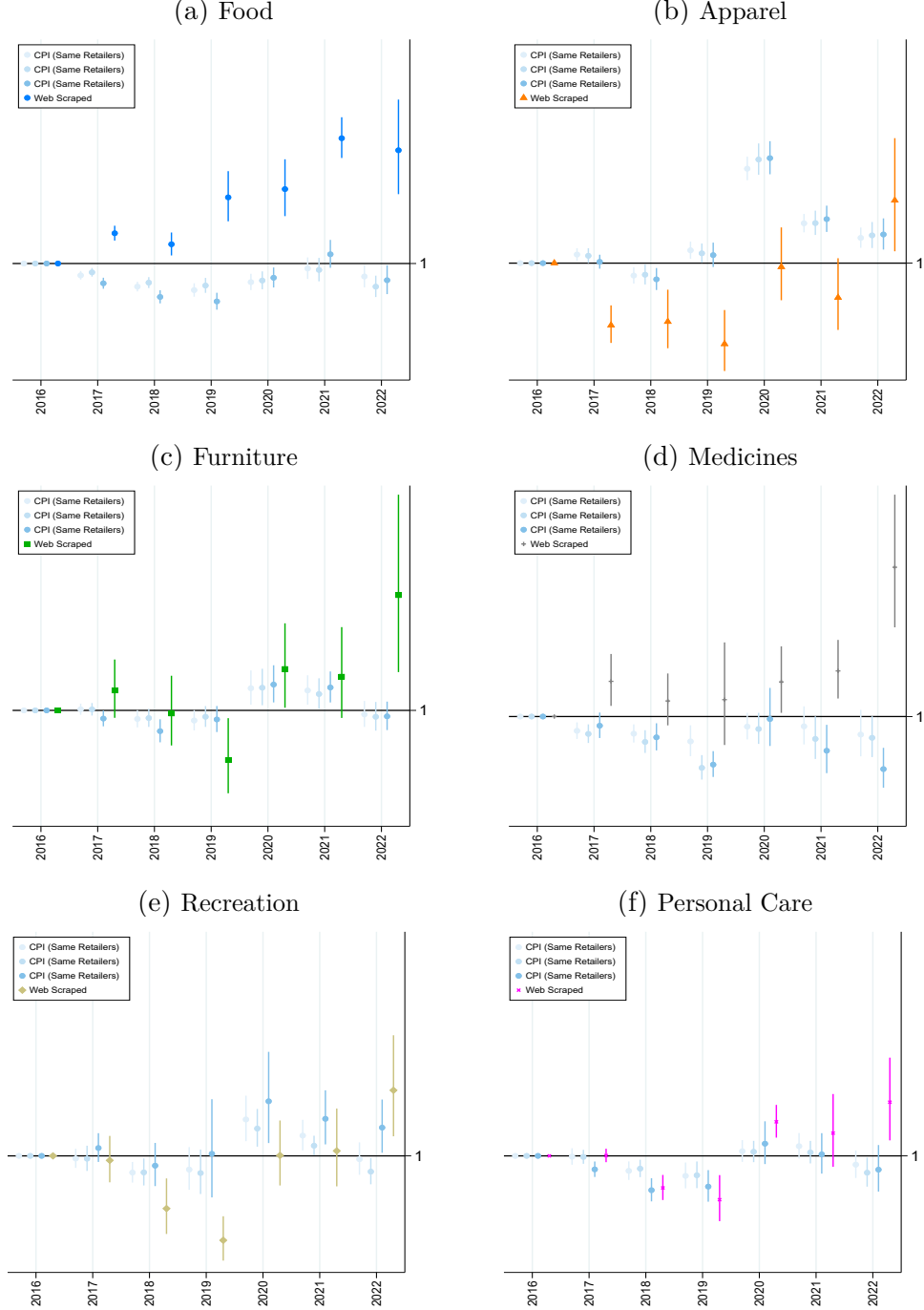
⁴⁰This result stemming from brick and mortar prices might seem at odds from the inflation rates observed in the first half of 2022. Though, even without the use of an empirical framework, the summary statistics from the frequency of price changes in Food items is in line with this result. See Panel 21a or Panel 22a in the Appendix.

Figure 8: Hazard Ratios from the CPI and Web Scraped Data



Note: Estimates from Equation 3 for CPI and web scraped price spells, separately. Complete, Interval Right Censored and Right Censored price spells from all COICOP Divisions analyzed so far (pooled regression). CPI samples depend on the type retailers: *Same retailers* are the same retail chains as the ones encompassed in the web scraped data, *Similar retailers* are the supermarkets, departmental stores and price clubs surveyed in the CPI, while *All* include all informants in the CPI. Panels depict coefficients reported in exponentiated form, which can be interpreted as hazard ratios. As hazard ratios do not tell us quantitatively by how much the hazard rate increases or decreases, the values in the y-axis are omitted but they share the same scale across panels. A hazard ratio greater than one indicates a higher hazard rate for a price change to occur with all other covariates held fixed; a hazard ratio below one implies a lower hazard rate than otherwise. Regressions' results are reported in Tables 10-16 in the Appendix. The failure event is defined as in Figure 4. Data from January 1st 2016 to June 30th 2022 for both data sources. Source: Own estimates using online prices compiled by Banco de México, as well as CPI prices gathered by INEGI.

Figure 9: Yearly Hazard Ratios by COICOP Division Across Sales Channels



Note: Estimates from Equation 3 for CPI and web scraped price spells, separately, by COICOP Division using Complete, Interval Right Censored and Right Censored price spells. CPI samples depend on the type retailers as explained in Figure 8. Panels depict coefficients reported in exponentiated form, which can be interpreted as hazard ratios. As hazard ratios do not tell us quantitatively by how much the hazard rate increases or decreases, the values in the y-axis are omitted but they share the same scale across panels. A hazard ratio greater than one indicates a higher hazard rate for a price change to occur with all other covariates held fixed; a hazard ratio below one implies a lower hazard rate than otherwise. Hazard ratios keep an ordinal association (e.g. greater values imply greater increase in the hazard rate). The failure event is defined as in Figure 4. Data from January 1st 2016 to June 30th 2022 for both data sources. Source: Own calculations using online prices compiled by Banco de México, as well as CPI prices gathered by INEGI.

5 Conclusions

Predictions for real economic outcomes based on macroeconomic models can differ significantly depending whether time- or state-dependent price modelling is in place. Using retail prices in Mexico gathered through web scraping by Banco de México, we estimate the hazard function for the duration of price spells, which allows us to test whether time- or state-dependent features contribute to explain the probability of price changes.

Our results indicate that a purely time- or state-dependent pricing model would lack some features observed in the data. On the one hand, estimates indicate that price spells exhibit greater risk of ending every seven days relative to other durations in between. This hazard shape would be implied by the Taylor (1980) pricing model. Advocating for state-dependency, on the other hand, results suggest that in 2017 prices were more likely to change than in 2016, 2018 and 2019; while 2020 and 2021 show greater hazard rates relative to 2017. Then, it is in 2022 when we observe the greatest probability of price changes and, hence, ever shorter price spells. Moreover, Food and Medicines prices seem to be more sensitive to variations in the USD/MXN exchange rate as they are more likely to change when the Mexican peso depreciates over the duration of the spell; while Apparel, Furniture, Recreation and Personal Care items are more likely to report shorter price spells when there is an increase in the real point of sales expenditure over the duration of the spell. Finally, despite composition differences in terms of products, retailers and sales channel, our estimates based on web scraped retail prices exhibit similar qualitative patterns than the ones found when using retail prices gathered via direct visit at brick and mortar stores. Hence, price-setting in both sales channels shows signs of time- and state-dependent pricing rules.

As nominal rigidities are a key element in many macroeconomic models, the analysis on how to best characterize price-setting patterns observed in granular data remains a vibrant research line. The census-like nature, as well as the higher frequency of observation that web scraped data brings would further contribute to improve models on price rigidities. This is especially true in periods of increased variability of output growth or inflation (e.g. since

the start of the COVID-19 pandemic) when firms might opt to revise their prices more often. Also, aside the nominal rigidities discussed in this paper, features from web scraped price data might as well enrich our understanding on the formation of expectations and informational rigidities.

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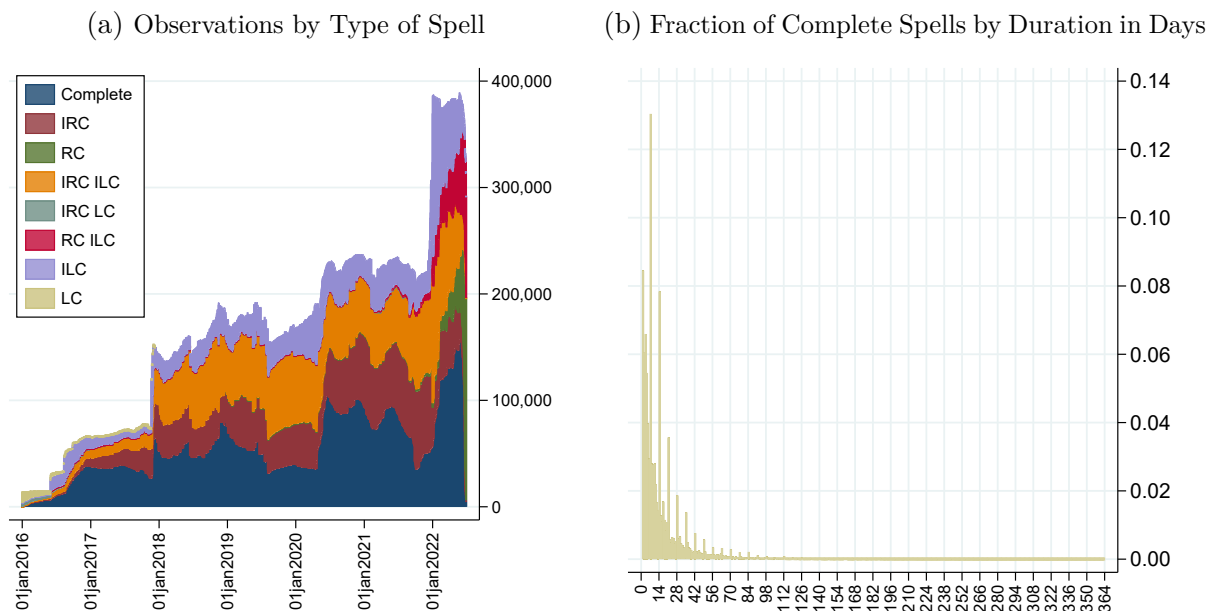
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6 Appendix - Summary Statistics

Figure 10: Type of Price Spells

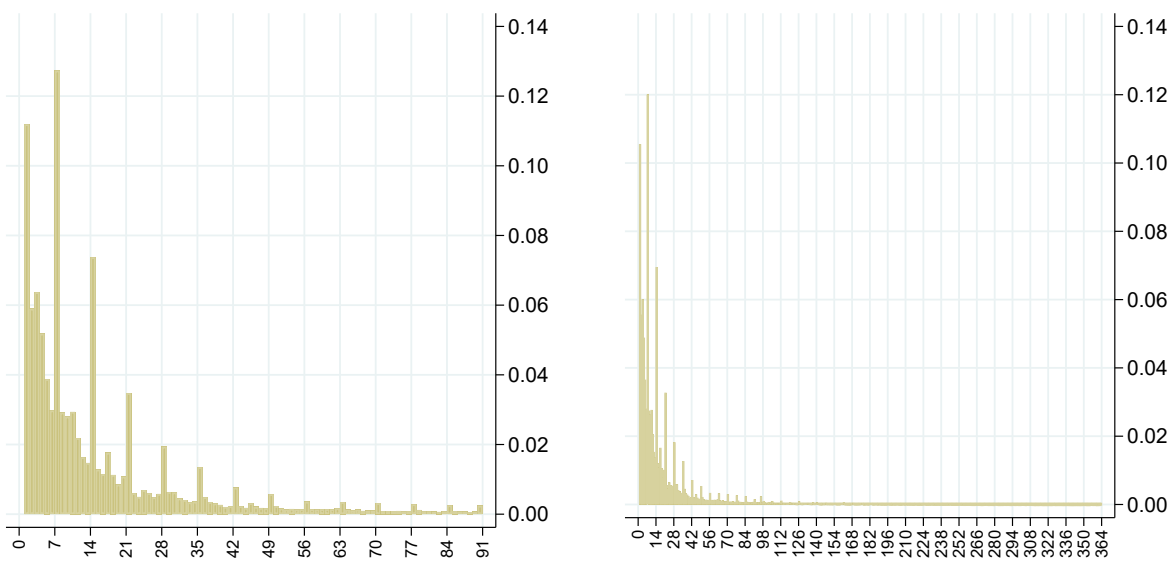


Note: These figures complement Figure 1 and Figure 2. Panel 10a breaks down the Left Censored (LC) and Others (in green) fraction of the spell partition. The acronyms in the legend stand for Interval Right Censored (IRC), Right Censored (RC), Interval Right Censored and Interval Left Censored (IRC ILC), Interval Right Censored and Left Censored (IRC LC), Right Censored and Interval Left Censored (RC ILC), Interval Left Censored (ILC) and Left Censored (LC). Panel 10b depicts the fraction of price spells by the duration in days with no length cap. Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

Figure 11: Fraction of Complete, RC and IRC Spells by Duration in Days

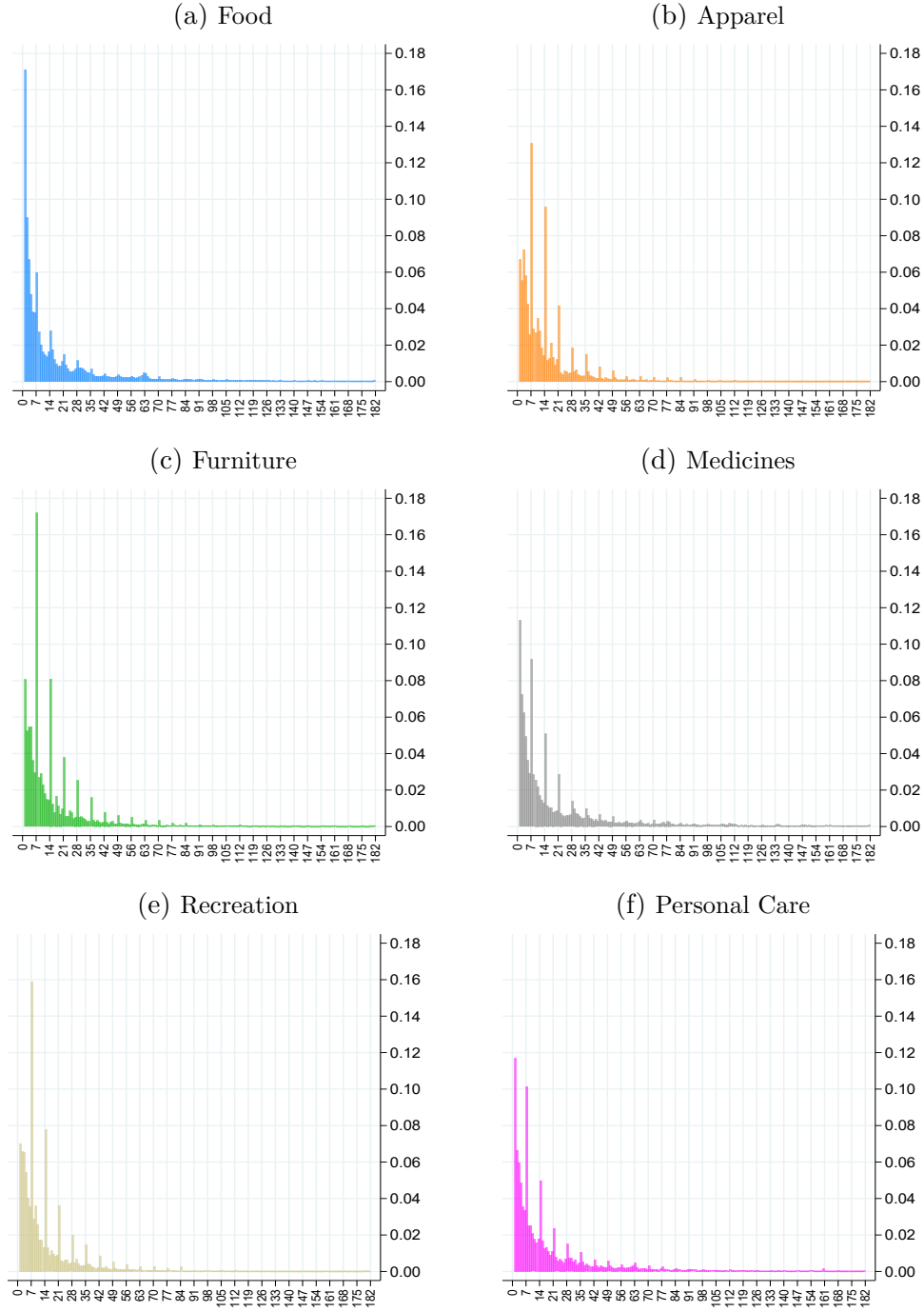
(a) Capped at 91 Days

(b) All Lengths



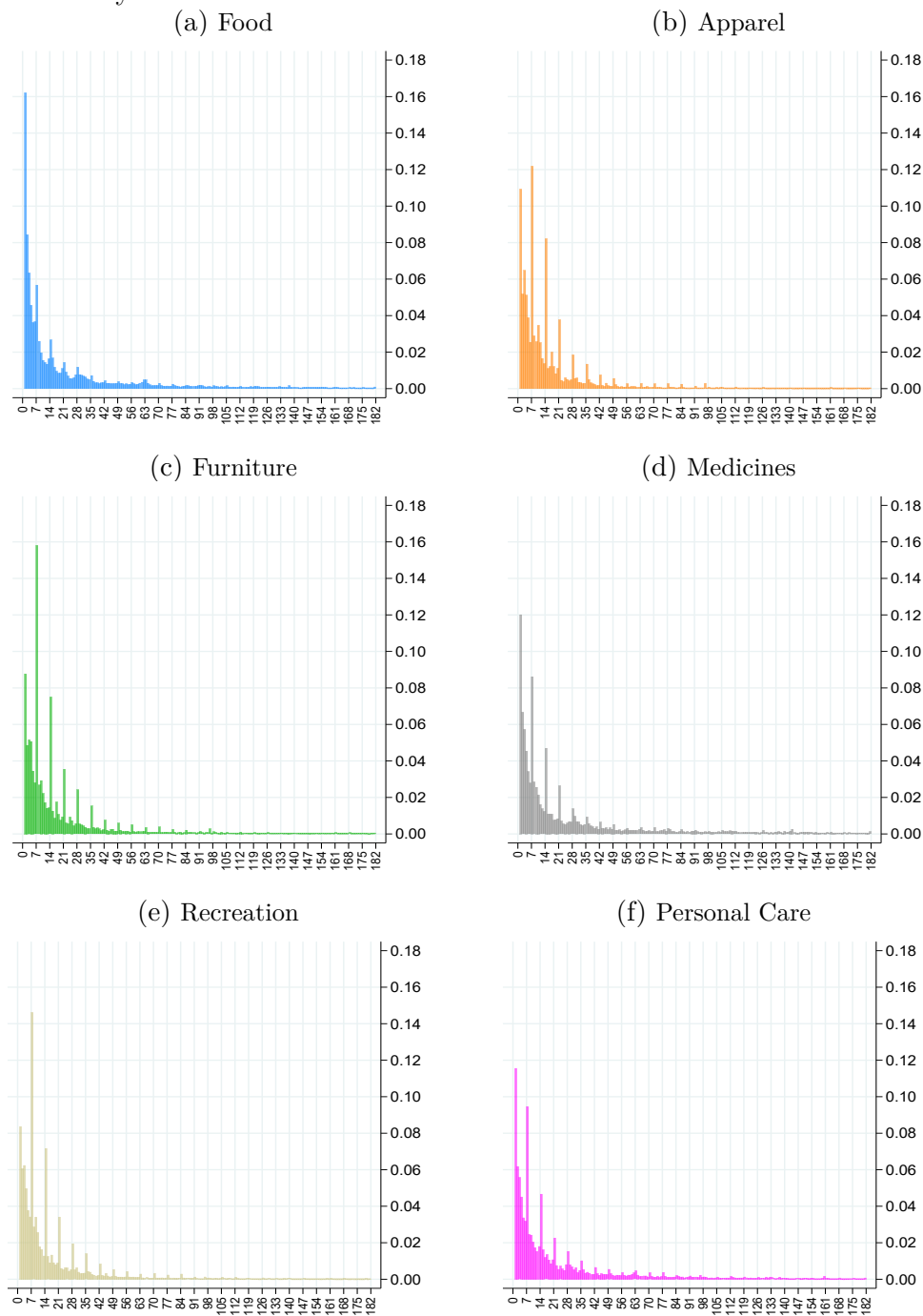
Note: This figure depicts the duration histogram using complete, RC and IRC spells. It complements Figure 2. Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

Figure 12: Fraction of Complete Spells by Duration in Days
Capped at 182 Days



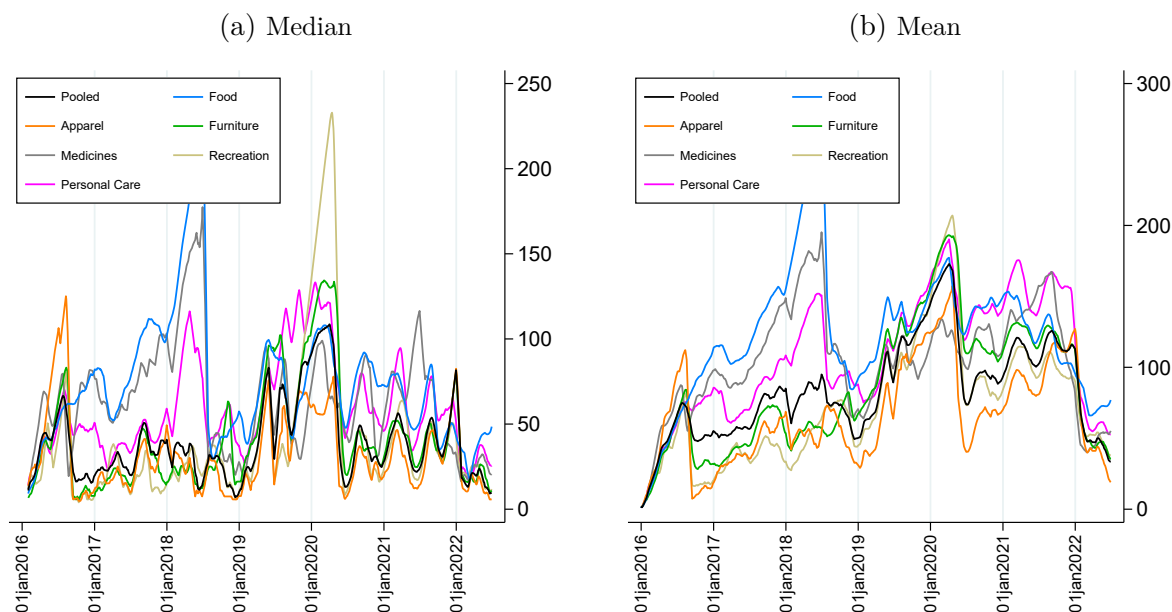
Note: This figure shows the distributions of duration in days from complete spells by COICOP Division. It complements Figure 2. Data from January 1st 2016 to June 30th 2022. Source: Own calculations based on online data compiled by Banco de México.

Figure 13: Fraction of Complete, RC and IRC Spells by Duration in Days
Capped at 182 Days



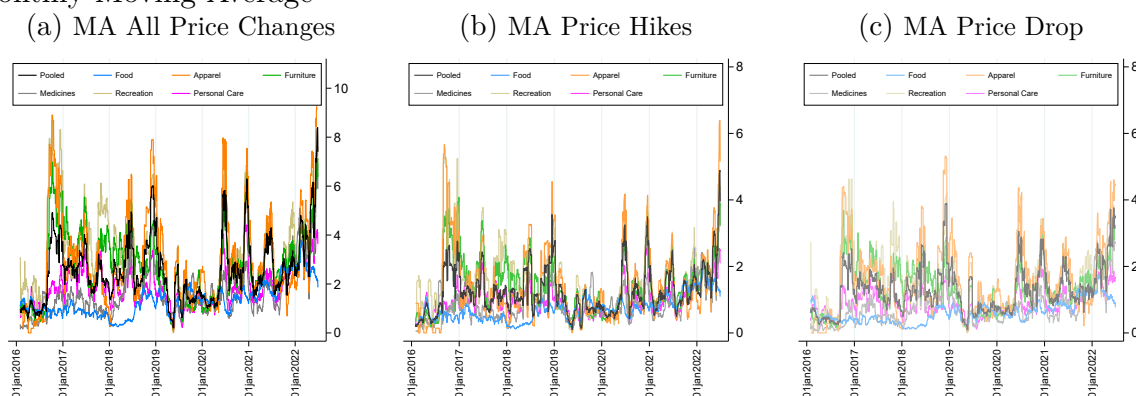
Note: This figure plots the distributions of duration in days from complete, RC and IRC price spells by COICOP Division. It adds on Figure 2. Data from January 1st 2016 to June 30th 2022. Source: Own calculations based on online data compiled by Banco de México.

Figure 14: Duration in Days of Complete, RC and IRC Price Spells
Monthly Moving Average



Note: This figure complements Figure 3. Source: Authors' estimates with web scraped data gathered by Banco de México.

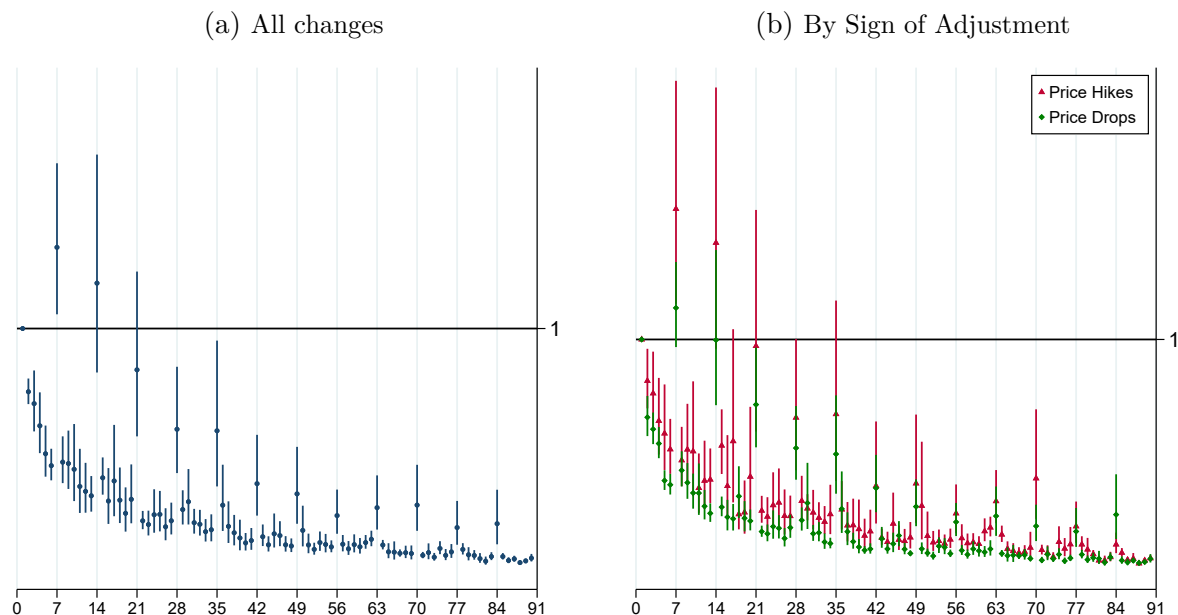
Figure 15: Frequency of Price Changes in Percent of Complete, RC and IRC Price Spells
Monthly Moving Average



Note: This figure complements Figure 3. Source: Authors' estimates with web scraped data gathered by Banco de México.

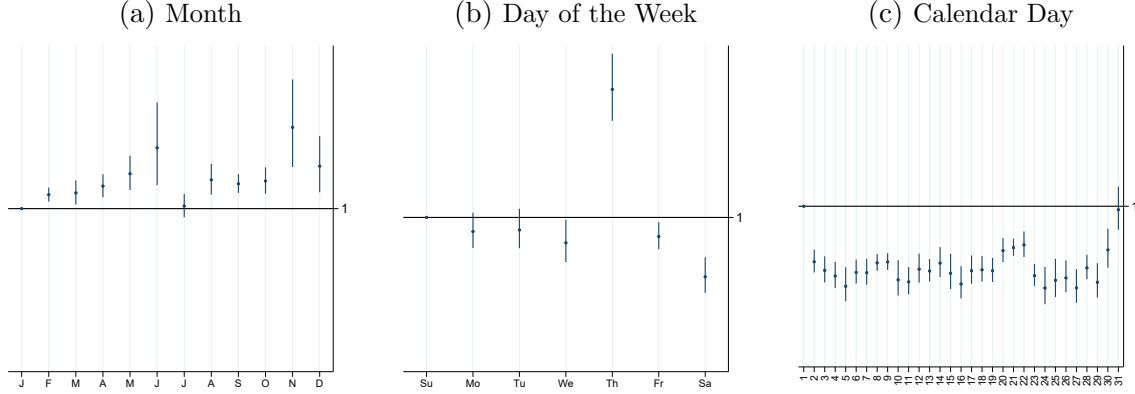
7 Appendix - Benchmark Model

Figure 16: Hazard Ratios of Baseline Hazard in Days as Scatter Plot



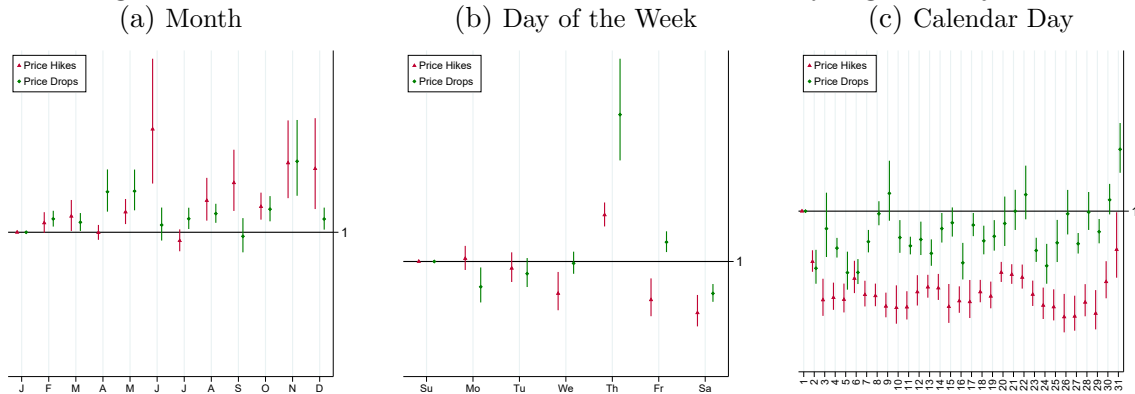
Note: These panels complement Panel 4a and Panel 5a. Bear in mind that exponentiated coefficients can be interpreted as hazard ratios since the cloglog model from Equation 3 is a discrete time proportional hazards framework. As hazard ratios do not tell us quantitatively by how much the hazard rate increases or decreases, the values in the y-axis are omitted but they share the same scale across panels. A hazard ratio greater than one indicates a higher hazard rate for a price change to occur with all other covariates held fixed; a hazard ratio below one implies a lower hazard rate than otherwise. Hazard ratios keep an ordinal association (e.g. greater values imply greater increase in the hazard rate). Regressions' results are reported in Tables 10-16. Estimates based on Complete, Interval Right Censored and Right Censored spells from all COICOP Divisions (pooled regression). Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

Figure 17: Hazard Ratios of Seasonal Fixed Effects in Benchmark Model



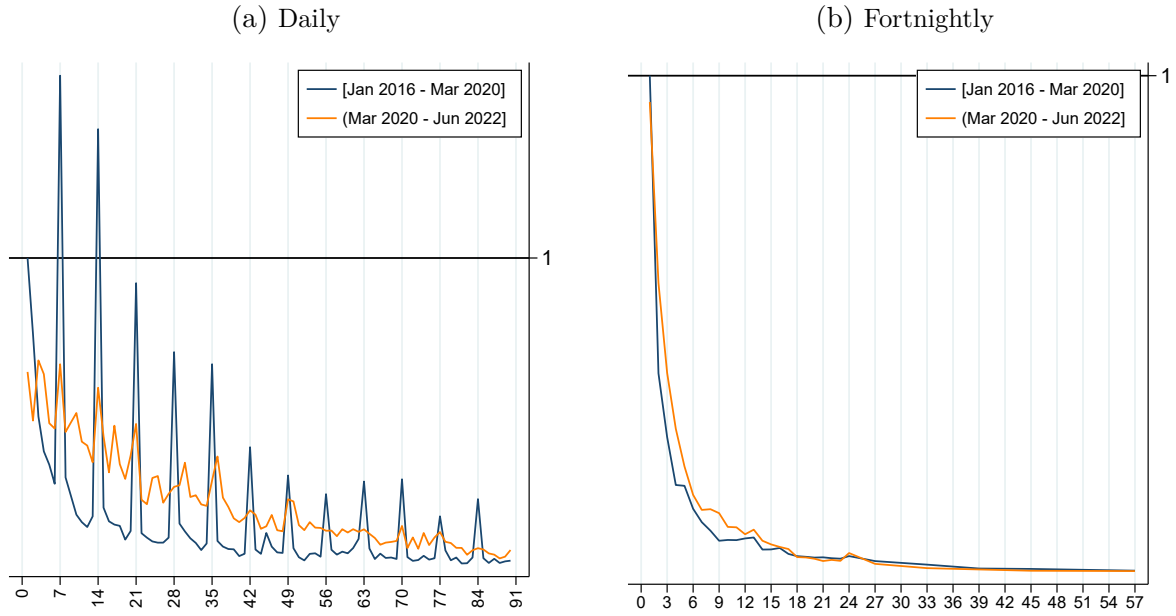
Note: Exponentiated coefficients of seasonal fixed effects computed using Equation 3. Exponentiated coefficients can be interpreted as hazard ratios since the cloglog model from Equation 3 is a discrete time proportional hazards framework. As hazard ratios do not tell us quantitatively by how much the hazard rate increases or decreases, the values in the y-axis are omitted. A hazard ratio greater than one indicates a higher hazard rate for a price change to occur with all other covariates held fixed; a hazard ratio below one implies a lower hazard rate than otherwise. Hazard ratios keep an ordinal association (e.g. greater values imply greater increase in the hazard rate). Regressions' results are reported in Tables 10-16. The failure event at the end of (complete) spells is equal to one if $p_{i,t} \neq p_{i,t-1}$; zero otherwise. Estimates based on Complete, Interval Right Censored and Right Censored spells from all COICOP Divisions (pooled regression). Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

Figure 18: Hazard Ratios of Seasonal Fixed Effects by Sign of Adjustment



Note: Exponentiated coefficients of seasonal fixed effects computed using Equation 3. Exponentiated coefficients can be interpreted as hazard ratios since the cloglog model from Equation 3 is a discrete time proportional hazards framework. As hazard ratios do not tell us quantitatively by how much the hazard rate increases or decreases, the values in the y-axis are omitted. A hazard ratio greater than one indicates a higher hazard rate for a price change to occur with all other covariates held fixed; a hazard ratio below one implies a lower hazard rate than otherwise. Hazard ratios keep an ordinal association (e.g. greater values imply greater increase in the hazard rate). Regressions' results are reported in Tables 10-16. Estimates based on Complete, Interval Right Censored and Right Censored spells from all COICOP Divisions (pooled regression). Data from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

Figure 19: Hazard Ratios of Baseline Hazards With and Without COVID-19 Dummy



Note: The COVID-19 dummy takes the value of 1 from April 2020 onwards, inclusive. Panel 19a depicts the daily baseline hazard as in Subsection 4.1. Panel 19b depicts the fortnightly baseline hazard as in Subsection 4.4. Estimates reported in exponentiated form. Bear in mind that exponentiated coefficients can be interpreted as hazard ratios since the cloglog model from Equation 3 is a discrete time proportional hazards framework. As hazard ratios do not tell us quantitatively by how much the hazard rate increases or decreases, the values in the y-axis are omitted. A hazard ratio greater than one indicates a higher hazard rate for a price change to occur with all other covariates held fixed; a hazard ratio below one implies a lower hazard rate than otherwise. Hazard ratios keep an ordinal association (e.g. greater values imply greater increase in the hazard rate). The failure event at the end of (complete) spells is equal to one if $p_{i,t} \neq p_{i,t-1}$; zero otherwise. Estimates based on Complete, Interval Right Censored and Right Censored spells from all COICOP Divisions (pooled regression) from January 1st 2016 to June 30th 2022. Source: Authors' calculations with online data compiled by Banco de México.

Table 10: Benchmark Estimates (1/7): Baseline Hazard I

	Daily Baseline Hazard			Fortnightly Baseline Hazard			CPI (Same Retailers)			CPI (Similar)	CPI (All)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	All Adjs
2	0.745***	0.825**	0.671***								
	[-8.34]	[-2.48]	[-6.20]								
3	0.697***	0.772**	0.621***								
	[-4.03]	[-2.46]	[-8.71]								
4	0.607***	0.656***	0.560***								
	[-4.87]	[-3.38]	[-9.68]								
5	0.494***	0.603***	0.404***								
	[-6.66]	[-3.36]	[-17.25]								
6	0.446***	0.536***	0.386***								
	[-11.10]	[-5.69]	[-16.55]								
7	1.328**	1.552***	1.133								
	[2.44]	[2.88]	[1.55]								
8	0.461***	0.490***	0.447***								
	[-7.46]	[-5.53]	[-9.54]								
9	0.455***	0.535***	0.395***								
	[-6.03]	[-3.98]	[-9.58]								
10	0.432***	0.528***	0.352***								
	[-4.66]	[-2.82]	[-9.79]								
11	0.362***	0.372***	0.351***								
	[-5.68]	[-5.85]	[-6.74]								
12	0.343***	0.403***	0.296***								
	[-7.24]	[-5.08]	[-11.44]								
13	0.325***	0.408***	0.266***								
	[-10.05]	[-6.30]	[-17.69]								
14	1.183	1.408*	0.998								
	[0.91]	[1.75]	[-0.01]								
15	0.397***	0.552***	0.292***								
	[-9.62]	[-4.76]	[-17.03]								
16	0.304***	0.381***	0.250***								
	[-6.43]	[-4.23]	[-10.64]								
17	0.385***	0.570*	0.243***								
	[-4.05]	[-1.82]	[-12.12]								
18	0.307***	0.262***	0.338***								
	[-6.47]	[-9.39]	[-6.68]								
19	0.254***	0.269***	0.245***								
	[-7.79]	[-6.34]	[-10.68]								
20	0.311***	0.420***	0.234***								
	[-6.13]	[-3.19]	[-15.16]								
21	0.833	0.972	0.725**								
	[-0.92]	[-0.12]	[-2.20]								
22	0.224***	0.277***	0.189***								
	[-17.87]	[-12.35]	[-26.22]								
23	0.209***	0.251***	0.180***								
	[-12.92]	[-9.56]	[-17.15]								
24	0.248***	0.300***	0.210***								
	[-7.89]	[-6.20]	[-10.86]								
25	0.250***	0.311***	0.203***								
	[-8.45]	[-6.01]	[-13.00]								
26	0.199***	0.254***	0.160***								
	[-9.91]	[-7.35]	[-14.93]								
27	0.224***	0.254***	0.205***								
	[-10.36]	[-9.15]	[-13.14]								
28	0.593***	0.670*	0.541***								
	[-2.89]	[-1.95]	[-4.24]								
29	0.269***	0.318***	0.237***								
	[-10.13]	[-7.81]	[-13.76]								
30	0.301***	0.286***	0.309***								
	[-6.47]	[-12.81]	[-5.25]								
31	0.216***	0.269***	0.180***								
	[-13.11]	[-8.46]	[-18.05]								
32	0.210***	0.247***	0.184***								
	[-12.49]	[-11.64]	[-15.17]								
33	0.180***	0.230***	0.145***								
	[-13.47]	[-11.34]	[-16.94]								
34	0.188***	0.262***	0.138***								
	[-11.44]	[-6.76]	[-24.07]								
35	0.587**	0.685	0.516***								
	[-2.16]	[-1.40]	[-3.31]								
AIC	1,377,932,473	791,101,795	799,471,772	1,413,756,840	807,718,675	819,419,021	1,024,396	709,983	631,544	2,904,112	4,413,866
Observations	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	1,056,673	1,056,673	1,056,673	3,075,706	5,362,097
Nonzero outcomes	6,871,954	3,365,464	3,506,490	6,871,954	3,365,464	3,506,490	240,979	137,892	103,087	670,282	927,839
Clusters	40	40	40	40	40	40	44	44	44	44	44

Note: This table continues in Table 11. Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Clusters at COICOP Class level. Base categories are the omitted categories in each set of fixed effects (first day of duration in this case). Source: Authors' own estimates with online data gathered by Banco de México and with survey data compiled by INEGI.

Table 11: Benchmark Estimates (2/7): Baseline Hazard II

	Daily Baseline Hazard			Fortnightly Baseline Hazard			CPI (Same Retailers)			CPI (Similar)	CPI (All)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	All Adjs
36	0.287*** [-5.43]	0.282*** [-7.01]	0.284*** [-5.57]								
37	0.201*** [-7.73]	0.215*** [-7.96]	0.188*** [-9.09]								
38	0.176*** [-9.93]	0.215*** [-7.18]	0.146*** [-16.49]								
39	0.154*** [-9.39]	0.199*** [-6.49]	0.123*** [-16.95]								
40	0.134*** [-15.12]	0.171*** [-9.87]	0.110*** [-29.54]								
41	0.144*** [-12.60]	0.190*** [-8.29]	0.115*** [-22.54]								
42	0.374*** [-4.55]	0.381*** [-3.51]	0.372*** [-6.06]								
43	0.159*** [-13.34]	0.163*** [-17.13]	0.158*** [-13.13]								
44	0.127*** [-16.87]	0.145*** [-14.47]	0.115*** [-22.06]								
45	0.171*** [-8.85]	0.222*** [-6.35]	0.137*** [-13.15]								
46	0.164*** [-11.70]	0.154*** [-11.18]	0.172*** [-11.35]								
47	0.127*** [-16.61]	0.148*** [-12.57]	0.114*** [-20.28]								
48	0.122*** [-18.43]	0.164*** [-10.59]	0.096*** [-38.84]								
49	0.333*** [-4.78]	0.392*** [-3.31]	0.294*** [-7.26]								
50	0.185*** [-7.68]	0.297*** [-3.67]	0.116*** [-20.01]								
51	0.126*** [-13.15]	0.170*** [-7.33]	0.098*** [-26.40]								
52	0.108*** [-19.70]	0.143*** [-13.12]	0.085*** [-24.61]								
53	0.136*** [-13.79]	0.148*** [-13.18]	0.127*** [-15.66]								
54	0.128*** [-14.06]	0.138*** [-15.83]	0.122*** [-15.12]								
55	0.118*** [-20.75]	0.155*** [-14.00]	0.095*** [-28.19]								
56	0.245*** [-7.74]	0.265*** [-6.86]	0.229*** [-9.61]								
57	0.129*** [-15.86]	0.161*** [-11.46]	0.109*** [-22.69]								
58	0.110*** [-17.23]	0.139*** [-15.07]	0.092*** [-22.33]								
59	0.128*** [-14.34]	0.144*** [-16.11]	0.115*** [-17.30]								
60	0.119*** [-15.98]	0.136*** [-18.23]	0.107*** [-16.94]								
61	0.136*** [-19.33]	0.190*** [-12.94]	0.102*** [-20.00]								
62	0.149*** [-17.92]	0.206*** [-15.44]	0.115*** [-15.25]								
63	0.277*** [-6.53]	0.317*** [-6.49]	0.254*** [-6.72]								
64	0.126*** [-26.82]	0.176*** [-17.48]	0.096*** [-31.27]								
65	0.098*** [-14.99]	0.116*** [-17.47]	0.087*** [-14.04]								
66	0.097*** [-12.38]	0.107*** [-16.42]	0.089*** [-12.07]								
67	0.092*** [-29.59]	0.099*** [-21.60]	0.086*** [-27.75]								
68	0.095*** [-17.68]	0.103*** [-18.67]	0.090*** [-19.09]								
69	0.092*** [-15.50]	0.121*** [-9.39]	0.075*** [-31.67]								
70	0.287*** [-5.45]	0.413*** [-3.24]	0.212*** [-8.55]								
AIC	1,377,932.473	791,101.795	799,471.772	1,413,756.840	807,718.675	819,419.021	1,024,396	709,983	631,544	2,904,112	4,413,866
Observations	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	1,056,673	1,056,673	1,056,673	3,075,706	5,362,097
Nonzero outcomes	6,871,954	3,365,464	3,506,490	6,871,954	3,365,464	3,506,490	240,979	137,892	103,087	670,282	927,839
Clusters	40	40	40	40	40	40	44	44	44	44	44

Note: This table continues in Table 12. Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Clusters at COICOP Class level. Base categories are the omitted categories in each set of fixed effects (first day of duration in this case). Source: Authors' own estimates with online data gathered by Banco de México and with survey data compiled by INEGI.

Table 12: Benchmark Estimates (3/7): Baseline Hazard III

	Daily Baseline Hazard			Fortnightly Baseline Hazard			CPI (Same Retailers)			CPI (Similar)	CPI (All)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	All Adjs
71	0.084*** [-32.42]	0.111*** [-23.34]	0.068*** [-27.62]								
72	0.095*** [-13.97]	0.098*** [-15.89]	0.092*** [-15.00]								
73	0.077*** [-24.90]	0.081*** [-22.38]	0.074*** [-25.17]								
74	0.112*** [-18.54]	0.145*** [-10.04]	0.092*** [-18.65]								
75	0.084*** [-18.42]	0.117*** [-12.99]	0.064*** [-26.58]								
76	0.098*** [-16.17]	0.135*** [-9.06]	0.076*** [-29.01]								
77	0.197*** [-7.31]	0.211*** [-7.57]	0.189*** [-7.74]								
78	0.108*** [-20.74]	0.134*** [-17.13]	0.092*** [-23.96]								
79	0.087*** [-15.83]	0.113*** [-11.83]	0.070*** [-22.99]								
80	0.084*** [-21.18]	0.093*** [-26.90]	0.078*** [-20.55]								
81	0.071*** [-18.98]	0.067*** [-34.56]	0.074*** [-13.95]								
82	0.061*** [-20.66]	0.067*** [-19.91]	0.058*** [-22.11]								
83	0.079*** [-24.84]	0.080*** [-19.96]	0.080*** [-22.60]								
84	0.212*** [-6.10]	0.134*** [-12.36]	0.260*** [-5.24]								
85	0.079*** [-30.61]	0.099*** [-24.80]	0.067*** [-22.87]								
86	0.063*** [-29.00]	0.069*** [-38.82]	0.059*** [-23.90]								
87	0.070*** [-31.09]	0.074*** [-18.42]	0.066*** [-32.06]								
88	0.055*** [-34.63]	0.054*** [-39.11]	0.056*** [-28.93]								
89	0.062*** [-44.78]	0.067*** [-37.47]	0.060*** [-48.91]								
90	0.073*** [-24.75]	0.076*** [-33.99]	0.074*** [-21.43]								
(90,105]	0.077*** [-26.64]	0.083*** [-37.49]	0.074*** [-25.72]								
(105,120]	0.069*** [-26.19]	0.075*** [-25.91]	0.066*** [-29.75]								
(120,135]	0.058*** [-28.15]	0.063*** [-22.23]	0.056*** [-26.12]								
(135,150]	0.052*** [-32.47]	0.060*** [-23.70]	0.046*** [-41.46]								
(150,165]	0.051*** [-41.18]	0.056*** [-27.09]	0.048*** [-33.01]								
(165,180]	0.049*** [-31.29]	0.068*** [-21.58]	0.039*** [-44.79]								
(180,210]	0.044*** [-33.02]	0.064*** [-19.97]	0.033*** [-37.85]								
(210,240]	0.034*** [-22.69]	0.053*** [-17.12]	0.023*** [-28.03]								
(240,270]	0.025*** [-27.88]	0.039*** [-18.92]	0.017*** [-35.14]								
(270,300]	0.020*** [-40.17]	0.031*** [-27.14]	0.014*** [-42.44]								
(300,330]	0.018*** [-34.21]	0.027*** [-26.70]	0.013*** [-34.10]								
(330,360]	0.020*** [-32.93]	0.029*** [-25.46]	0.015*** [-27.22]								
(360,...]	0.007*** [-29.92]	0.012*** [-30.65]	0.004*** [-26.12]								
AIC	1,377,932,473	791,101,795	799,471,772	1,413,756,840	807,718,675	819,419,021	1,024,396	709,983	631,544	2,904,112	4,413,866
Observations	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	1,056,673	1,056,673	1,056,673	3,075,706	5,362,097
Nonzero outcomes	6,871,954	3,365,464	3,506,490	6,871,954	3,365,464	3,506,490	240,979	137,892	103,087	670,282	927,839
Clusters	40	40	40	40	40	40	44	44	44	44	44

Note: This table continues in Table 13. Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Clusters at COICOP Class level. Base categories are the omitted categories in each set of fixed effects (first day of duration in this case). Source: Authors' own estimates with online data gathered by Banco de México and with survey data compiled by INEGI.

Table 13: Benchmark Estimates (4/7): Baseline Hazard IV

	Daily Baseline Hazard			Fortnightly Baseline Hazard			CPI (Same Retailers)			CPI (Similar)	CPI (All)
	(1) All Adjs	(2) Hikes	(3) Drops	(4) All Adjs	(5) Hikes	(6) Drops	(7) All Adjs	(8) Hikes	(9) Drops	(10) All Adjs	(11) All Adjs
1st month				0.503*** [-6.76]	0.532*** [-6.00]	0.484*** [-7.85]	0.799*** [-13.45]	0.789*** [-13.27]	0.852*** [-5.46]	0.796*** [-13.34]	0.807*** [-10.67]
1.5 months				0.340*** [-10.32]	0.356*** [-10.77]	0.333*** [-10.44]	0.650*** [-20.08]	0.638*** [-17.49]	0.722*** [-11.18]	0.644*** [-19.01]	0.643*** [-19.75]
2 months				0.231*** [-18.47]	0.247*** [-17.23]	0.223*** [-20.67]	0.549*** [-18.78]	0.533*** [-9.93]	0.631*** [-12.85]	0.589*** [-16.43]	0.590*** [-16.24]
2.5 months				0.196*** [-24.64]	0.219*** [-32.30]	0.183*** [-19.23]	0.477*** [-17.92]	0.469*** [-8.70]	0.545*** [-15.98]	0.502*** [-19.46]	0.502*** [-19.81]
3 months				0.143*** [-31.46]	0.133*** [-47.10]	0.155*** [-20.63]	0.440*** [-23.91]	0.423*** [-10.07]	0.518*** [-13.69]	0.463*** [-22.86]	0.474*** [-20.03]
3.5 months				0.114*** [-51.20]	0.109*** [-26.10]	0.121*** [-31.41]	0.410*** [-38.49]	0.393*** [-8.66]	0.484*** [-9.16]	0.422*** [-31.77]	0.429*** [-24.80]
4 months				0.102*** [-26.12]	0.098*** [-17.19]	0.108*** [-26.90]	0.365*** [-31.45]	0.355*** [-9.14]	0.431*** [-10.69]	0.389*** [-29.33]	0.407*** [-22.01]
4.5 months				0.086*** [-30.42]	0.082*** [-14.35]	0.091*** [-28.98]	0.363*** [-35.79]	0.341*** [-7.80]	0.439*** [-7.70]	0.364*** [-28.92]	0.379*** [-21.90]
5 months				0.076*** [-27.48]	0.079*** [-16.21]	0.076*** [-35.75]	0.360*** [-30.00]	0.346*** [-8.65]	0.427*** [-5.88]	0.370*** [-31.13]	0.388*** [-19.12]
5.5 months				0.075*** [-23.11]	0.074*** [-16.10]	0.079*** [-21.88]	0.326*** [-34.30]	0.311*** [-10.45]	0.392*** [-10.09]	0.342*** [-28.36]	0.363*** [-19.70]
6 months				0.073*** [-33.61]	0.089*** [-23.18]	0.063*** [-38.65]	0.314*** [-22.92]	0.345*** [-9.50]	0.326*** [-18.42]	0.324*** [-17.45]	0.356*** [-13.89]
6.5 months				0.077*** [-20.70]	0.095*** [-15.84]	0.068*** [-18.84]	0.308*** [-13.85]	0.335*** [-7.73]	0.324*** [-18.64]	0.323*** [-20.92]	0.337*** [-18.53]
7 months				0.052*** [-22.85]	0.072*** [-16.14]	0.040*** [-35.12]	0.278*** [-19.38]	0.317*** [-7.89]	0.279*** [-17.61]	0.292*** [-21.35]	0.322*** [-16.87]
7.5 months				0.050*** [-13.60]	0.068*** [-11.32]	0.039*** [-16.45]	0.275*** [-22.22]	0.306*** [-9.76]	0.283*** [-12.75]	0.292*** [-32.43]	0.309*** [-27.60]
8 months				0.050*** [-17.83]	0.074*** [-13.24]	0.036*** [-24.82]	0.290*** [-31.01]	0.303*** [-11.64]	0.321*** [-13.68]	0.288*** [-36.84]	0.310*** [-25.41]
8.5 months				0.041*** [-15.83]	0.056*** [-11.70]	0.032*** [-20.37]	0.253*** [-19.71]	0.296*** [-10.45]	0.246*** [-16.59]	0.270*** [-26.95]	0.298*** [-23.53]
9 months				0.032*** [-20.79]	0.046*** [-16.06]	0.024*** [-26.65]	0.271*** [-34.42]	0.320*** [-11.26]	0.262*** [-13.40]	0.286*** [-33.93]	0.295*** [-28.27]
9.5 months				0.031*** [-23.25]	0.042*** [-15.83]	0.024*** [-35.07]	0.244*** [-38.06]	0.258*** [-12.56]	0.267*** [-15.00]	0.269*** [-39.05]	0.282*** [-25.56]
10 months				0.029*** [-22.47]	0.041*** [-16.99]	0.021*** [-26.19]	0.278*** [-20.60]	0.316*** [-10.79]	0.280*** [-12.45]	0.284*** [-37.41]	0.300*** [-26.05]
10.5 months				0.027*** [-24.77]	0.034*** [-18.49]	0.022*** [-29.02]	0.264*** [-21.97]	0.284*** [-8.24]	0.283*** [-10.73]	0.288*** [-46.29]	0.308*** [-26.66]
11 months				0.027*** [-18.65]	0.038*** [-14.91]	0.019*** [-20.72]	0.300*** [-21.55]	0.350*** [-9.10]	0.290*** [-7.74]	0.290*** [-41.67]	0.318*** [-21.61]
11.5 months				0.025*** [-22.64]	0.032*** [-18.68]	0.021*** [-19.67]	0.310*** [-27.62]	0.328*** [-7.58]	0.336*** [-7.02]	0.324*** [-24.11]	0.332*** [-25.06]
12 months				0.036*** [-18.95]	0.047*** [-15.00]	0.029*** [-19.77]	0.273*** [-16.52]	0.379*** [-7.34]	0.199*** [-12.88]	0.316*** [-17.92]	0.343*** [-14.84]
(12-15] months				0.020*** [-21.41]	0.033*** [-18.30]	0.010*** [-27.10]	0.246*** [-27.32]	0.320*** [-13.93]	0.204*** [-21.57]	0.256*** [-28.15]	0.281*** [-18.80]
(15-18] months				0.011*** [-16.35]	0.015*** [-16.73]	0.008*** [-14.85]	0.201*** [-29.31]	0.250*** [-12.08]	0.179*** [-13.23]	0.208*** [-33.84]	0.238*** [-23.97]
(18-21] months				0.006*** [-17.45]	0.009*** [-15.36]	0.004*** [-17.74]	0.162*** [-25.62]	0.219*** [-11.46]	0.126*** [-19.62]	0.177*** [-20.13]	0.227*** [-14.80]
(21-24] months				0.004*** [-18.51]	0.005*** [-17.22]	0.003*** [-17.97]	0.182*** [-17.13]	0.242*** [-8.04]	0.147*** [-13.53]	0.208*** [-34.56]	0.235*** [-17.44]
>24 months				0.002*** [-16.05]	0.003*** [-16.15]	0.001*** [-14.38]	0.162*** [-17.38]	0.212*** [-10.99]	0.135*** [-22.97]	0.172*** [-27.78]	0.224*** [-11.76]
AIC	1,377,932,473	791,101,795	799,471,772	1,413,756,840	807,718,675	819,419,021	1,024,396	709,983	631,544	2,904,112	4,413,866
Observations	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	1,056,673	1,056,673	1,056,673	3,075,706	5,362,097
Nonzero outcomes	6,871,954	3,365,464	3,506,490	6,871,954	3,365,464	3,506,490	240,979	137,892	103,087	670,282	927,839
Clusters	40	40	40	40	40	40	44	44	44	44	44

Note: This table continues in Table 14. Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Clusters at COICOP Class level. Base categories are the omitted categories in each set of fixed effects (first fortnight of duration i.e. 0.5 months). Source: Authors' own estimates with online data gathered by Banco de México and with survey data compiled by INEGI.

Table 14: Benchmark Estimates (5/7): Yearly Hazard

	Daily Baseline Hazard			Fortnightly Baseline Hazard			CPI (Same Retailers)			CPI (Similar)	CPI (All)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	All Adjs
2017	1.110*** [4.28]	1.114*** [4.86]	1.095** [2.51]	1.111*** [3.79]	1.113*** [4.44]	1.099** [2.34]	0.950*** [-2.94]	0.965* [-1.89]	0.939*** [-2.72]	0.980** [-2.04]	0.972*** [-2.78]
2018	1.016 [0.39]	0.986 [-0.34]	1.040 [0.90]	1.018 [0.42]	0.987 [-0.32]	1.046 [0.96]	0.882*** [-6.88]	0.853*** [-7.52]	0.940 [-1.57]	0.928*** [-7.05]	0.917*** [-9.26]
2019	0.935 [-1.05]	0.898* [-1.83]	0.986 [-0.20]	0.915 [-1.26]	0.884* [-1.92]	0.954 [-0.60]	0.902*** [-2.78]	0.895*** [-3.91]	0.931 [-1.52]	0.931*** [-2.67]	0.920*** [-3.34]
2020	1.346*** [7.47]	1.295*** [6.90]	1.465*** [6.82]	1.273*** [8.05]	1.225*** [6.21]	1.363*** [8.40]	1.110 [1.52]	1.045** [2.03]	1.177 [1.23]	1.054 [0.93]	1.038 [0.76]
2021	1.316*** [5.99]	1.312*** [5.99]	1.369*** [5.68]	1.246*** [3.78]	1.254*** [4.84]	1.256*** [3.08]	1.081*** [2.67]	1.054** [2.19]	1.106* [1.77]	1.027 [0.83]	1.035 [1.22]
2022	1.698*** [8.39]	1.679*** [7.44]	1.807*** [8.16]	1.621*** [8.99]	1.612*** [8.52]	1.677*** [8.16]	0.975 [-0.68]	1.055* [1.73]	0.879* [-1.74]	0.942* [-1.89]	0.969 [-1.22]
AIC	1,377,932,473	791,101,795	799,471,772	1,413,756,840	807,718,675	819,419,021	1,024,396	709,983	631,544	2,904,112	4,413,866
Observations	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	1,056,673	1,056,673	1,056,673	3,075,706	5,362,097
Nonzero outcomes	6,871,954	3,365,464	3,506,490	6,871,954	3,365,464	3,506,490	240,979	137,892	103,087	670,282	927,839
Clusters	40	40	40	40	40	40	44	44	44	44	44

Note: This table continues in Table 15. Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Clusters at COICOP Class level. Base categories are the omitted categories in each set of fixed effects. Source: Authors' own estimates with online data gathered by Banco de México and with survey data compiled by INEGI.

Table 15: Benchmark Estimates (6/7): Monthly Hazard

	Daily Baseline Hazard			Fortnightly Baseline Hazard			CPI (Same Retailers)			CPI (Similar)	CPI (All)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	All Adjs
February	1.090*** [4.06]	1.069* [1.83]	1.098*** [3.48]	1.103*** [4.82]	1.078** [2.12]	1.111*** [3.71]	1.014 [1.05]	1.014 [0.77]	1.015 [0.70]	0.990 [-0.84]	0.990 [-1.01]
March	1.102*** [2.69]	1.118** [2.15]	1.073** [2.27]	1.118*** [3.14]	1.133** [2.43]	1.083** [2.55]	1.011 [0.76]	0.991 [-0.23]	1.035 [0.96]	0.982 [-1.06]	0.987 [-0.71]
April	1.145*** [4.12]	0.998 [-0.08]	1.298*** [4.28]	1.155*** [4.90]	1.001 [0.02]	1.306*** [4.74]	1.039 [1.34]	0.985 [-0.37]	1.104 [0.99]	1.023* [1.66]	1.015 [1.08]
May	1.226*** [4.41]	1.149*** [3.39]	1.302*** [4.52]	1.248*** [4.80]	1.163*** [3.78]	1.322*** [4.87]	1.093** [2.09]	1.142*** [3.85]	1.005 [0.04]	1.068*** [2.71]	1.058** [2.36]
June	1.393*** [3.41]	1.758*** [4.29]	1.053 [0.89]	1.439*** [3.78]	1.792*** [4.43]	1.094 [1.61]	0.983 [-0.23]	0.934** [-2.12]	1.055 [0.31]	0.959 [-1.34]	0.968 [-1.33]
July	1.017 [0.45]	0.937 [-1.48]	1.099*** [2.61]	1.013 [0.32]	0.933 [-1.45]	1.088** [2.21]	0.842*** [-7.78]	0.851*** [-5.75]	0.854** [-2.51]	0.848*** [-16.17]	0.848*** [-15.11]
August	1.186*** [3.99]	1.233*** [3.22]	1.137*** [4.10]	1.201*** [4.35]	1.248*** [3.42]	1.148*** [4.25]	1.027 [1.24]	1.055* [1.94]	0.984 [-0.59]	1.018 [1.09]	1.001 [0.05]
September	1.160*** [5.58]	1.363*** [3.70]	0.970 [-0.46]	1.160*** [6.22]	1.372*** [3.86]	0.973 [-0.37]	0.998 [-0.06]	0.975 [-0.79]	1.018 [0.24]	0.960*** [-3.07]	0.949*** [-3.35]
October	1.179*** [4.46]	1.188*** [4.04]	1.169*** [3.88]	1.160*** [4.76]	1.187*** [4.44]	1.147*** [3.38]	0.988 [-0.59]	0.909*** [-2.58]	1.082 [1.26]	0.964** [-2.04]	0.964** [-2.13]
November	1.525*** [4.49]	1.510*** [4.29]	1.521*** [4.52]	1.558*** [4.99]	1.538*** [4.65]	1.554*** [5.16]	1.071 [1.04]	1.055 [1.54]	1.069 [0.59]	1.044 [0.84]	1.052 [1.11]
December	1.274*** [3.35]	1.467*** [3.33]	1.097** [2.47]	1.295*** [3.73]	1.489*** [3.53]	1.107*** [2.96]	1.128* [1.74]	1.087*** [3.06]	1.151 [0.88]	1.040 [1.10]	1.054** [2.03]
AIC	1,377,932,473	791,101,795	799,471,772	1,413,756,840	807,718,675	819,419,021	1,024,396	709,983	631,544	2,904,112	4,413,866
Observations	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	1,056,673	1,056,673	1,056,673	3,075,706	5,362,097
Nonzero outcomes	6,871,954	3,365,464	3,506,490	6,871,954	3,365,464	3,506,490	240,979	137,892	103,087	670,282	927,839
Clusters	40	40	40	40	40	40	44	44	44	44	44

Note: This table continues in Table ???. Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Clusters at COICOP Class level. Base categories are the omitted categories in each set of fixed effects. Source: Authors' own estimates with online data gathered by Banco de México and with survey data compiled by INEGI.

Table 16: Benchmark Estimates (7/7): Calendar Day and Weekly Hazard

	Daily Baseline Hazard			Fortnightly Baseline Hazard			CPI (Same Retailers)			CPI (Similar)	CPI (All)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	All Adjs
2nd	0.636*** [-7.64]	0.669*** [-7.48]	0.625*** [-5.20]	0.644*** [-7.12]	0.672*** [-7.01]	0.638*** [-4.92]					
3rd	0.579*** [-7.28]	0.417*** [-5.95]	0.885 [-1.01]	0.575*** [-7.23]	0.418*** [-6.17]	0.874 [-1.12]					
4th	0.542*** [-7.65]	0.433*** [-8.02]	0.757*** [-6.40]	0.545*** [-8.45]	0.436*** [-8.49]	0.757*** [-6.61]					
5th	0.475*** [-6.27]	0.420*** [-7.61]	0.597*** [-4.88]	0.462*** [-6.75]	0.414*** [-8.23]	0.570*** [-5.21]					
6th	0.566*** [-8.06]	0.558*** [-6.05]	0.598*** [-7.39]	0.551*** [-8.26]	0.565*** [-5.42]	0.558*** [-7.82]					
7th	0.564*** [-7.45]	0.451*** [-8.39]	0.800*** [-4.76]	0.576*** [-8.22]	0.469*** [-9.72]	0.800*** [-4.63]					
8th	0.629*** [-10.37]	0.444*** [-9.57]	0.983 [-0.42]	0.647*** [-14.07]	0.456*** [-10.90]	1.010 [0.20]					
9th	0.635*** [-10.32]	0.376*** [-8.98]	1.117 [1.23]	0.621*** [-11.17]	0.369*** [-9.52]	1.081 [0.81]					
10th	0.517*** [-5.82]	0.366*** [-5.84]	0.827*** [-2.88]	0.504*** [-6.57]	0.363*** [-6.16]	0.781*** [-3.73]					
11th	0.504*** [-7.63]	0.371*** [-7.86]	0.772*** [-6.75]	0.491*** [-8.75]	0.364*** [-8.40]	0.740*** [-8.61]					
12th	0.586*** [-6.47]	0.470*** [-7.04]	0.814*** [-3.00]	0.551*** [-7.71]	0.449*** [-8.18]	0.749*** [-4.01]					
13th	0.575*** [-8.49]	0.502*** [-9.07]	0.723*** [-5.32]	0.544*** [-9.49]	0.487*** [-8.89]	0.663*** [-6.63]					
14th	0.626*** [-5.89]	0.496*** [-8.03]	0.886*** [-2.17]	0.613*** [-8.87]	0.494*** [-9.17]	0.848*** [-3.05]					
15th	0.561*** [-5.53]	0.373*** [-5.76]	0.924 [-1.50]	0.565*** [-6.68]	0.387*** [-6.48]	0.904** [-1.97]					
16th	0.490*** [-6.55]	0.411*** [-8.31]	0.661*** [-4.50]	0.472*** [-7.23]	0.406*** [-9.21]	0.620*** [-5.23]					
17th	0.577*** [-6.73]	0.405*** [-5.84]	0.909** [-2.24]	0.559*** [-7.37]	0.399*** [-6.19]	0.861*** [-3.71]					
18th	0.583*** [-7.33]	0.470*** [-9.52]	0.805*** [-3.65]	0.567*** [-8.13]	0.461*** [-10.13]	0.774*** [-4.42]					
19th	0.577*** [-7.92]	0.442*** [-8.13]	0.835*** [-2.95]	0.557*** [-8.48]	0.428*** [-8.58]	0.805*** [-3.57]					
20th	0.709*** [-6.06]	0.598*** [-9.18]	0.919 [-0.94]	0.686*** [-6.17]	0.588*** [-10.14]	0.879 [-1.35]					
21st	0.729*** [-8.06]	0.584*** [-9.58]	1.000 [-0.00]	0.741*** [-7.65]	0.599*** [-10.86]	1.009 [0.12]					
22nd	0.746*** [-5.13]	0.565*** [-8.04]	1.109 [1.28]	0.766*** [-4.05]	0.587*** [-7.01]	1.121 [1.26]					
23rd	0.545*** [-9.09]	0.454*** [-8.50]	0.742*** [-5.49]	0.539*** [-9.99]	0.455*** [-9.26]	0.725*** [-5.45]					
24th	0.463*** [-5.79]	0.382*** [-7.08]	0.641*** [-4.30]	0.458*** [-6.13]	0.384*** [-7.41]	0.620*** [-4.58]					
25th	0.514*** [-5.41]	0.371*** [-7.16]	0.792*** [-2.63]	0.498*** [-5.94]	0.365*** [-7.65]	0.756*** [-3.20]					
26th	0.530*** [-6.39]	0.306*** [-5.79]	0.983 [-0.23]	0.513*** [-7.09]	0.302*** [-6.13]	0.926 [-0.99]					
27th	0.464*** [-6.42]	0.310*** [-6.34]	0.786*** [-5.51]	0.452*** [-7.66]	0.308*** [-7.10]	0.749*** [-7.47]					
28th	0.596*** [-7.58]	0.402*** [-6.89]	0.993 [-0.10]	0.602*** [-9.71]	0.414*** [-8.13]	0.976 [-0.33]					
29th	0.501*** [-6.08]	0.329*** [-5.70]	0.865*** [-3.09]	0.502*** [-7.13]	0.339*** [-6.32]	0.842*** [-3.61]					
30th	0.714*** [-3.72]	0.536*** [-5.43]	1.074 [1.51]	0.682*** [-4.48]	0.520*** [-6.01]	1.007 [0.16]					
31st	0.977 [-0.31]	0.748** [-2.01]	1.406*** [5.76]	0.945 [-0.79]	0.735** [-2.23]	1.345*** [4.96]					
Monday	0.903 [-1.49]	1.027 [0.48]	0.763** [-2.49]	0.890 [-1.40]	0.985 [-0.21]	0.775** [-2.18]					
Tuesday	0.914 [-1.20]	0.937 [-0.87]	0.886 [-1.55]	0.884 [-1.28]	0.896 [-1.17]	0.872 [-1.39]					
Wednesday	0.827** [-2.14]	0.700*** [-2.76]	0.983 [-0.32]	0.791** [-2.02]	0.674*** [-2.60]	0.941 [-0.77]					
Thursday	1.877*** [10.13]	1.436*** [9.09]	2.375*** [8.51]	2.134*** [9.48]	1.663*** [8.27]	2.673*** [8.75]					
Friday	0.870*** [-2.57]	0.641*** [-3.20]	1.181*** [3.98]	0.906 [-1.30]	0.666** [-2.48]	1.231*** [6.29]					
Saturday	0.593*** [-5.02]	0.519*** [-4.59]	0.701*** [-5.87]	0.571*** [-4.27]	0.504*** [-4.17]	0.666*** [-4.45]					
2nd Fortnight							1.167*** [11.48]	1.215*** [9.54]	1.076*** [7.09]	1.148*** [14.50]	1.154*** [11.51]
AIC	1,377,932,473	791,101,795	799,471,772	1,413,756,840	807,718,675	819,419,021	1,024,396	709,983	631,544	2,904,112	4,413,866
Observations	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	220,322,049	1,056,673	1,056,673	1,056,673	3,075,706	5,362,097
Nonzero outcomes	6,871,954	3,365,464	3,506,490	6,871,954	3,365,464	3,506,490	240,979	137,892	103,087	670,282	927,839
Clusters	40	40	40	40	40	40	44	44	44	44	44

Note: This table continues in Table ???. The CPI does not report the actual day prices are collected. Instead, they are reported as observed in the first or second fortnight of every month. Thus, in addition to the monthly fixed effect in the CPI regression, we include fortnightly fixed effects. Base categories are the omitted categories in each set of fixed effects (1st calendar day, Sunday and First fortnight). Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Clusters at COICOP Class level. Source: Authors' own estimates with online data gathered by Banco de México and with survey data compiled by INEGI.

Table 17: Hazard of Time Varying Covariates in Food (Alternative Specification)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops
Size of Last Price Change (Abs Val, p.p.)	1.110*** [5.03]	1.086*** [3.34]	1.135*** [5.18]	1.118*** [5.10]	1.089*** [3.34]	1.146*** [5.41]	1.108*** [4.93]	1.083*** [3.23]	1.134*** [5.14]
Negative Last Price Change=1	1.058*** [3.21]	3.090*** [25.27]	0.314*** [-33.42]	1.055*** [2.87]	3.062*** [24.15]	0.314*** [-33.18]	1.059*** [3.23]	3.095*** [25.13]	0.314*** [-33.15]
FX Depreciation (Abs Val Level, p.p.)	0.000*** [-8.99]	0.001*** [-6.15]	0.000*** [-11.89]				0.000*** [-11.36]	0.000*** [-8.80]	0.000*** [-13.35]
Negative FX Depreciation (Dummy)	0.763*** [-12.72]	0.746*** [-10.42]	0.780*** [-11.17]				0.770*** [-13.09]	0.751*** [-10.28]	0.789*** [-11.71]
Real PoS Variation (Abs Val Level, p.p.)				2.512 [1.16]	11.687** [2.50]	0.269* [-1.85]	631.558*** [9.95]	2271.525*** [9.66]	98.585*** [7.60]
Negative Real PoS Variation (Dummy)				0.825*** [-6.46]	0.853*** [-5.97]	0.819*** [-5.74]	0.884*** [-5.19]	0.915*** [-4.25]	0.878*** [-4.55]
AIC	339,015,890	206,191,063	198,458,273	340,791,272	207,045,880	199,455,259	338,698,775	206,001,185	198,348,594
Observations	29,109,518	29,109,518	29,109,518	29,109,518	29,109,518	29,109,518	29,109,518	29,109,518	29,109,518
Nonzero outcomes	612,169	326,558	285,611	612,169	326,558	285,611	612,169	326,558	285,611
Clusters	67	67	67	67	67	67	67	67	67

Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Standard errors clustered by product category.
Source: Authors' own calculations using daily online data.

Table 18: Hazard of Time Varying Covariates in Apparel (Alternative Specification)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops
Size of Last Price Change (Abs Val, p.p.)	1.079 [0.93]	0.448*** [-8.67]	1.977*** [6.69]	1.085 [0.96]	0.451*** [-8.33]	1.965*** [6.74]	1.089 [1.01]	0.451*** [-8.35]	1.988*** [6.80]
Negative Last Price Change=1	0.992 [-0.47]	5.836*** [33.26]	0.226*** [-19.67]	0.989 [-0.64]	5.829*** [33.08]	0.225*** [-19.65]	0.990 [-0.59]	5.830*** [33.16]	0.225*** [-19.72]
FX Depreciation (Abs Val Level, p.p.)	2.107 [1.16]	2.188* [1.89]	0.789 [-0.25]				1.914 [1.19]	1.600 [0.66]	1.165 [0.18]
Negative FX Depreciation (Dummy)	0.966 [-1.16]	0.998 [-0.07]	0.906** [-2.25]				0.958 [-1.53]	0.993 [-0.30]	0.897*** [-2.64]
Real PoS Variation (Abs Val Level, p.p.)				1.015 [0.01]	2.190 [0.49]	0.163* [-1.86]	0.697 [-0.40]	1.645 [0.26]	0.140*** [-2.66]
Negative Real PoS Variation (Dummy)				1.088*** [2.83]	1.065*** [2.62]	1.073 [1.52]	1.094*** [3.67]	1.064*** [2.72]	1.095** [2.42]
AIC	322,258,304	170,246,855	185,811,437	322,234,381	170,236,471	185,840,117	322,210,747	170,235,260	185,777,045
Observations	84,584,797	84,584,797	84,584,797	84,584,797	84,584,797	84,584,797	84,584,797	84,584,797	84,584,797
Nonzero outcomes	3,214,825	1,501,950	1,712,875	3,214,825	1,501,950	1,712,875	3,214,825	1,501,950	1,712,875
Clusters	24	24	24	24	24	24	24	24	24

Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Standard errors clustered by product category.
Source: Authors' own calculations using daily online data.

Table 19: Hazard of Time Varying Covariates in Furniture (Alternative Specification)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops
Size of Last Price Change (Abs Val, p.p.)	1.192*** [3.10]	1.031 [0.38]	1.349*** [3.30]	1.192*** [3.06]	1.029 [0.36]	1.351*** [3.31]	1.190*** [3.09]	1.028 [0.34]	1.349*** [3.30]
Negative Last Price Change=1	1.055** [2.01]	3.819*** [21.51]	0.284*** [-20.93]	1.058** [2.09]	3.818*** [21.55]	0.285*** [-20.78]	1.055** [2.00]	3.815*** [21.63]	0.284*** [-20.89]
FX Depreciation (Abs Val Level, p.p.)	0.127 [-1.44]	0.179 [-1.34]	0.055* [-1.85]				0.055* [-1.87]	0.035** [-2.51]	0.054* [-1.65]
Negative FX Depreciation (Dummy)	0.905*** [-2.80]	0.917 [-1.60]	0.881*** [-4.86]				0.906*** [-2.86]	0.914* [-1.67]	0.883*** [-4.96]
Real PoS Variation (Abs Val Level, p.p.)				4.736** [2.39]	37.225*** [4.64]	0.274* [-1.71]	24.817*** [2.99]	301.763*** [5.55]	1.214 [0.16]
Negative Real PoS Variation (Dummy)				0.980 [-0.74]	1.014 [0.46]	0.953* [-1.76]	1.001 [0.04]	1.036 [1.45]	0.977 [-1.03]
AIC	301,107,263	172,769,537	174,527,209	301,245,788	172,786,923	174,651,869	301,057,941	172,690,664	174,525,451
Observations	37,631,114	37,631,114	37,631,114	37,631,114	37,631,114	37,631,114	37,631,114	37,631,114	37,631,114
Nonzero outcomes	1,175,315	584,733	590,582	1,175,315	584,733	590,582	1,175,315	584,733	590,582
Clusters	44	44	44	44	44	44	44	44	44

Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Standard errors clustered by product category.
Source: Authors' own calculations using daily online data.

Table 20: Hazard of Time Varying Covariates in Medicines (Alternative Specification)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops
Size of Last Price Change (Abs Val, p.p.)	1.517*** [12.06]	1.448*** [8.73]	1.561*** [15.69]	1.530*** [11.34]	1.459*** [8.34]	1.577*** [15.34]	1.515*** [11.91]	1.446*** [8.69]	1.559*** [15.31]
Negative Last Price Change=1	1.166*** [4.99]	3.605*** [7.43]	0.325*** [-9.03]	1.172*** [5.08]	3.621*** [7.56]	0.328*** [-8.88]	1.171*** [4.99]	3.624*** [7.58]	0.327*** [-8.92]
FX Depreciation (Abs Val Level, p.p.)	0.011*** [-2.76]	0.114* [-1.78]	0.001*** [-2.78]				0.003*** [-3.64]	0.017*** [-3.54]	0.000*** [-3.09]
Negative FX Depreciation (Dummy)	0.818*** [-3.09]	0.823*** [-3.13]	0.822*** [-3.19]				0.826*** [-3.44]	0.827*** [-3.52]	0.834*** [-3.53]
Real PoS Variation (Abs Val Level, p.p.)				11.197*** [5.54]	37.244*** [17.09]	1.728 [0.64]	197.270*** [5.16]	326.803*** [8.72]	49.697** [2.56]
Negative Real PoS Variation (Dummy)				0.869 [-1.23]	0.921 [-0.82]	0.823 [-1.54]	0.925 [-0.83]	0.970 [-0.96]	0.883 [-1.21]
AIC	91,204,065	54,377,521	50,512,635	91,364,563	54,414,631	50,642,336	91,122,901	54,325,773	50,483,565
Observations	18,465,526	18,465,526	18,465,526	18,465,526	18,465,526	18,465,526	18,465,526	18,465,526	18,465,526
Nonzero outcomes	385,848	202,029	183,819	385,848	202,029	183,819	385,848	202,029	183,819
Clusters	15	15	15	15	15	15	15	15	15

Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Standard errors clustered by product category.
Source: Authors' own calculations using daily online data.

Table 21: Hazard of Time Varying Covariates in Recreation (Alternative Specification)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops
Size of Last Price Change (Abs Val, p.p.)	1.002 [0.01]	0.736 [-1.10]	1.316 [1.50]	0.999 [-0.00]	0.737 [-1.10]	1.314 [1.49]	1.001 [0.01]	0.734 [-1.11]	1.319 [1.51]
Negative Last Price Change=1	1.194*** [4.20]	5.059*** [20.30]	0.288*** [-9.66]	1.195*** [4.21]	5.058*** [20.10]	0.288*** [-9.65]	1.194*** [4.18]	5.063*** [20.23]	0.288*** [-9.63]
FX Depreciation (Abs Val Level, p.p.)	1.256 [0.21]	0.106*** [-2.86]	3.472 [0.64]				0.875 [-0.13]	0.039*** [-4.89]	5.318 [0.83]
Negative FX Depreciation (Dummy)	0.953* [-1.86]	0.965 [-0.98]	0.916*** [-4.18]				0.948** [-1.96]	0.958 [-1.13]	0.912*** [-3.98]
Real PoS Variation (Abs Val Level, p.p.)				2.832 [1.31]	6.129 [1.43]	0.442 [-0.64]	3.031* [1.65]	45.099*** [3.54]	0.175*** [-5.12]
Negative Real PoS Variation (Dummy)				1.039 [1.09]	1.052 [1.41]	1.019 [0.52]	1.050 [1.36]	1.067* [1.68]	1.036 [0.94]
AIC	177,078,773	98,613,707	102,386,027	177,084,504	98,622,209	102,413,080	177,067,182	98,591,765	102,379,825
Observations	28,297,447	28,177,774	28,297,447	28,297,447	28,177,774	28,297,447	28,297,447	28,177,774	28,297,447
Nonzero outcomes	981,935	491,805	490,130	981,935	491,805	490,130	981,935	491,805	490,130
Clusters	11	11	11	11	11	11	11	11	11

Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Standard errors clustered by product category.
Source: Authors' own calculations using daily online data.

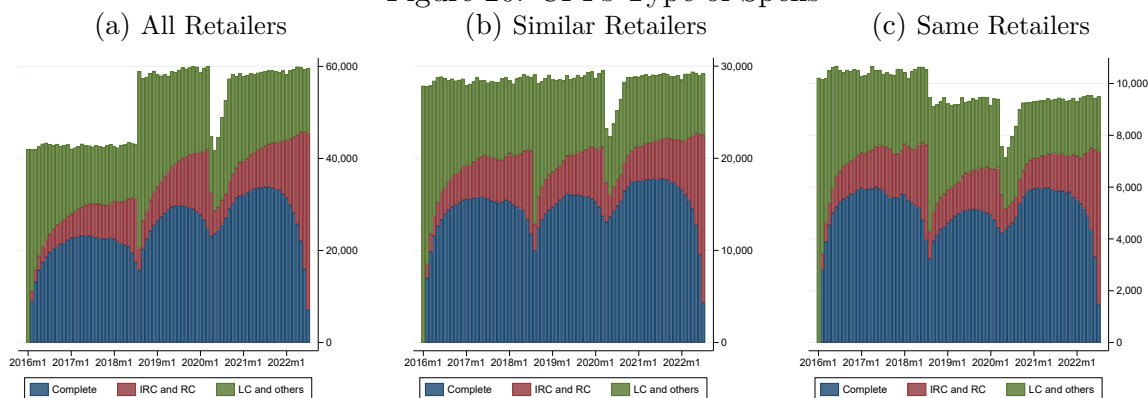
Table 22: Hazard of Time Varying Covariates in Personal Care (Alternative Specification)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops	All Adjs	Hikes	Drops
Size of Last Price Change (Abs Val, p.p.)	1.265*** [9.25]	1.188*** [3.34]	1.287*** [10.88]	1.281*** [9.60]	1.201*** [3.52]	1.307*** [11.57]	1.264*** [9.15]	1.187*** [3.30]	1.287*** [10.96]
Negative Last Price Change=1	1.023 [0.69]	3.008*** [21.49]	0.285*** [-37.57]	1.019 [0.56]	2.960*** [20.31]	0.285*** [-36.68]	1.024 [0.70]	3.011*** [21.21]	0.285*** [-37.61]
FX Depreciation (Abs Val Level, p.p.)	0.001*** [-4.87]	0.001*** [-6.03]	0.001*** [-4.29]				0.001*** [-5.52]	0.001*** [-7.31]	0.001*** [-4.60]
Negative FX Depreciation (Dummy)	0.789*** [-7.25]	0.787*** [-6.18]	0.757*** [-9.91]				0.792*** [-7.76]	0.787*** [-6.55]	0.762*** [-10.60]
Real PoS Variation (Abs Val Level, p.p.)				0.091** [-2.36]	0.132* [-1.85]	0.018** [-2.28]	10.003*** [4.40]	36.269*** [4.08]	1.542 [0.38]
Negative Real PoS Variation (Dummy)				0.884** [-2.56]	0.927 [-1.42]	0.864*** [-3.13]	0.927* [-1.67]	0.975 [-0.50]	0.910** [-2.09]
AIC	160,487,579	94,494,485	92,876,390	161,227,127	94,938,205	93,313,931	160,455,808	94,478,618	92,862,303
Observations	22,233,647	22,233,647	22,233,647	22,233,647	22,233,647	22,233,647	22,233,647	22,233,647	22,233,647
Nonzero outcomes	501,862	258,389	243,473	501,862	258,389	243,473	501,862	258,389	243,473
Clusters	13	13	13	13	13	13	13	13	13

Statistical significance against 1. * p<0.10, ** p<0.05, *** p<0.01. t statistics in squared parentheses. Standard errors clustered by product category.
Source: Authors' own calculations using daily online data.

8 Appendix - CPI Data

Figure 20: CPI's Type of Spells



Note: CPI samples depend on the type retailers included in the estimation sample: “Same retailers” are the same retail chains as the ones encompassed in the web scraped data, “Similar retailers” are the supermarkets, departmental stores and price clubs surveyed in the CPI, while “All” include all price informants in the CPI. Data from January 2016 to June 2022. Source: Authors’ calculations based on INEGI’s data.

Table 23: CPI's Spell Type Distribution Using All Retailers by COICOP Division

COICOP Division		Spells		Type of Spell (%)									
		Number (thousands)	Share (%)	Complete	RC	IRC	LC	ILC	RC-LC	RC-ILC	IRC-LC	IRC-ILC	
Using All Retailers													
1	Food and Beverages	576	37.87	69.06	8.05	4.11	8.34	3.70	5.06	1.00	0.66	0.02	
3	Apparel	269	17.67	41.27	12.30	4.05	12.46	3.54	20.46	3.05	2.80	0.07	
5	Furnishings and Home Prods.	350	22.98	60.08	10.69	3.15	10.96	2.69	9.99	1.39	1.04	0.01	
6	Medicines	110	7.26	69.79	7.69	4.15	7.72	4.02	5.05	0.84	0.73	0.02	
9	Recreation	86	5.63	49.20	12.71	3.14	12.87	2.69	15.74	1.89	1.68	0.07	
12	Personal Care	131	8.59	68.73	8.63	3.01	8.72	2.76	6.41	0.96	0.77	0.01	
Using Similar Retailers to Online Data													
1	Food and Beverages	389	37.30	74.83	7.35	2.78	7.45	2.64	3.95	0.57	0.43	0.00	
3	Apparel	194	18.61	44.99	11.89	3.75	12.03	3.30	18.94	2.65	2.39	0.06	
5	Furnishings and Home Prods.	255	24.46	62.58	10.65	2.45	10.76	2.18	9.54	1.03	0.80	0.00	
6	Medicines	38	3.64	66.75	8.78	3.73	8.87	4.04	6.22	0.92	0.68	0.01	
9	Recreation	63	6.03	52.24	12.75	2.21	12.87	1.90	15.43	1.39	1.20	0.00	
12	Personal Care	104	9.95	71.95	8.15	2.62	8.18	2.47	5.34	0.69	0.60	0.00	
Using Same Retailers to Online Data													
1	Food and Beverages	130	34.81	74.12	7.59	2.77	7.60	2.74	4.14	0.59	0.45	0.01	
3	Apparel	93	24.92	54.58	11.01	3.20	11.23	2.80	13.81	1.81	1.53	0.03	
5	Furnishings and Home Prods.	83	22.15	61.21	10.90	2.48	11.12	2.11	10.15	1.16	0.86	0.00	
6	Medicines	10	2.64	65.15	8.71	3.69	8.79	4.49	7.08	1.17	0.91	0.02	
9	Recreation	23	6.05	52.83	12.67	2.15	12.86	1.86	15.01	1.46	1.15	0.00	
12	Personal Care	35	9.44	72.35	8.01	2.70	8.08	2.56	5.08	0.67	0.55	0.00	

Note: This table summarizes all price spells that can be constructed in the CPI data set. Importantly, CPI samples depend on the type retailers included: "Same retailers" are the same retail chains as the ones encompassed in the web scraped data, "Similar retailers" are the supermarkets, departmental stores and price clubs surveyed in the CPI, while "All" include all price informants in the CPI. The column *Share* under the title *Spells* adds up to one. Rows under the title *Type of Spell* add up to one i.e. it provides a partition on the type of spells by COICOP Division. Data from January 2016 to June 2022. Source: Own computations using data gathered by INEGI.

Table 24: CPI's Duration Distribution of Complete Spells by COICOP Division

COICOP Division		Spells		Duration (Fortnights)								Ending as (%)	
		Number (thousands)	Share (%)	Mean	P5	P10	P25	P50	P75	P90	P95	Price Hike	Price Drop
<i>Using All Retailers</i>													
1	Food and Beverages	398	42.88	4	1	1	1	2	4	10	16	59.42	40.58
3	Apparel	111	11.96	5	1	1	1	2	6	12	19	61.30	38.70
5	Furnishings and Home Prods.	210	22.64	4	1	1	1	2	4	8	12	58.42	41.58
6	Medicines	77	8.30	5	1	1	1	3	6	12	17	65.26	34.74
9	Recreation	42	4.54	4	1	1	1	2	4	10	16	57.54	42.46
12	Personal Care	90	9.68	4	1	1	1	2	4	8	12	57.04	42.96
<i>Using Similar Retailers to Online Data</i>													
1	Food and Beverages	291	43.39	3	1	1	1	2	4	7	11	56.22	43.75
3	Apparel	87	13.02	5	1	1	1	2	5	11	17	60.07	39.91
5	Furnishings and Home Prods.	160	23.80	3	1	1	1	2	3	7	10	56.64	43.33
6	Medicines	25	3.78	5	1	1	1	3	6	12	16	63.47	36.43
9	Recreation	33	4.90	3	1	1	1	2	4	7	11	55.39	44.57
12	Personal Care	75	11.13	3	1	1	1	2	4	7	11	56.00	43.98
<i>Using Same Retailers to Online Data</i>													
1	Food and Beverages	96	39.87	3	1	1	1	2	4	7	11	57.15	42.82
3	Apparel	51	21.02	4	1	1	1	2	4	8	13	57.66	42.33
5	Furnishings and Home Prods.	51	20.96	3	1	1	1	2	3	6	10	56.77	43.22
6	Medicines	6	2.66	5	1	1	2	3	6	12	16	62.12	37.75
9	Recreation	12	4.94	3	1	1	1	2	3	7	11	56.21	43.76
12	Personal Care	25	10.55	3	1	1	1	2	4	7	11	56.61	43.37

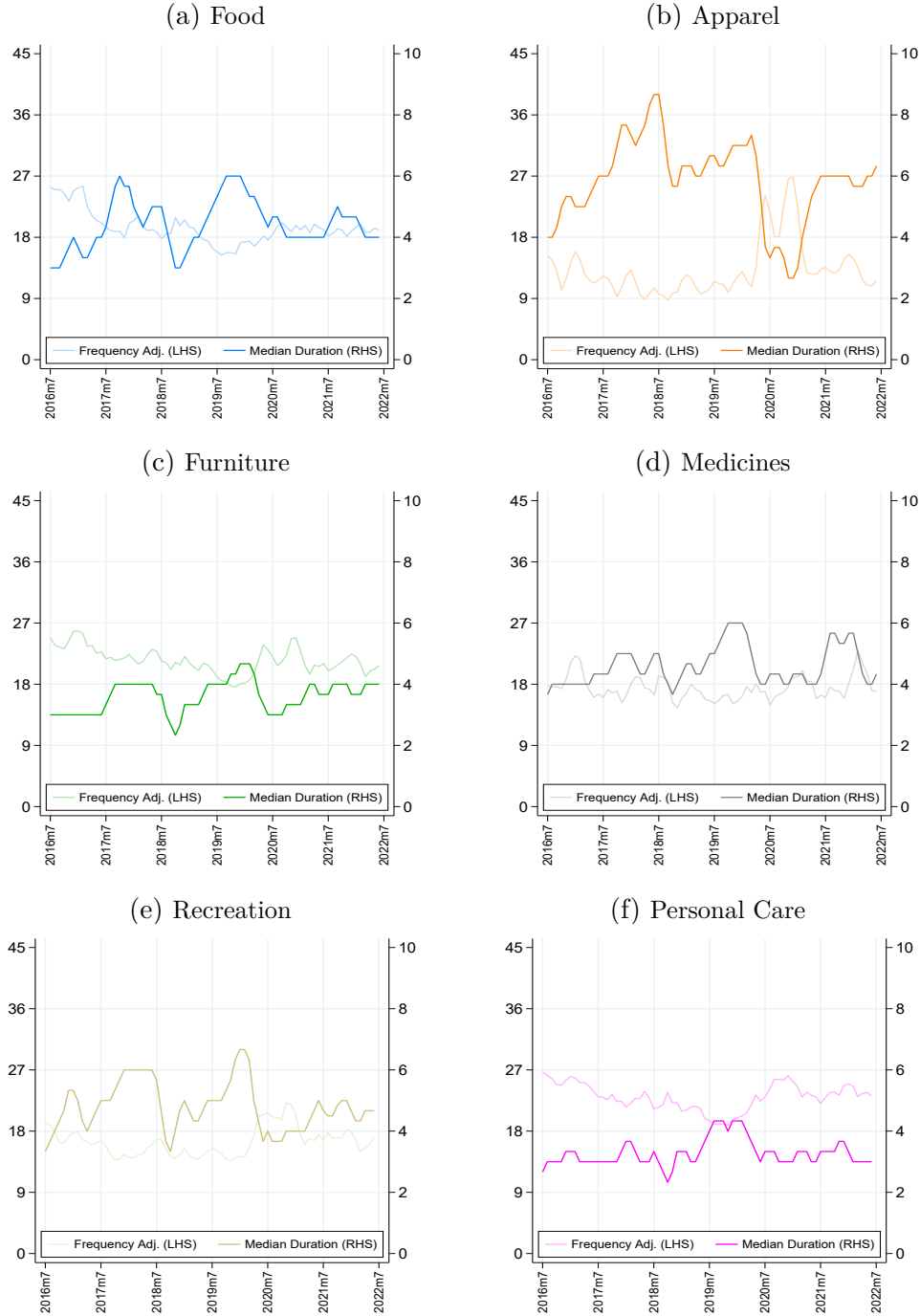
Note: This table summarizes the duration distribution of complete price spells by COICOP Division. Importantly, CPI samples depend on the type retailers included: "Same retailers" are the same retail chains as the ones encompassed in the web scraped data, "Similar retailers" are the supermarkets, departmental stores and price clubs surveyed in the CPI, while "All" include all price informants in the CPI. The column *Share* under the title *Spells* adds up to one. Moments in the duration distribution under the title *Duration* are computed by COICOP Division and reported in days. As this table considers only complete price spells, it is observed how each spell ended (either as price hike or as a price drop). Thus, rows under the title *Ending as add up to one*. Data from January 2016 to June 2022. Source: Own calculations based on data compiled by INEGI.

Table 25: CPI's Duration Distribution of Complete, RC and IRC Spells by COICOP Division

COICOP Division		Spells		Duration (Fortnights)								Ending as (%)	
		Number (thousands)	Share (%)	Mean	P5	P10	P25	P50	P75	P90	P95	Price Hike	Price Drop
<i>Using All Retailers</i>													
1	Food and Beverages	468	41.33	5	1	1	1	2	5	11	17	50.53	34.51
3	Apparel	155	13.68	6	1	1	1	3	7	16	23	43.90	27.72
5	Furnishings and Home Prods.	259	22.83	4	1	1	1	2	4	9	14	47.49	33.79
6	Medicines	90	7.96	6	1	1	2	3	7	13	18	55.79	29.71
9	Recreation	56	4.92	5	1	1	1	2	5	12	19	43.52	32.11
12	Personal Care	105	9.28	4	1	1	1	2	4	9	13	48.78	36.74
<i>Using Similar Retailers to Online Data</i>													
1	Food and Beverages	330	41.34	3	1	1	1	2	4	8	12	49.52	38.54
3	Apparel	118	14.72	5	1	1	1	2	6	14	21	44.57	29.61
5	Furnishings and Home Prods.	193	24.15	3	1	1	1	2	4	8	12	46.84	35.83
6	Medicines	30	3.76	5	1	1	1	3	7	12	17	53.45	30.68
9	Recreation	42	5.29	4	1	1	1	2	4	8	13	43.06	34.65
12	Personal Care	86	10.74	4	1	1	1	2	4	8	12	48.71	38.26
<i>Using Same Retailers to Online Data</i>													
1	Food and Beverages	110	38.16	3	1	1	1	2	4	8	12	50.15	37.57
3	Apparel	64	22.25	4	1	1	1	2	4	10	16	45.75	33.59
5	Furnishings and Home Prods.	62	21.44	3	1	1	1	2	4	7	11	46.59	35.47
6	Medicines	8	2.65	6	1	1	2	3	7	13	18	52.20	31.72
9	Recreation	15	5.31	4	1	1	1	2	4	8	13	43.89	34.17
12	Personal Care	29	10.17	4	1	1	1	2	4	8	12	49.31	37.78

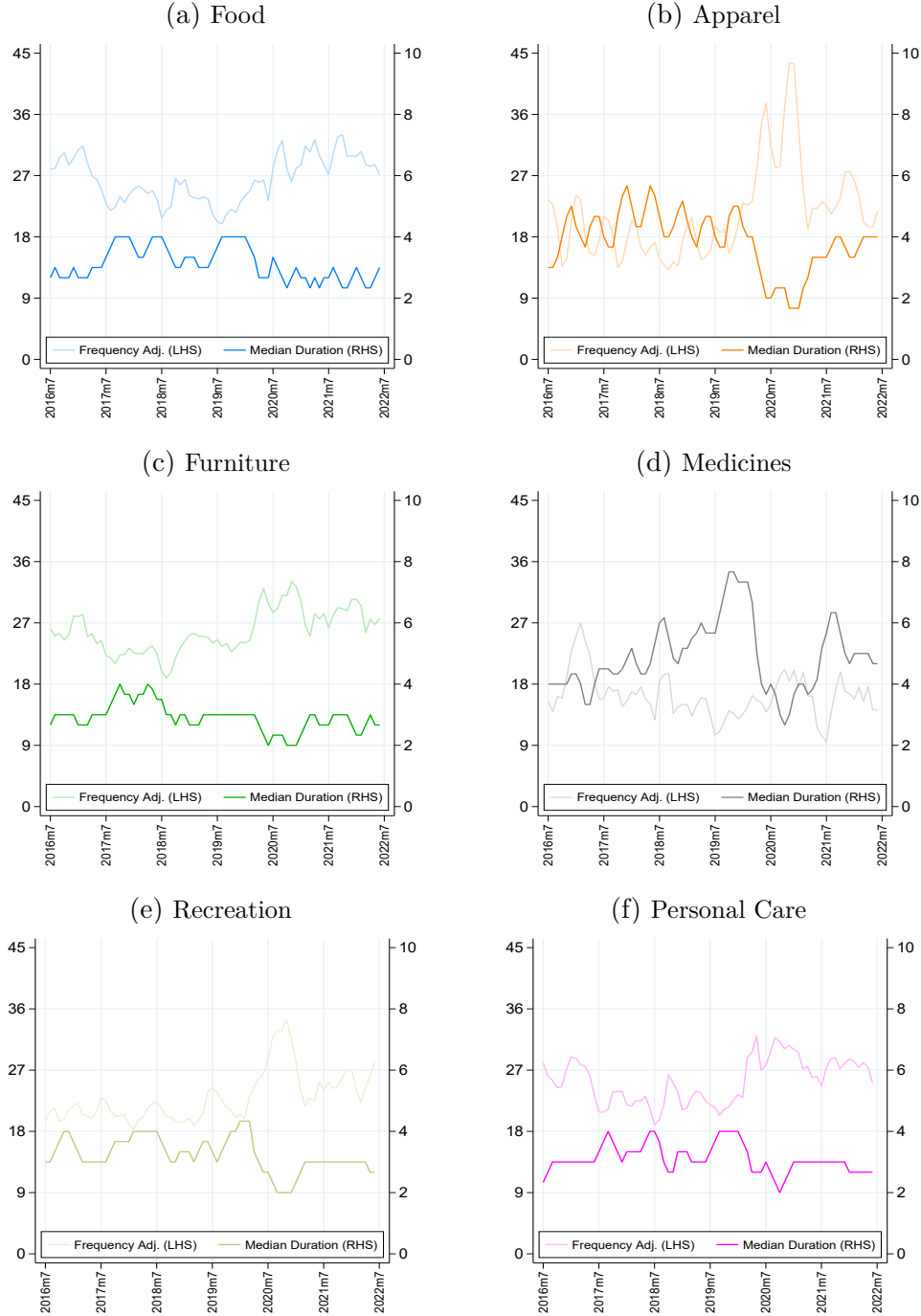
Note: This table summarizes the duration distribution of price spells by COICOP Division. Importantly, CPI samples depend on the type retailers included in the estimation sample: "Same retailers" are the same retail chains as the ones encompassed in the web scraped data, "Similar retailers" are the supermarkets, departmental stores and price clubs surveyed in the CPI, while "All" include all price informants in the CPI. The column *Share* under the title *Spells* adds up to one. Moments in the duration distribution under the title *Duration* are computed by COICOP Division and reported in days. Although this table considers complete spells, it is not observed how each spell ended since it also considers right-censored and interval right-censored price spells. Thus, rows under the title *Ending as* do not add up to one. Data from January 2016 to June 2022. Source: Own calculations based on data compiled by INEGI.

Figure 21: Frequency of Price Changes in Percentages (LHS) & Median Duration in Fortnights (RHS)
All Retailers
Quarterly Moving Averages



Note: This figure uses Complete, RC and IRC spells. It depicts the median duration (fortnights) and the frequency of price changes (%) by COICOP Division in all retailers in the CPI survey in Mexico. Fortnightly series are smoothed using a three month moving average. Only the second fortnight of every month is shown for illustration purposes. For every point in time we compute, on the one hand, the on-going duration of the active spells at the time and, on the other hand, the fraction of prices changing relative to its previous fortnight. Data from January 2016 to June 2022. Source: Authors' computations with data compiled by INEGI.

Figure 22: Frequency of Price Changes in Percentages (LHS) & Median Duration in Fortnights (RHS)
Same Retailers as Online Data
Quarterly Moving Averages



Note: This figure uses Complete, RC and IRC spells. “Same retailers” are the same retail chains as the ones encompassed in the web scraped data. It depicts the median duration (fortnights) and the frequency of price changes (%) by COICOP Division in the CPI survey in Mexico from the same retailers as the ones we have web scraped data. Fortnightly series are smoothed using a three month moving average. Only the second fortnight of every month is shown for illustration purposes. For every point in time we compute, on the one hand, the on-going duration of the active spells at the time and, on the other hand, the fraction of prices changing relative to its previous fortnight. Data from January 2016 to June 2022. Source: Authors’ computations with data compiled by INEGI.