Stylized Facts From Prices at Multi-Channel Retailers in Mexico*

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July 2021

Abstract

Nominal rigidities are a key ingredient in macroeconomic models. Using web scraping techniques, this paper characterizes the frequency, size and dispersion of price changes from product categories observed in eight large retailers in Mexico, and compare them with price statistics stemming from brick and mortar stores of the same retailers. Strikingly, the evidence suggests that prices observed in brick and mortar stores (offline) change more frequently than those observed on websites (online). However, given a price change, online prices tend to exhibit larger price changes than their offline counterparts. When focusing on period affected by the Covid-19 pandemic, the results suggest that, the above relationship across sales channel holds, the frequency of price changes increased roughly by the same magnitude in both sales channels and the average size of price adjustments did not change relative to previous years. Results from this paper highlight that importance of recognizing the differences between survey and web scraped data, specially as metrics on price rigidities are key elements in monetary policy models.

JEL: E31, L16.

*I would like to thank Alejandrina Salcedo, Josué Cortés, Denisse Dueñas, Gerardo Avilez, Lenin Arango and participants at CEMLA-Banco de España seminar in Big Data for their useful comments. This paper has benefited from Banco de Mexico's EconLab initiative. All errors remain mine.

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1 Introduction

Nominal rigidities are a key ingredient in macroeconomic models. A leading explanation for the effects of monetary policy on output are the infrequent price adjustments. Thus, theoretical literature has shown that the nature of nominal price rigidities has implications for the conduct of monetary policy, as well as determining the response of inflation and output to a wide variety of shocks

The aim of this paper is to characterize the frequency, size and dispersion of price changes as observed on the website of eight large retailers in Mexico between 2016 and 2020 and compare them with the same price moments using data from brick and mortar stores of the same retailers. That is, this study focuses on the stylized facts from consumer prices at multi-channel retailers.[1] In particular, price moments are calculated for fairly homogeneous product categories and for each of the sales channels (online and offline) within a given retailer. These statistics are then compared at retailer level across sales channels. The homogeneous product categories are the lowest level of aggregation of the Mexican CPI, known as *genéricos* by Mexico's National Statistical Institute (INEGI). Examples of product categories include milk, butter, soap, dish washer, women trousers, men trousers, etc.

Additionally, this paper sheds light on the extent to which the Covid19 pandemic have affected price setting behavior in both online and offline channels. As documented at the time, stockouts for certain types of goods; compulsory but temporal closure of brick and mortar stores (offline); rapid transition to online shopping by consumers, which in turn might have lead multi-channel retailers to step-up their website (online) operations; as well as the transitory adaptation in the price survey taking place in the offline sales channel, are only a few factors that could have reshaped the frequency and size of price adjustments across channels in the wake of the Covid19 pandemic. To that end, price statistics are reported for two periods of time, from 2016 to 2019 and during the 2020 Covid19 pandemic.

Looking at the pre-pandemic data, the evidence suggests that prices observed in brick and mortar stores (offline) change more frequently than those observed on websites (online). However, given a price change, online prices tend to change by larger amounts than offline

[1] Multi-channel retailer is the term use in the literature for an outlet offering its products through different sales channels. Examples of sales channels are brick and mortar stores, websites, catalogues, by phone, among others. This paper studies the first two sales channels for eight retailers. For more on studies regarding multi-channel retailers, see Cavallo (2017) and references therein.

prices. For most retailers, the categories' extensive margins of price adjustments across channels exhibit a positive relationship. That is, product categories changing prices more frequently online prices are also those reporting offline adjustments more often. The positive relationship is also positive for the intensive margin but not for the majority of retailers under study. With respect to the distribution of price changes, this study shows that online price changes are more centered at focal points (multiples of 5% in the ±20% range) than offline price adjustments. When standardizing price changes by product category and retailer, the majority of retailers exhibit a small fraction of small price changes in their online distribution; while this is less the case in the distributions drawn from offline price changes.

The study then takes a closer look at the 2020 data, affected by the Covid-19 pandemic. For the product categories and retailers in the study, the results indicate that, first, the less frequent but larger online prices changes, relative to offline prices changes, holds in 2020. Second, the frequency of price changes increased, on average, by around 5 p.p. in both online and offline sales channels, while the average size of price adjustments did not change relative to previous years. Third, despite the average size being the same, the distribution of price changes and standardized price adjustments report fatter tails than before.

Regarding the data used in this research, I use two main data sources. The first one is compiled by Banco de México and encompasses online prices gathered by web scraping techniques. In broad terms, this technique consists of a robot visiting the website of eight retailers, which in turn collects products' description and price. The retailers in the sample includes supermarkets, price clubs and departmental stores. For half of the retailers price collection starts in 2016, while for the other half the price history begins in 2017. All in all, the online data set comprehends over 14 million price quotes from more than 150 thousand different products across the eight retailers. The second data source comes from the price survey undertaken by INEGI in brick and mortar stores for CPI calculation purposes. I use observations from the same eight retail chains for which online prices are available only. From 2016 to 2020, the price survey comprehends a little less than one million price quotes from about 22 thousand different products.

The methodological approach taken in this study centers at comparing the stylized facts of price setting behavior calculated by sales channel for product categories in a given retailer. These product categories contain fairly homogeneous types of products across sales channels (e.g. soft drinks, beers, refrigerators). However, the products within each category per sales channel might differ, mainly because of the price collection techniques in place. On the one hand, the online price data comes from web scraping techniques, which parses all products displayed on websites. On the other hand, the offline price data comes from the CPI survey that samples goods per product category. Hence, the online data contains the universe of goods offered on websites, while the offline data includes a sample of goods offered in stores.

Rationalizing sample differences across sales channels is fundamental for understanding and drawing conclusions from price statistics stemming from these two different data sources. The last part of this paper presents evidence on the compositional differences between sales channels. For instance, I find that more than half of the price categories under analysis report (i) greater average price and (ii) greater share of missing products (turnover) in their online sample than in their offline counterpart for the vast majority of retailers. Hence, it is possible that, the online price collection considers product varieties not typically considered in (offline) price surveys, which might in turn explain the results previously discussed.[2]

This paper contributes to three strands in the literature on price rigidities. First, this study complements the rapid growing body of research on the study of web scraped prices as input for policy analysis. Research at central banks by Macias et al. (2019) and Hull et al. (2017) evaluate the use of web scraped data for improving their nowcast and short-term inflation forecasts, respectively.[3] This paper adds on this literature by providing evidence on the transition from survey data to web scraped data when calculating metrics on nominal rigidities. These metrics, which are used to inform macroeconomic models, have been typically computed employing data from price surveys.[4] The findings in this paper show that, following the same methodology benchmarked by papers using survey data, changing the scope of price collection and data sources (i.e. all prices on websites) might not reflect the same degree of price stickiness as found in survey data. An open question remains on whether and when survey and/or census-like data should be employed for computing aggregate price moments. Further research is needed as big data sources are ever more prevalent in policy work.

[2]High-end or low-end goods, special editions or seasonal varieties could be among the divergence in the sample composition. Although this study does no corroborate whether products in one dataset is a subset of the other dataset, Cavallo (2017) reports that multi-channel retailers tend offer the same set of goods across sales channels using data from 10 countries.

[3]Another line of research in this literature comes from National Statistical Offices (NSO). Their work focuses on highlighting the benefits and challenges of switching from traditional price collection methods to web scraped methods. See Flower (2019); Konny et al. (2019); Van Loon and Roels (2018); Griffioen and Ten Bosch (2016); Rafael and Reyes (2019); Auer and Boettcher (2016); Glassock and Holt (2019).

[4]See, among others, Bils and Klenow (2004), Nakamura and Steinsson (2008), Dhyne et al. (2006).

Second, this research contributes to the comparison of stylized facts of price adjustments across sales channels of the same retailers. Cavallo (2017) is perhaps the most representative example in this strand. This paper differs from Cavallo (2017) by looking at the frequency and size of price changes of product categories, while the former focuses on individual products. The results in this paper are at odds to Cavallo (2017) since the author finds that products tend to change at same frequencies across channels. I provide an extensive discussion on potential drivers on the misalignments of results, in particular the difference in the composition of goods within categories mainly dictated by the universe versus sample approach used in the price collection methods.

Third, this study complements the literature on sticky prices using web scraped prices. Papers by Cavallo (2018), Coronado et al. (2020) and Peña and Prades (2021) are great references in this field. Cavallo (2018) exhibits the small size in the distribution of web scraped prices changes around zero. The author argues that previous findings drawn from survey data reporting a large share of small price variations might be explained by imputations and the use of average prices. This study confirms that the distributions of online price changes report a minor fraction of small price changes. However, this paper provides evidence that, despite abstracting from imputations and average prices, the distribution of offline price changes still reports a non-negligible size around zero.[5] Moreover, Coronado et al. (2020) and Peña and Prades (2021) provide statistics on the frequency of price changes for Peru and Chile, respectively. This paper differs from Coronado et al. (2020) in the scope of product categories under study (more than 100 relative to 11 product categories). Furthermore, Peña and Prades (2021) calculate price moments for intra-year periods. In contrast, metrics on nominal rigidities reported in this paper are computed for periods of time of at least one year long, limiting the effects of seasonal patterns.

The paper is organized as follows. Section 2, presents the data characteristics of web scraped and CPI prices. Section 3 describes the methodology followed for computing the price moments discussed throughout the paper. Section 4 centers at presenting the comparison across channels using the pre-2020 data, while Section 5 shows evidence of the price-setting behavior during the Covid-19 pandemic in 2020. Section 6 discusses sample differences across sales channels that could potentially explain why price moments are dif-

[5]The brick and mortar data in this study is the one used for computing the CPI in Mexico. To that end, INEGI uses a number of check for keeping to a minimum the number of measurement errors. Hence, this should be less of a problem generating small price changes.

ferent online and offline. Section 7 concludes.

2 Data

In this section, I outline both data sets analysed in the paper. The online price data set is compiled by Banco de Mexico. The offline price data set comes from the CPI microdata gathered by INEGI. The price comparison is done for retailers appearing in both online and offline data sets. These outlets are commonly known as "multi-channel" retailers as they offer their clients multiple consumption channels, in this case online and offline. For further price collection methods and summary statistics, please refer to the Appendix.

2.1 Online

The online price collection, compiled by Banco de Mexico, is carried out by a robot parsing out the website of eight retailers with online presence in Mexico. They are three supermarkets, two price clubs and three departamental stores. These retail chains have brick-and-mortar stores in different cities throughout Mexico and are encompassed in INEGI's (offline) price survey.

In broad terms, the price collection takes place as follows. First, the robot gathers data from each and every item displayed on the website. Per product, the robot collects the product's identifier, description and price(s). Normal and posted prices are available for six retailers, while for the remaining two retailers posted prices are gathered.[6] After the price collection is completed, goods are manually classified into "product categories", which are equivalent to the most disaggregated level of aggregation of categories in the CPI, known as *genéricos* by INEGI. Thus, one should interpret product categories as clusters of fairly homogeneous goods and similar to one further level of disaggregation from the UN's COICOP classification. Examples of product categories are Milk, Eggs, Women Trousers, Men Trousers, Fridges or Televisions.

As it is described extensively in the methodology section, the stylized facts calculated by product category and retailer provides a point of comparison between online (websites) and offline (brick and mortar) price-setting without having to match products across sale chan-

[6] Posted prices are considered those paid by consumer, including sales, although they are not flagged out by a sales indicator.

nels, as in Cavallo (2017). This study draws stylized facts from the universe of goods observed in a given retailer's website and compare them to the stylized facts calculated from a sample of fairly similar goods observed on the shelves of brick and mortar stores of the same retailer.[7]

The start and end dates of collection, as well as the frequency of price collection, vary by retailer. Dates and frequency of observation were mainly dictated by technological/resource constraints and not by design.[8] As Table 1 shows, the earliest price collection took place for one retailer in January 2016, three started in the Spring and Summer 2016, while the remaining four commencing date was in late 2017. End dates are more homogeneous throughout retailers, being December 31st 2020 the last price collection.

Moreover, the frequency of price collection varies not only between retailers but also within retailer. For instance, as reported in Table 1, the data set contains nearly daily observations for three retailers. In contrast, five retailers are observed at lower frequencies, with Retailer 6 being parsed out nearly every seven days apart. Hence, the number of days in the online survey vary per retailer: there are over 1,100 days of prices available for Retailer 2, while only around 100 for Retailer 6. However, the number of weeks and fortnights for which there is at least one day of observation in such week/fortnight is not so different across retailers, as reported shown in Table 1. For instance, although Retailer 2 is nearly 10 fold Retailer 6 in terms of daily observations, fortnightly information (i.e. at least one price collection every 15 days) is only doubled between these two retailers (76 and 39 fortnights, respectively). If one considers 24 fortnights as one year, there is more than two years of data for each retailer except Retailer 6, for which there are 39 fortnights available.

The online price survey considers all products available on the website on the collection date. Considering all available products contrasts to studies like Cavallo (2017) where items to be surveyed are selected beforehand. By analyzing all products for calculating the stylized facts presented in the next section, this study provides a complete picture of retailers' price-setting behavior online. All in all, the online data set comprehends over 14 million price quotes from more than 150 thousand different products across the eight retailers.

[7]One might be concerned on whether retailers offer the same, or at least similar, set of goods on their website than those offered in their brick and mortar stores. Cavallo (2017) finds that in most retailers across different countries, goods in brick and mortar stores also appear on their websites and viceversa.

[8]Issues at the Bank's server and/or a change on the website's layout were among the most common situations impeding the robot to successfully survey retailers' websites on a given day.

2.2 Offline

The offline price data set comes from the price survey undertaken by INEGI for CPI calculation purposes. Although INEGI surveys numerous retailers (from supermarkets, automobile dealerships, hairdressers, restaurants, among many others), this analysis centres at the same eight retail chains for which online prices are available.

The CPI price survey takes place, in broad terms, by price collectors visiting on a regular basis physical stores. Upon their visit, prices for pre-defined fixed basket of goods are gathered. That is, price collectors are equipped with a checklist of products to be priced per retailer. Products' characteristics are outlined in the checklist (e.g. size, color, model, etc.) in order to identify the same set of products on the same store in every visit. INEGI classifies each and every product into "product categories", known as *genéricos*, and, as mentioned before, product categories are interpreted as clusters of fairly homogeneous goods.

There are a number of characteristics that are worth highlighting steaming from the offline price data. First, this data source comes from a survey. That is, it only considers a sample of goods exhibited on the shelves per product category and retailer, contrasting with the online price data set which contains all goods displayed on their websites. The number of products by product category and retailer is set by INEGI.[9]

Second, the CPI survey takes place across different locations in Mexico. In order to maximize the sample size of products observed per price category in each retailer, all prices observed in the retailer, regardless the store (branch), are considered for the computation of moments. Thus, in the context of the offline price survey, the term *retailer* should be understood as retail chain composed of the various branches included in the price survey. The validity of considering goods in different stores for calculating the frequency and size of price adjustments at retailer level comes from the fact that, although price levels might be different across stores, price-setting dynamics are mainly dictated by corporates and less so by local store managers. In fact, using data from the US, Cavallo (2017) reports evidence of little price dispersion within stores of the same retailer, while DellaVigna and Gentzkow

[9] According to the income-expenditure survey, INEGI sets the sample size per product category. Then, INEGI divides the sample size by type of retailer (e.g. supermarket, street market, departamental store, etc) using also information from the income-expenditure survey. However, the number of items to be priced is not evenly spread across retailers within type of retailers. The retailers (intra type of retailer) are chosen by price collectors based on their expertise on the field. For more on sample sizes per product category and price informants, see the CPI Methodological Handout.

(2019) and Nakamura et al. (2011) document uniform prices across different branches of the same retailer. Table 1 reports the number of stores per retailer in the offline price data set. Retailer 4 and Retailer 8 are only observed in 8 different locations, while Retailer 3 is surveyed in 76 different stores.

Third, the survey considers sales prices in all retailers as long as (i) they are not conditional on purchasing a minimum of goods different than one and (ii) they are not clearance prices.[10] However, in contrast to the online price survey, price collectors do not register the normal price in addition to the sales price.

Forth, the price survey by INEGI takes place on a timely and regular basis as it is the stepping stone of measuring inflation in Mexico. Hence, there are no uneven pricing date gaps as in the online price survey. On the one hand, all product categories related to food and beverages categories are priced on a weekly basis. On the other hand, all non-food categories are priced on a fortnightly fashion.[11] This distinction between weekly and fortnightly priced categories will carry on forward in our analysis in order to bring closer the comparison between online and offline price statistics.

Fifth, prices from the CPI survey, as in the online price dataset, are actual price quotes and not average prices nor imputations. These distinctions are important as studies like Cavallo (2018) and Alvarez et al. (2016) attribute averages prices or imputations to biases toward more frequent and smaller in magnitude prices changes.

Sixth, we use data from first week of 2016 until the last week in 2020 for all retailers. The decision to consider the complete time span, and not dropping observations at times of problems with the web scraping, was taken to have the richest possible price-setting history. Apart from the Covid19 pandemic in 2020, the time mismatches are considered to be minor since the CPI survey does not have time gaps, while the web scraped data have few blackout periods by retailer. Nonetheless, the results do not change qualitatively if one restricts the CPI time span to exactly match the same weeks/fortnights for which there is online data available as reported in the Appendix.

All in all, the offline price survey comprehends a little less than one million price quotes

[10]For the first case, for instance, 3x2 discounts are not included but 2x1 are considered as a 50% price decrease. For the second case, aggressive price drops due to "last item" sales are not included.

[11]The CPI survey also prices a number of services but they are neglected from the analysis as our online price data set considers goods prices only. Although some of the retailers considered in both online and offline data sets offer few services (e.g. hair salon or car maintenance), none of the service fees were on display through their website.

from about 22 thousand different products. These prices gauge more than 8.5% of the official Mexican CPI.

Table 1: Data by Retailer from 2016 to 2019

	Online								Offline					
	Start date	End date	Days	Fortnights	Observations (Thousands)	Products (Thousands)	Frequency of Observation (Days)	Sales	Start date	End date	Observations (Thousands)	Products (Thousands)	Outlets Locations	CPI Weight (%)
Retailer 1	01jan2016	01jan2020	1,087	76	1,984.1	4.9	1.3		01jan2016	01jan2020	12.2	0.3	11	0.4
Retailer 2	31may2016	01jan2020	1,280	88	2,069.9	4.8	1.0		01jan2016	01jan2020	31.2	0.7	30	1.9
Retailer 3	21nov2017	01jan2020	627	48	1,228.1	5.2	1.2	✓	01jan2016	01jan2020	168.6	4.8	76	4.6
Retailer 4	21nov2017	01nov2019	440	40	169.2	1.2	1.6	✓	01jan2016	01jan2020	3.4	0.1	8	0.1
Retailer 5	21nov2017	27dec2019	511	47	378.5	2.2	1.5	✓	01jan2016	01jan2020	31.5	1.2	40	0.4
Retailer 6	21nov2017	06aug2019	91	39	918.6	50.6	6.9	✓	01jan2016	01jan2020	133.5	4.7	53	0.6
Retailer 7	11aug2016	29dec2019	320	78	556.8	20.9	3.9	✓	01jan2016	01jan2020	91.2	3.5	42	0.5
Retailer 8	12aug2016	01jan2020	561	83	778.0	62.3	2.2	✓	01jan2016	01jan2020	14.3	0.6	8	0.1

Note: A fortnight is counted if there is at least one observed day in the fortnight. *Fortnights* are defined from the 1st until the 15th, and from the 16th until the last day of the month. *Observations* are the number of prices in the dataset. *Products* represent the number of unique identifiers in the retailer. *Frequency of Observation* is the mean number of days between price observations. *Outlets Locations* stands for the number of stores in the retail chain encompassed in the CPI survey. *CPI weight* represents the total weight from the individual products priced at the retailer (includes weights from food-categories).

3 Methodology

In this section I outline the methodology followed for calculating the stylized facts of price adjustments in both data sets. First, I start by defining what constitute a price change and how the frequencies of price adjustments are calculated, which, in turn, they would help dealing with the mixed frequencies of observations between the offline and online price data. Second, I provide a description on the calculation of the size of price adjustments. Finally, further details are provided on the different price normalizations for computing price distributions.

I consider a price change if the price of the product with a specific product identifier, which belongs to a product category and a given retail chain at time t is different from its price at time $t-k$. Since in the CPI survey prices for food categories are collected once a week and for non-food categories every fortnight, k is 7 and 14 for prices collected in brick and mortar stores. Hence, prices changes in the web scraped data are also calculated using the 7 and 14 days price difference for products in food and non-food categories, respectively In fact, Cavallo (2018) follows a similar strategy when comparing prices from web scraped and scanner data sources.

Next, I calculate the frequency of price adjustment for product category j in the retail chain r in the distribution channel $v \in \{\text{Offline, Online}\}$ as:

$$FreqPriceChange^{v}_{j,r} = \frac{\sum_{i\in\Theta^{v}_{j,r}} \mathbb{1}_{\text{ if } p_{i,j,c,t}\neq p_{i,j,c,t-k}}}{\sum_{i\in\Theta^{v}_{j,r}} \mathbb{1}_{\text{ if } p_{i,j,c,t}\& p_{i,j,c,t-k} \text{ observed}}} \tag{1}$$

where, $p_{i,j,c,t}$ is the price (in logs) of product i, which belongs to product category j, offered by retailer r on day t. The sums in both numerator and denominator run through the set of products offered by distribution channel, that is $i \in \Theta^{v}_{j,r}$

An obvious concern arises since price collection on websites happens nearly everyday, while price collection in physical stores is carried out at lower frequencies. Although measuring price changes with similar days apart in both types of price collection ameliorates different the nature of price collection in both data sets, having repeated observations of a given product in one week (as in the web scraped data) creates a moving average effect per product that might not produce the same statistics as having a single observation per product in one week (as in the CPI survey).[12]

In order to further make both types of price collection comparable, I opt to keep one observation per week in the online data set for computing the frequency and size of price adjustments. In fact, this is a similar methodology followed by INEGI in the CPI data set: price collectors visit the same store 7 or 14 days apart, and price collectors are encouraged to visit retail chains on the same weekday as their peers. The day of the week in the web scraped data set is selected, per retailer, as the day that maximizes the Spearman correlation coefficient of the frequency of price adjustment of the categories in the retailer across distribution channels. In other words, the frequencies of offline price adjustments of the categories priced in a given retailer are compared to those from the online survey calculated using only one day of the week at a time.[13] I decide to use the Spearman correlation coefficient as it focuses on the ordinal relationship of the variables' observations to be compared. Since I do not know, at least a priori, if there is a meaningful relationship on the magnitudes of the frequencies of adjustments between channels of distribution, the Spearman coefficient offers a broad picture on whether the product category changing more often in brick and mortar stores is associated with the category also changing more frequently on websites without punishing for their misalignment in magnitudes.

The Spearman correlation coefficients for each day of the week and retailer are summa-

[12]For more on the moving average effect of having repeated observations of a given product in one week, as instead of just one observation, see the Appendix.

[13]If retailers were to change prices once a week in both distribution channels, picking any given day of the week of the online survey would make little difference on the stylized facts of price adjustments. However, price setting behavior is more complex that that.

rized in Table 2 for non-food price categories (priced every other week) and in Table 3 for food price categories (priced every week) using data from 2016 to 2019.[14] The second to last column under the title "7-Days" calculates the Spearman correlation by retailer pooling all days of week. Not surprisingly, as this column use all days, it turns out to be suboptimal relative to the day with the greatest correlation. Finally, the last column highlights the day of the week reporting the greatest point estimate of the Spearman correlation by retailer, which are the ones to be used in the benchmark results.

For non-food categories, Table 2 shows that for some retailers the day of the week considered in the online data for the analysis makes little difference when comparing them to the offline data. For instance, Retailer 1 and Retailer 2 report a Spearman coefficient around 0.75 regardless the day of the week. In contrast, for some retailers the day of the week matters when comparing price changes across distribution channels. Retailer 5 exhibits a closer qualitatively relationship between the online and offline frequency of price adjustments on Wednesdays than, for instance, Fridays, 0.61 and 0.36, respectively. Similarly for Retailer 6, the maximum correlation is calculated using Friday data, whilst the minimum is Wednesday, 0.67 and -0.65, respectively.[15] Moreover, although most of the retailers report at least a day with a positive and statistically significant Spearman correlation, Retailer 3 and Retailer 4 are the exception showing no day with a statistically significant correlation different from zero. Since the stylized facts are presented by retailer, I include these two retailers despite in the analysis and let the data speak for itself.

For food categories, a similar message is conveyed by looking at Table 3. Retailer 1 and Retailer 2, there are not big differences on the day chosen for the analysis. Retailer 3 and Retailer 4 exhibit the maximum Spearman correlation coefficient on Wednesday and Tuesday, respectively. Finally, Retailer 5 report no statistically significant coefficient but I use Friday nevertheless.

Having discussed how this study uses only one day of the week by retailer in the online dataset for calculating the price statistics, I continue by providing further details on how the size of price changes are computed in the paper, which they will be also calculated using one day of the week.

[14] For price moments using 2020 data, see Section 5.

[15] One could see this case arising if price collectors in the CPI survey consistently visit the brick and mortar stores Wednesday and Friday of Retailer 5 and Retailer 6, respectively. Unfortunately, given the available information in the data set, it is not possible to verify this is actually the case.

Table 2: Non-Food Categories

Spearman Correlation of the Frequency of Online and Offline Prices Changes

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Avg 7-Days	Max Corr
Retailer 1	0.78 ***	0.76 ***	0.77 ***	0.76 ***	0.73 ***	0.75 ***	0.76 ***	0.76 ***	Sunday
Retailer 2	0.63 ***	0.64 ***	0.64 ***	0.64 ***	0.68 ***	0.64 ***	0.65 ***	0.65 ***	Thursday
Retailer 3	-0.14	-0.15	-0.14	-0.15	-0.13	-0.13	-0.13	-0.14	Saturday
Retailer 4	0.18	0.20	0.21	0.17	0.10	0.29	0.25	0.20	Friday
Retailer 5	0.55 ***	0.55 ***	0.60 ***	0.67 ***	0.62 ***	0.55 ***	0.55 ***	0.58 ***	Wednesday
Retailer 6				-0.54 ***		0.66 ***		0.06 ***	Friday
Retailer 7	0.09					0.21	0.35 **	0.22	Saturday
Retailer 8						0.27	0.36 **	0.31 *	Saturday

Note: Each Spearman correlation coefficient is calculated as follows. First, price changes are calculated as the 14-day log price difference using the weekday in question only. Then, the frequencies of online price adjustment by category and retailer are calculated. Finally, the frequency of online price adjustment is compared with the frequency of offline price changes via a Spearman correlation coefficient. The last column, under the title "Avg 7-Days", considers the 14-day apart price changes using all days and not one day at the time. The lack of online price collection in certain days for few retailers prevents calculating the Spearman correlation, generating few empty cells in the table. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Food Categories

Spearman Correlation of the Frequency of Online and Offline Prices Changes

	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Avg 7-Days	Max Corr
Retailer 1	0.85 ***	0.85 ***	0.86 ***	0.87 ***	0.87 ***	0.85 ***	0.85 ***	0.86 ***	Thursday
Retailer 2	0.62 ***	0.64 ***	0.61 ***	0.61 ***	0.62 ***	0.61 ***	0.61 ***	0.62 ***	Monday
Retailer 5	0.04	0.10	0.09	0.10	0.10	0.13	0.06	0.09	Friday

Note: Each Spearman correlation coefficient is calculated as follows. First, price changes are calculated as the 7-day log price difference using the weekday in question only. Then, the frequencies of online price adjustment by category and retailer are calculated. Finally, the frequency of online price adjustment is compared with the frequency of offline price changes via a Spearman correlation coefficient. The last column, under the title "Avg 7-Days", considers the 7-day apart price changes using all days and not one day at the time. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The size of (non-zero) price adjustment of a given product is calculated as the difference of $p_{i,j,c,t}$ and $p_{i,j,c,t-k}$. Following the literature on nominal rigidities, like Dhyne et al, aggregates at category or retailer level are computed using the absolute value of prices changes. This strategy has been adopted for avoiding any cancelling effects between price hikes and price drops resulting in a close to zero average. In particular, the average size of price adjustments, conditional a price change, for product category j in retailer r and distribution channel $v \in \{\text{Offline, Online}\}$ is calculated as:

$$SizePriceChange^{v}_{j,r} = \frac{\sum_{i \in \Theta^{v}_{j,r}} |\Delta^{(k)} p_{i,j,c,t}| \quad \times \quad \mathbb{1}_{\text{ if } \Delta^{(k)} p_{i,j,c,t} \neq 0}}{\sum_{i \in \Theta^{v}_{j,r}} \mathbb{1}_{\text{ if } \Delta^{(k)} p_{i,j,c,t} \neq 0}} \tag{2}$$

where $\Delta^{(k)} p_{i,j,c,t}$ denotes the percentage change of product's i price adjustment (in log approximation) relative to its price k days ago, $k = 7$ and $k = 14$ for food and non-food categories respectively. Hence, $SizePriceChange^{v}_{j,r}$ should be interpreted as the average of the absolute value of the percentage change (in log approximation) of products belonging to the category j, retailer r and offered by distribution channel, that is $i \in \Theta^{v}_{j,r}$.

Finally, I study how likely it is to observe extreme price changes, given a price adjustment, across distribution channels by looking a the kurtosis of the distribution of price changes. In contrast to the frequency and size of price changes reported at the product category, retailer level and distribution channel, the kurtosis is calculated at retailer and distribution channels only. Since the kurtosis is quite sensitive if observations come from random variables with heterogeneous parameters, prices changes are normalized by product category and retailer such that,

$$z_{i,j,r,t} = \frac{\Delta^{(k)} p_{i,j,r,t} - \mu_{j,c}}{\sigma_{j,r}} \tag{3}$$

where $\mu_{j,r}$ and $\sigma_{j,r}$ are the mean and the standard deviation of the product category j and retailer r. Notice that Expression 3 standarizes prices changes regardless their distribution channel.

4 Stylized Facts of Online and Offline Price-Setting

4.1 Frequency of Price Adjustments

Table 4 reports the benchmark results on the frequency of price changes for non-food categories by retailer. The first two columns report the average frequency of price adjustments across categories in each retailer. The third column is the p-value of a mean equality t-test between the online and offline average frequency, while the forth column shows the number of price categories in both online and offline datasets.[16]

For most retailers, there is a statistically significant difference on the average frequency of price changes between their online and offline channels. Notably, from Retailer 1 to Retailer 5 favor the idea of more frequent price adjustments offline than in the online channel. In contrast, Retailer 6 and Retailer 8 exhibit greater average frequency of adjustments in their online prices than in their offline counterparts. The null-hypothesis of equality is not rejected at 10% significance level for Retailer 7.

The following set of three columns in Table 4 focuses on comparing the frequency of price changes of individual price categories. In particular, I run z-tests on the equality of proportions of price changes for each product category and count how many are statistically different (5%) in favor of more changes in a given channel or not. The first of the three columns reports the number of categories where the online price survey exhibited greater proportion of price changes, while the second shows the number of categories for which the null-hypothesis

[16]As mentioned in the Section 2, price moments are calculated using categories included in both online and offline datasets simultaneously.

of equality could not be rejected, and the last column of the bloc highlights the number number of categories where the frequency of price changes is greater offline than online.

In line with the first two columns, on the one hand, Retailer 1 to Retailer 5 show a great number of individual categories reporting more frequent price changes through their offline channel than on their online platforms. For instance, 21 out of 38 product categories in Retailer 1 and 27 out of 38 categories in Retailer 2 exhibit this price-setting behavior. On the other hand, Retailer 6 and Retailer 8 have more price categories changing more frequently their online princes than their offline prices.

Although retailers have more price categories favoring more frequent price changes on either sales channel, some categories seem to change at similar frequencies across channels. For example, despite 24 product categories in Retailer 5 change more frequently offline than online, for 19 categories we cannot reject equality on their proportion of price changes across channels, while 5 categories actually change more often online than offline. Notice also Retailer 8, where 18, 4 and 12 categories change more often online than offline, seem to be equal and adjust more frequently offline than online, respectively.

The third bloc of columns report the Spearman correlation coefficient, as well as its p-value. These coefficients are the same as those reported in Table 2 as they are the ones that maximize the ordinal relationship between online and offline frequencies of price adjustments.

The last set of columns shows the slope from an OLS regression, where the dependent variable is the frequency of price changes per category from the online dataset and the independent variable is the offline frequency of adjustment, plus a constant. Apart from Retailer 3, all coefficients are positive and statistically significant different from zero. Thus, categories changing more frequently on retailers' websites are also adjusting more frequently in bric and mortar stores, despite their order of magnitudes might differ. In fact, for Retailer 7 and Retailer 8 we cannot reject the view that the OLS slope is different from one. This result might be indicative that, although the overall average frequency of price changes is different, as in Retailer 8, retailers might use price-setting strategies shifting the frequencies of adjustments from one sales channel (relative to the other one) by a constant factor.

Figure 1 depicts the data used in Table 4. The frequency of price changes from the online channel is highlighted in the vertical axis, while the horizontal axis comes from the offline price survey. Each scatter represents one price category, the OLS sloped discussed in Table 4 and the 45 degree line are depicted as the solid and dashed lines, respectively. As mentioned above, most scatters lie below the 45 degree line for Retailers 1 to 5, whilst the opposite happens for Retailers 6 to 8; and, with the exception of Retailer 3, scatters exhibit a positive relationship in the frequency of price changes across their sales channels for all retailers.

Table 5 reports results from food and beverages categories at retailer level, which are priced on a weekly basis. Three retailers are considered in this table since the remaining retailers do not offer food and beverage products and/or the sample size of product categories is too small.[17] In all three retailers the fraction of price changes is greater in the offline channel than in the online counterpart. The difference between channels is in fact greater for these type of goods than for the non-food categories. For instance, Retailer 2 shows more than 15 p.p. difference across channels (14% and 32% for online and offline, respectively), while in Retail 5 the frequency of offline price changes nearly doubles its online counterpart. Moreover, in line with the findings from the non-food categories, the OLS slope from the three retailers also show a positive relationship between the frequency of price changes across their channels. However, the slope from Retailer 5 is not statistically significant different from zero.

The panels in Figure 2 illustrate how the frequency of online price changes relate to the frequency of offline price adjustments by retailer. Again, the frequency of price changes through the offline channels is greater than through the online platforms as most scatters lie below the 45 degree line. Nonetheless, the positive relationship is quite robust, particularly in Retailer 1 and Retailer 2.

Table 4: Non-Food Categories

Frequency of Price Adjustment by Retailer

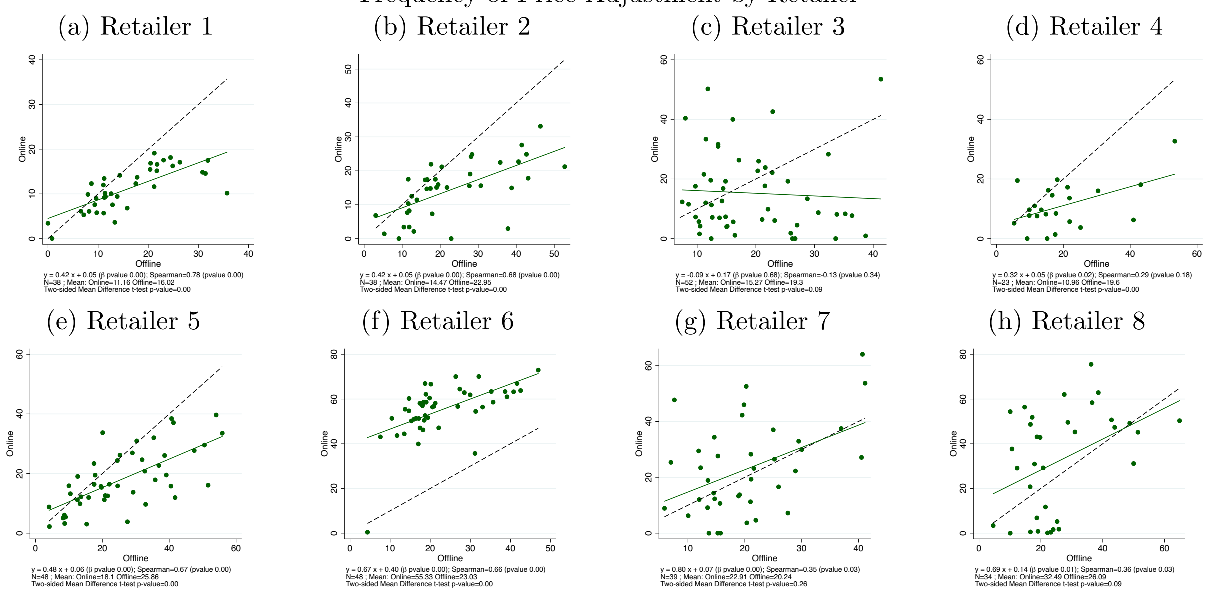
	Frequency of Price Changes				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	11.16	16.02	0.00	38	1	16	21	0.78	0.00	0.42	0.00	0.00
Retailer 2	14.47	22.95	0.00	38	2	9	27	0.68	0.00	0.42	0.00	0.00
Retailer 3	15.27	19.30	0.09	52	15	9	28	-0.13	0.34	-0.09	0.68	0.00
Retailer 4	10.96	19.60	0.00	23	1	10	12	0.29	0.18	0.32	0.02	0.00
Retailer 5	18.10	25.86	0.00	48	5	19	24	0.67	0.00	0.48	0.00	0.00
Retailer 6	55.33	23.03	0.00	48	47	0	1	0.66	0.00	0.67	0.00	0.02
Retailer 7	22.91	20.24	0.26	39	14	10	15	0.35	0.03	0.80	0.00	0.45
Retailer 8	32.49	26.09	0.09	34	18	4	12	0.36	0.03	0.69	0.01	0.26

Note: The average frequency of online price changes comes from the day maximizing the Spearman between online and offline prices. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions using online prices as dependent variable, offline prices as the independent variable, plus a constant. The last three columns report the number of categories where, using two-sided z-test of proportion differences, the difference is statistically insignificant at 5% (Equal), greater fraction of online price changes than offline changes at 5% significance level ($On > Off$), and greater proportionof offline price changes than online adjustments at 5% significance level ($Off > On$).

[17] A threshold of 20 categories per retailer is put in place for calculating averages.

Figure 1: Non-Food Categories

Frequency of Price Adjustment by Retailer



(a) Retailer 1 (b) Retailer 2 (c) Retailer 3 (d) Retailer 4

(e) Retailer 5 (f) Retailer 6 (g) Retailer 7 (h) Retailer 8

Table 5: Food Categories

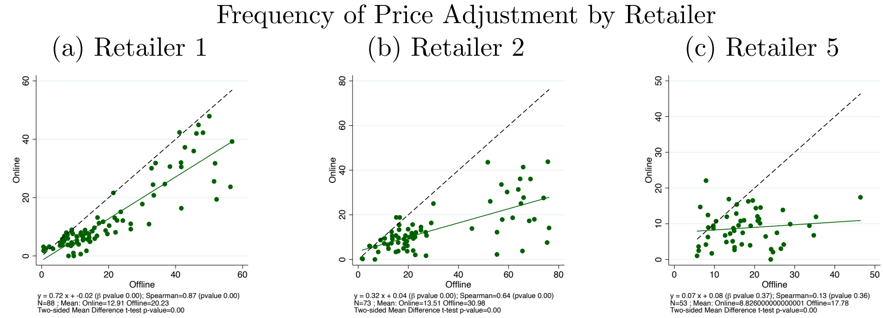
Frequency of Price Adjustment by Retailer

	Frequency of Price Changes				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	12.91	20.23	0.00	88	1	29	58	0.87	0.00	0.72	0.00	0.00
Retailer 2	13.51	30.98	0.00	73	2	7	64	0.64	0.00	0.32	0.00	0.00
Retailer 5	8.83	17.78	0.00	53	3	16	34	0.13	0.36	0.07	0.37	0.00

Note: The average frequency of online price changes comes from the day maximizing the Spearman between online and offline prices. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions using online prices as dependent variable, offline prices as the independent variable, plus a constant. The last three columns report the number of categories for which the p-value of a two-sided z-test of proportion differences is greater than 0.05 (Equal), greater fraction of online price changes than offline changes at 5% significance level ($On > Off$), and greater proportion of offline price changes than online adjustments at 5% significance level ($Off > On$).

Figure 2: Food Categories

Frequency of Price Adjustment by Retailer



(a) Retailer 1 (b) Retailer 2 (c) Retailer 5

4.2 Absolute Size of Price Adjustments

Moving on to the average size of price changes, Table 6 reports price moments for non-food categories as defined by Equation 2. Similarly to the previous subsection, the first two columns shows the average by retailer across product categories priced in both online and offline channels. Notably, the average size of non-zero price changes by retailer of online price changes are greater the averages of offline price adjustments in all eight retailers. Point averages across channels are also statistically significant from each other as shown by the p-values from mean difference t-tests in column three. Point differences ranges from nearly 2 p.p. (Retailer 1) to about 15 p.p. (Retailer 2) in favor of greater price changes online than offline. Thus, in contrast to the frequency of price changes, where offline prices tend to change more frequently than online prices, the size of price changes of non-food categories seems to be greater for prices observed online than those offline.

The number of individual categories reporting greater size of price adjustments when compared across channels using mean difference t-tests are also leaned towards online price changes being greater than offline price adjustments. Note, however, it is not uncommon to find few categories reporting no statistically different sizes of price changes between channels, or even reporting greater changes offline than online.

The third bloc of columns in Table 6 report the Spearman correlation coefficient of the size of price adjustments across channels of the categories within the retailer.[18] Only Retailer 1 and Retailer 5 report a correlation positive and statistically significant at 10%. Nonetheless, most point estimates are positive, except for Retailer 2.

The last bloc of columns of Table 6 includes the slope from an OLS estimation using as a dependent variable the size of online price changes, as an independent variable the size of offline price changes, as well as a constant. In most cases the OLS slopes are positive. However, only Retailer 1 and Retailer 4 exhibit a positive and statistically significant slope. In fact, for Retailer 4 we are unable to reject the hypothesis of a 1-to-1 relationship between the magnitudes of prices changes online and offline.[19] Thus, there seems to persist the positive relationship across categories within retailers in the case of the size of price changes as found on the frequency of price adjustments. Nonetheless, as mentioned, the relationship is weaker and statistically insignificant in most cases.

Figure 3 shows the data used for computing Table 6. It seems like most scatters lay above the 45 degree line denoted by the dashed line, meaning that point estimates on the size of

[18]These coefficients are not the same as the ones reported in Table 2 or Table 4. Those coefficients are calculated by comparing the frequency of price changes across channels. In contrast, this coefficient is computed using the absolute value of price adjustments.

[19]Retailer 7 cannot reject a slope equal to one but neither the slope equal to zero.

online price changes is greater than the size of offline prices of such category. The OLS slope is also depicted for each retailer as a solid line. Despite being positive in most cases, one can also see the relationship between the size of online and offline prices changes across sales channels is less clear cut than how often prices adjust. See, for instance, Retailer 6.

The comparison of food and beverages categories across channels is presented in Table 7. For these categories, the average size of online price changes seems to be greater than the magnitude of offline price adjustments in all retailers. In fact, averages are statistically significant different from each other. Differences between the size of online and offline price variations range from 1 p.p (Retailer 1) to 23 p.p. (Retailer 2). These differences are also reflected in the second bloc of columns. For example, the number of categories with no statistically significant average size (within category) for Retailer 1 is more than half (45 out of 75 categories), while the majority of categories in Retailer 2 report greater online price changes than their offline counterparts.

The OLS slopes are positive and statistically significant for two out of the three retailers in the sample. These are Retailer 1 and Retailer 5. Furthremore, in all three retailers in the sample offering food and beverages, the hypothesis of a unit slope is rejected.

The average size of online and offline price changes per category is depicted in Figure 4. Similarly to the case of non-food categories, most scatter lay above the 45 degree line, implying that the average magnitude of price changes is greater online than offline.

All in all, the size of prices changes by retailer is different between channels, favoring price changes of greater magnitudes online than offline. However, categories adjusting by a greater margin online might not necessarily be those changing by a greater magnitude offline, as it was the case for the fraction of price changes.

4.3 Distribution of Price Changes

Having presented the average size of price changes, we now turn into the distribution of price changes. In contrast to the previous subsection where the sign of price variations are neglected by calculating the absolute size of price adjustments, the distribution of price changes encompasses information on price hikes (positive changes) or price drops (negative adjustments). As before, these distributions only consider non-zero price changes, price changes are calculated as the first difference of log prices and they are depicted separately

Table 6: Non-Food Categories

Size of Price Changes

	Size of Price Adjustments				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	12.69	10.95	0.01	31	15	13	3	0.49	0.01	0.44	0.01	0.00
Retailer 2	24.29	9.72	0.00	33	27	6	0	-0.24	0.18	-0.21	0.71	0.04
Retailer 3	22.65	13.47	0.00	41	34	5	2	0.19	0.23	0.21	0.48	0.01
Retailer 4	22.22	14.27	0.00	13	10	2	1	0.45	0.13	0.57	0.10	0.21
Retailer 5	15.79	9.44	0.00	41	30	9	2	0.28	0.08	0.15	0.75	0.08
Retailer 6	19.16	16.85	0.00	48	26	9	13	0.23	0.11	0.16	0.38	0.00
Retailer 7	21.45	14.13	0.00	33	24	5	4	0.12	0.50	0.48	0.23	0.19
Retailer 8	20.93	18.64	0.10	25	10	10	5	0.32	0.12	0.26	0.12	0.00

Note: Using data from 2016 to 2019 and non-food categories only. Prices changes do not consider the sign of adjustment (absolute value). The average size of online price changes comes from the weekday maximizing the Spearman between online and offline prices. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions using online prices as dependent variable, offline prices as the independent variable, plus a constant. The Equality Test columns report the number of categories where, using a two-sided t-test of mean differences, the difference is statistically insignificant at 5% (Equal), greater absolute value mean size of online price changes than offline changes ($On > Off$) or greater offline price adjustments than online changes ($Off > On$) at 5% significance level.

Figure 3: Non-Food Categories

Size of Price Changes

(a) Retailer 1 (b) Retailer 2 (c) Retailer 3 (d) Retailer 4

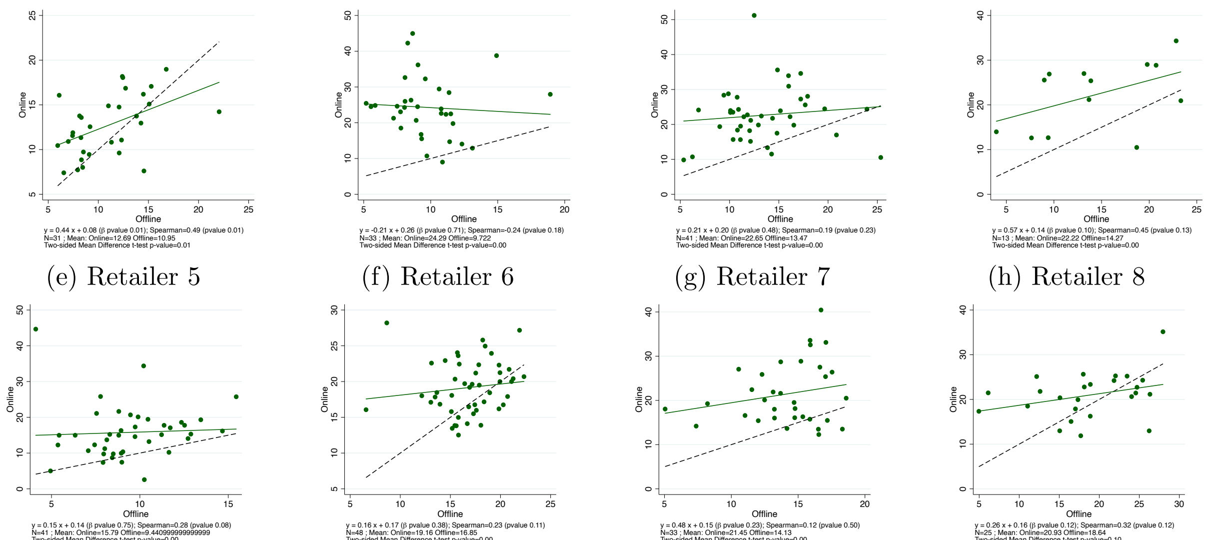


Table 7: Food Categories

Size of Price Changes

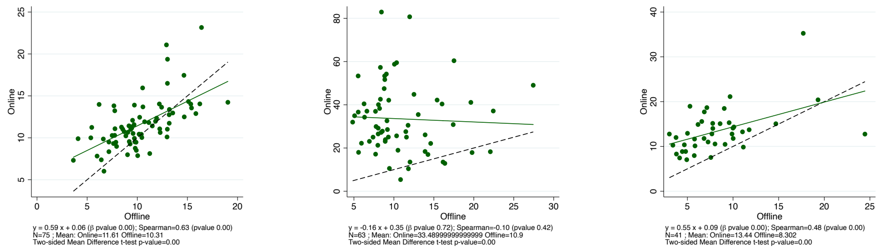
	Size of Price Adjustments				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	11.61	10.31	0.00	75	24	45	6	0.63	0.00	0.59	0.00	0.00
Retailer 2	33.49	10.90	0.00	63	55	5	3	-0.10	0.42	-0.16	0.72	0.01
Retailer 5	13.44	8.30	0.00	41	29	11	1	0.48	0.00	0.55	0.00	0.01

Note: Using data from 2016 to 2019 and non-food categories only. Prices changes do not consider the sign of adjustment (absolute value). The average size of online price changes comes from the weekday maximizing the Spearman between online and offline prices. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions using online prices as dependent variable, offline prices as the independent variable, plus a constant. The Equality Test columns report the number of categories where, using a two-sided t-test of mean differences, the difference is statistically insignificant at 5% (Equal), greater absolute value mean size of online price changes than offline changes ($On > Off$) or greater offline price adjustments than online changes ($Off > On$) at 5% significance level.

Figure 4: Food Categories

Size of Price Changes

(a) Retailer 1 (b) Retailer 2 (c) Retailer 5



for non-food and food categories.

The distributions pool all price changes in any given retailer by sales channel. Solid colored bars come from price changes observed on websites, while those with black borders illustrate price adjustments observed at brick and mortar stores. Each bar in the distributions bins price changes in multiples of 2.5 p.p.

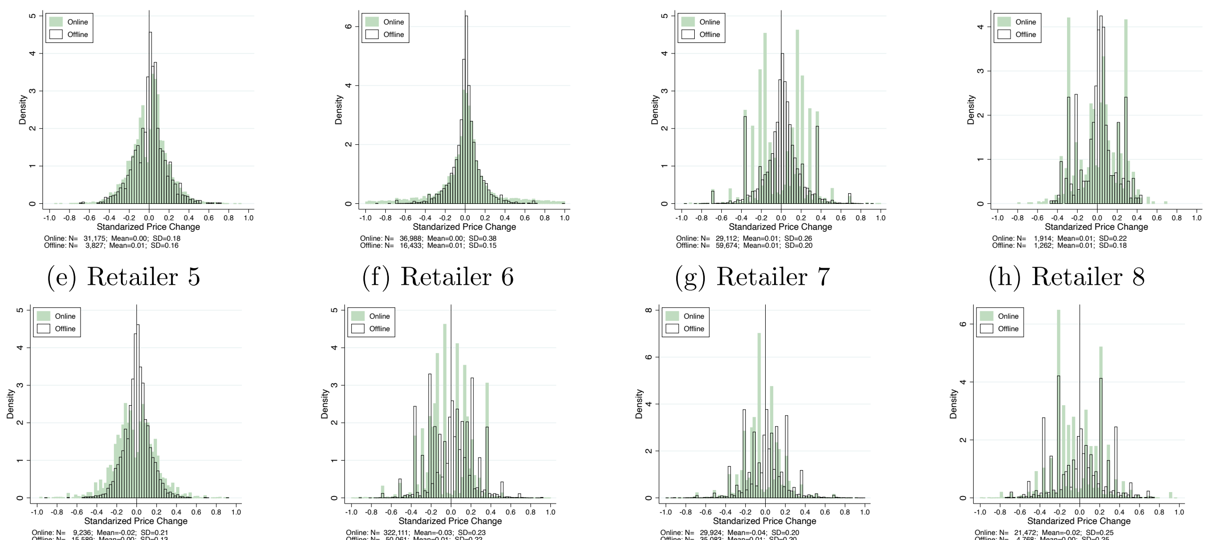
Although Figure 5 depicts the distribution of price adjustments for non-food categories only, it seems that muti-channel retailers offering both food and non-food goods (Retailer 1, Retailer 2 and Retailer 5) report changes along different values on the horizontal axis of the distribution in both sales channels. However, multi-channel retailers offering non-food categories only seem to set their price variations mainly at focal points (multiples of 5 between ±20). This characteristic is particularly acute in the distribution of online prices but it is present in the offline distribution as well. See the panel for Retailer 6 or Retailer 8.

Another interesting pattern standing out is the size of the distributions around zero (small prices changes) between sales channel. See, for instance, Retailer 3. The distribution of online prices changes exhibits a small fraction of small adjustments (±2), while the offline distribution is centered around these small variations. Alvarez et al. (2016) and Cavallo (2017) attribute the non-trivial size of small price changes to imputations and use of average prices commonly used in CPI surveys. Despite imputations and average prices are used by INEGI when computing the CPI, these two factors are not present in calculating moments of offline price changes in this paper. That is, imputations are filtered out since the dataset includes an indicator variable flagging out these cases; and observed prices are employed instead of the average prices used when computing the Mexican CPI.

All in all, greater share of prices changes at focal points, as well as a small faction of price changes around zero (small price changes), align with the fact that, on average, prices displayed on websites change by a greater margin that those in the brick and mortar stores as described in the previous subsection and reported in Table 6.

Figure 5: Non-Food Categories

Distribution of Non-Zero Price Changes

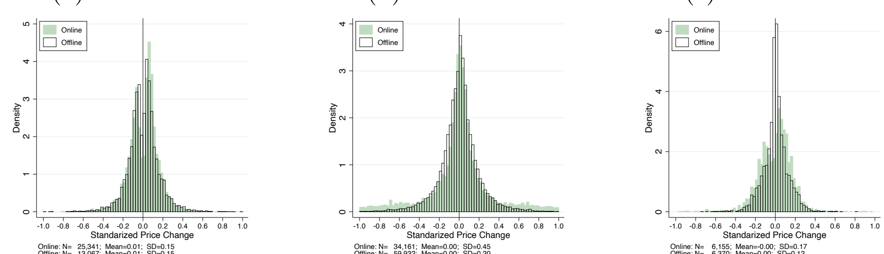


(a) Retailer 1 (b) Retailer 2 (c) Retailer 3 (d) Retailer 4

(e) Retailer 5 (f) Retailer 6 (g) Retailer 7 (h) Retailer 8

Figure 6: Food Categories

Distribution of Non-Zero Price Changes



(a) Retailer 1 (b) Retailer 2 (c) Retailer 5

4.4 Kurtosis of Price Changes

Continuing the comparison of the size of price changes across sales channels, we study the kurtosis of the distribution of standardizing prices changes.[20] The kurtosis summarizes the share of extreme values at the tails (large price changes) relative to the size of the distribution around zero (small price changes). Since leading pricing models in New Keynesian literature

[20]Alvarez et al. (2016) highlight that calculating the kurtosis from a distribution that comes from heterogeneous distributions might bias estimates of the kurtosis.

imply different shapes on the distribution of prices changes, the kurtosis has attracted the attention the researchers.[21]

Small and large price changes might be different across sales channels because of a number of reasons. Websites might respond with large price changes when facing a surge in demand causing low inventories (e.g. in the wake of Covid-19). In contrast, brick and mortar stores might adjust their prices based on finite rule-of-thumbs strategies. Menu costs might also be different across sales platforms. Modifying online price tags could be easier than modifying those in physical stores, and therefore being reflected in the share of large relative to small price changes.

Figure 7 and Figure 8 show the distribution of standardized price changes, as defined in Equation 3 from Section 3, for non-food and food categories, respectively.

For non-food categories, two out of eight multi-channel retailers report greater kurtosis in the online distribution than in the offline counterpart, in four cases the opposite happens, while in two cases the point estimates are the same. The absence of a clear pattern between retailers adds on Cavallo (2017) conclusions that retailers tend to have very heterogeneous price-setting strategies across their sales channels.

Most online and offline distributions report a value close to three, which is similar to that of a normal distribution. A notable exception is Retailer 2, reporting kurtosis of 7.96 and 5.64 for its online and offline distributions, respectively (the Laplace distribution exhibits a kurtosis of six).

Furthermore, the distribution of online price resembles more a bimodal distribution, while the offline distribution is centered at zero. In other words, the distribution of standardized price changes highlights that online prices changes report a smaller fraction of tiny price changes, while offline prices adjustments are more likely to report small variations.[22] Retailer 6, Retailer 7 and Retailer 8 exemplify these cases, for instance.

Regarding food categories, Figure 8 shows that the kurtosis of online distributions are

[21] On the one hand, price-setters facing a menu cost when adjusting their prices would be seen as a small share of tiny price changes. On the other hand, price-setters facing a constant probability of adjusting their prices could generate a non-negligible fraction of small prices changes. More specific, the kurtosis as a sufficient statistic for rationalizing the real effects of monetary policy by different models is studied by Alvarez et al. (2016).

[22] The size of the distributions around zero in Figure 7 and Figure 8 reflect the share of small price changes relative to its mean (category and retailer level). However, the mean change is close to zero as positive and negative price changes cancel out. Notice the mean of distributions in Figure 5 and Figure 6.

greater than the kurtosis of offline distributions in all three cases. Thus, the distribution of online standardized price changes report a greater share of large price changes i.e. fatter tails than the offline distribution. Also, notice that Retailer 1 and Retailer 3 exhibit not many small price changes online, while in thei offline channel small price changes are more common. The opposite happens for Retailer 2.

Figure 7: Non-Food Categories

Standardized Non-Zero Price Changes

(a) Retailer 1 (b) Retailer 2 (c) Retailer 3 (d) Retailer 4 (e) Retailer 5 (f) Retailer 6 (g) Retailer 7 (h) Retailer 8

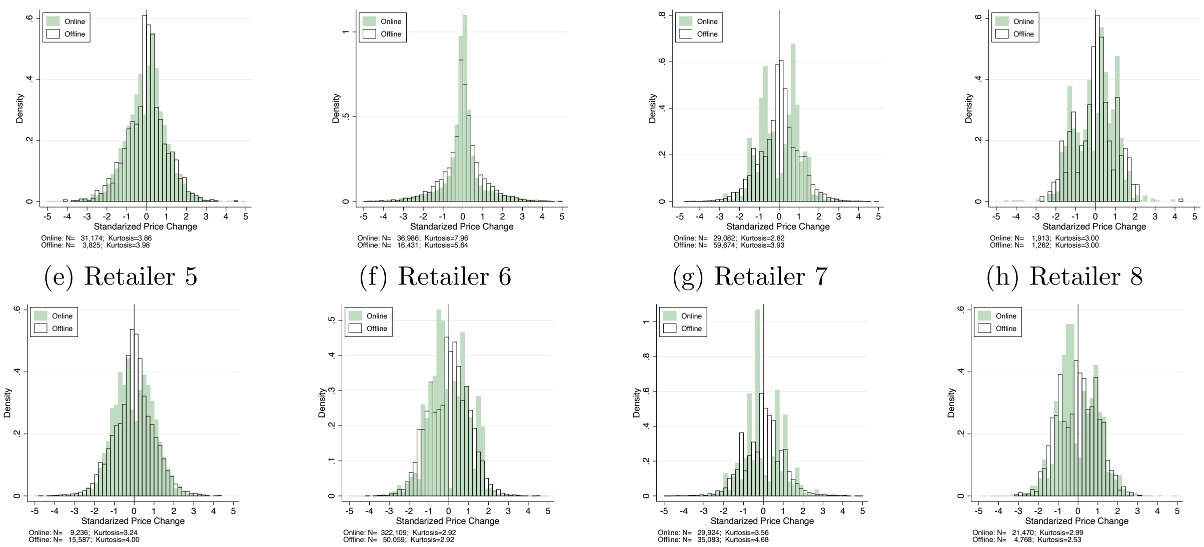
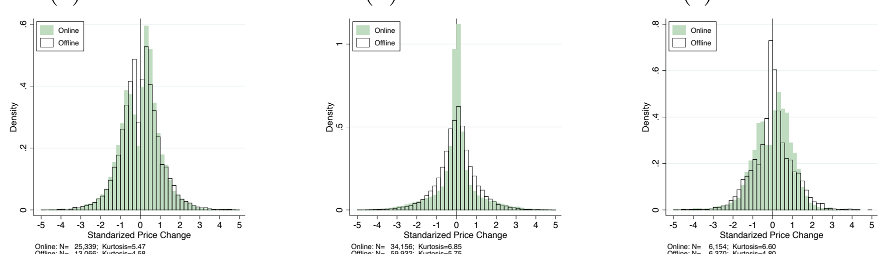


Figure 8: Food Categories

Standardized Non-Zero Price Changes

(a) Retailer 1 (b) Retailer 2 (c) Retailer 5



5 Data from 2020

This section is devoted to analyze the stylized facts of price setting using data from 2020. Due to the Covid-19 pandemic, the relation between online and offline price setting strategies in multi-channel retailers could have been different compared to previous years.

Stock-outs because of sudden surge in demand for certain goods; compulsory but temporal closure of brick and mortar stores; rapid transitioning to online shopping by consumers, which in turn might have lead multi-channel retailers to improve their websites; as well as price collectors from the National Statistical Office started monitoring goods' prices through the internet and not by actual visits to physical stores, are only a few factors that could have reshaped the frequency and size of price adjustments in the wake of the Covid-29 pandemic.

The same analysis as in the previous Section is performed but using 2020 data only. That is, it also uses the day of the week maximizing the Spearman correlation of the frequency of online and offline price changes in the 2016-2019 period. Using such day of the week, the frequency, size and distributions of online price variations are calculated and compared to their offline counterparts.

The whole year of 2020 is considered in order to have the annual cross-section. The strategy avoids any seasonal imbalance of using data from March onwards (making price moments less comparable with those from the previous Section).

Moreover, as non-essential business were ordered to temporarily shut down, price collection in physical stores from retailers in our sample selling mainly non-food categories (e.g. departamental stores) was affected. In those cases, the statistical office considered prices as *missing* on the early days, and then used imputations for computing the CPI.[23] All price variations stemming from imputations are excluded as the dataset includes an indicator variable for those cases. Then, for the multi-channel retailers in our sample, INEGI's price collectors started gathering prices from the retailers' websites. Unfortunately, it is not possible to distinguish between prices collected through the internet from those gathered from actual visits to physical stores.[24] Nonetheless, the offline dataset kept reporting prices from a sample (fixed basket) of goods as the CPI methodology implies (and not monitoring all products displayed on websites as in the online dataset).

Missing observations, in addition to the small number of products effectively observed per category in the CPI survey, contributed to having less product categories per retailer than in the 2016-2019 period. The share of missing products is revisited in Section 6.

[23] See INEGI's press releases at the time.

[24] As mentioned in Section 2, offline price moments are calculated using prices from different branches of the same retailer. As the reopening of non-essential business took place in a staggered fashion across Mexico, it could be the case that at certain moment some price collectors were visiting brick and mortar stores, while some other price collectors were still checking prices through digital channels.

5.1 Frequency of Price Changes in 2020

Table 8 reports the average frequency of price changes by retailer using data from 2020. Although slightly less clear than for the 2016-2019 period, the majority of retailers change their prices more frequently offline than online, on average. That is, four retailers report greater average frequency of price changes offline than online, while the opposite happens in three cases, and in one case the difference is statistically insignificant. In terms of the OLS slope relating the frequencies of online and offline price changes, six are positive and statistically significant different from zero and one case is not statistically different from one.

Table 9 offers a comparison between periods, 2016-2019 and 2020. In general, retailers exhibiting greater price flexibility in a given sales channel in the pre-2020 period relative to the other one also show the same pattern in the 2020 period. For instance, on the one hand, Retailer 1, Retailer 2, Retailer 3, as well as Retailer 5 exhibit greater fraction of price changes offline than online in both pre-2020 and 2020 periods. On the other hand, the frequency of online price changes is greater than the frequency of offline price changes in both periods for Retailer 6 and Retailer 8. Exceptions are Retailer 4 and Retailer 7. Retailer 4, having reported greater share of offline price changes than on its website from 2016 to 2019, in 2020 the mean frequency of price changes across sales channels is about the same and the difference is statistically insignificant. Finally, after exhibiting a statistically insignificant difference between its frequencies of online and offline price changes in the pre-2020 period, Retailer 7 shows greater online price flexibility in the 2020 period.[25]

All in all, it seems that prices tend to change more frequently offline than online for non-food categories regardless if one focuses on the 2016-2019 or the 2020 period.

Regarding the variation in point estimates of the frequencies of adjustments between pre-2020 and 2020 within retailers' sales channel, Table 9 shows that six out of the eight retailers increase their online average frequency, while eight out of eight retailers do so in their offline channel. Retailer 4 and Retailer 7 stand out by exhibiting an increase of more than 10 p.p. on the frequency of adjustments through their digital channel, whilst an increase of around 5 p.p. in physical stores. On the other side, Retailer 6 reports an increase of 19 p.p. in its offline frequency and a decrease of 2 p.p. in its online frequency. Across retailers, the average

[25]With respect to the change in OLS slopes across time periods, only Retailer 4 moved from positive to statistically insignificant relationship between sales channels. In terms of the actual slope, Table 4 and Table 8 show that the largest increase and decrease across period is observed in Retailer 7 (from 0.8 to 1.1) and Retailer 8 (from 0.7 to 0.3), respectively.

difference between the 2020 and the pre-2020 frequency of price adjustments for non-food categories is 5.1 p.p. and 5.8 p.p. for the online and offline channel, respectively. Bear also in mind that, on average, there are 7 product categories less per retailer in 2020 relative to the pre-2020 data. Missing observations in both channels, which in turn particularly affect the small number of varieties effectively observed per category in the CPI dataset, contributed to having less product categories per retailer in 2020 than in the 2016-2019 period.

Regarding food categories, Table 10 shows that on average offline prices change more frequently than online prices in all three retailers. This is the same as it is found using the pre-2020 data.

The largest variations by retailer when comparing the 2020 to the pre-2020 online data come from Retailer 2 and Retailer 1, 4.2 p.p. and -2.5 p.p., respectively, as shown in Table 11. In the offline channel, Retailer 5 reports an increase of 1.7 p.p. and Retailer 2 exhibits a decrease of 2.9 p.p. Across retailers, the average of the difference between the 2020 and the pre-2020 data for food categories is 0.1 p.p. and -1.3 p.p. for the online and offline channel, respectively.

Table 8: Non-Food Categories in 2020

Frequency of Price Adjustment by Retailer

	Frequency of Price Changes				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	12.10	16.16	0.01	27	2	13	12	0.63	0.00	0.38	0.00	0.00
Retailer 2	17.76	24.13	0.00	26	1	11	14	0.57	0.00	0.57	0.00	0.00
Retailer 3	14.46	20.98	0.01	42	9	14	19	-0.07	0.68	-0.05	0.77	0.00
Retailer 4	23.76	25.96	0.68	13	2	7	4	0.16	0.60	0.37	0.28	0.08
Retailer 5	23.39	29.61	0.00	48	5	16	27	0.71	0.00	0.78	0.00	0.08
Retailer 6	53.05	42.74	0.00	33	20	12	1	0.46	0.01	0.54	0.01	0.02
Retailer 7	36.03	25.22	0.00	40	27	10	3	0.67	0.00	1.06	0.00	0.81
Retailer 8	40.92	34.32	0.02	32	13	17	2	0.39	0.03	0.26	0.05	0.00

Note: The average frequency of online price changes comes from the day maximizing the Spearman between online and offline prices. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions using online prices as dependent variable, offline prices as the independent variable, plus a constant. The last three columns report the number of categories where, using two-sided z-test of proportion differences, the difference is statistically insignificant at 5% (Equal), greater fraction of online price changes than offline changes at 5% significance level ($On > Off$), and greater proportion of offline price changes than online adjustments at 5% significance level ($Off > On$).

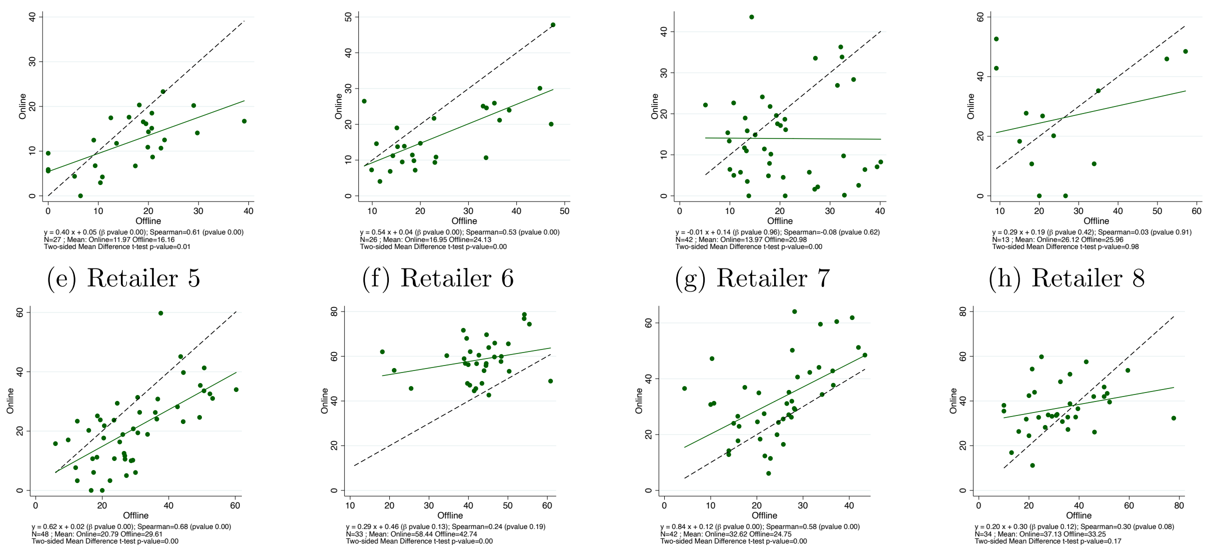
5.2 Size of Price Adjustments in 2020

Regarding the size of price adjustments for non-food categories, as reported in Table 12, four multi-channel retailers do not exhibit a statistically significant difference on their averages. In three cases, however, online prices change by a larger magnitude than offline prices.[26] Thus, in contrast to the pre-2020 data, the 2020 period is characterized by mixed evidence on

[26] Retailer 4 is omitted due to small sample issues as shown in the Appendix.

Figure 9: Non-Food Categories in 2020

Frequency of Price Adjustment by Retailer



(a) Retailer 1 (b) Retailer 2 (c) Retailer 3 (d) Retailer 4

(e) Retailer 5 (f) Retailer 6 (g) Retailer 7 (h) Retailer 8

Table 9: Comparison Between 2016-2019 and 2020 for Non-Food Categories

Frequency of Price Adjustment by Retailer

	Data 2016-2019				Data 2020				Difference (p.p.)		
	Average		Ho: Equality	Categories	Average		Ho: Equality	Categories			
	Online	Offline	p-value		Online	Offline	p-value		Online	Offline	Categories
	(a)	(b)	(c)	(d)	(f)	(g)	(h)	(i)	(f) - (a)	(g) - (b)	(i) - (d)
Retailer 1	11.16	16.02	0.00	38	12.10	16.16	0.01	27	0.94	0.14	-11
Retailer 2	14.47	22.95	0.00	38	17.76	24.13	0.00	26	3.29	1.18	-12
Retailer 3	15.27	19.30	0.09	52	14.46	20.98	0.01	42	-0.81	1.68	-10
Retailer 4	10.96	19.60	0.00	23	23.76	25.96	0.68	13	12.80	6.36	-10
Retailer 5	18.10	25.86	0.00	48	23.39	29.61	0.00	48	5.29	3.75	0
Retailer 6	55.33	23.03	0.00	48	53.05	42.74	0.00	33	-2.28	19.71	-15
Retailer 7	22.91	20.24	0.26	39	36.03	25.22	0.00	40	13.12	4.98	1
Retailer 8	32.49	26.09	0.09	34	40.92	34.32	0.02	32	8.43	8.23	-2

Note: The first and second bloc of columns come from Table 4 and Table 8, respectively. The third set of columns are calculated as the difference of point estimates of the corresponding columns from the first two blocs.

Table 10: Food Categories in 2020

Frequency of Price Adjustment by Retailer

	Frequency of Price Changes				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	10.39	17.55	0.00	74	0	38	35	0.71	0.00	0.57	0.00	0.00
Retailer 2	17.74	28.09	0.00	60	4	15	41	0.72	0.00	0.60	0.00	0.00
Retailer 5	7.50	19.50	0.00	42	0	10	32	0.39	0.01	0.12	0.16	0.00

Note: The average frequency of online price changes comes from the day maximizing the Spearman between online and offline prices. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions using online prices as dependent variable, offline prices as the independent variable, plus a constant. The last three columns report the number of categories where, using two-sided z-test of proportion differences, the difference is statistically insignificant at 5% (Equal), greater fraction of online price changes than offline changes at 5% significance level ($On > Off$), and greater proportion of offline price changes than online adjustments at 5% significance level ($Off > On$).

Figure 10: Food Categories in 2020

Frequency of Price Adjustment by Retailer

(a) Retailer 1 (b) Retailer 2 (c) Retailer 5

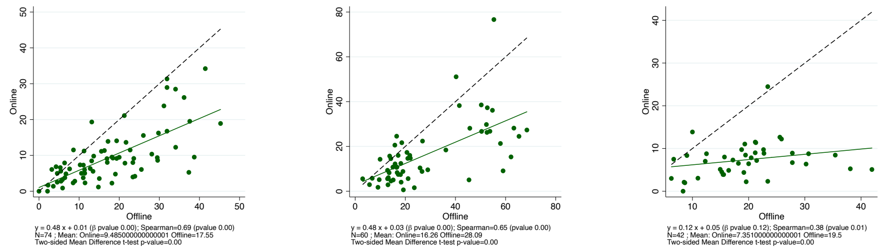


Table 11: Comparison Between 2016-2019 and 2020 for Food Categories

Frequency of Price Adjustment by Retailer

	Data 2016-2019				Data 2020				Difference (p.p.)		
	Average		Ho: Equality	Categories	Average		Ho: Equality	Categories			
	Online	Offline	p-value		Online	Offline	p-value		Online	Offline	Categories
	(a)	(b)	(c)	(d)	(f)	(g)	(h)	(i)	(f) - (a)	(g) - (b)	(i) - (d)
Retailer 1	12.91	20.23	0.00	88	10.39	17.55	0.00	74	-2.52	-2.68	-14
Retailer 2	13.51	30.98	0.00	73	17.74	28.09	0.00	60	4.23	-2.89	-13
Retailer 5	8.83	17.78	0.00	53	7.50	19.50	0.00	42	-1.33	1.72	-11

Note: The first and second bloc of columns come from Table 5 and Table 10, respectively. The third set of columns are calculated as the difference of point estimates of the corresponding columns from the first two blocs.

whether the online channel varies prices by larger sizes on average than the offline channel.

The OLS slope, relating the size of price changes across sales channels, is positive and statistically significant in four out of seven cases.[27] From these four cases, Retailer 3, Retailer 6 and Retailer 8 report a slope not statistically significant different from one, implying a one to one relationship (plus a constant) on the size of adjustments between sales channels. Qualitatively, the OLS slopes from 2020 summarized in Table 12 do not tell a different story than the findings described in the pre-2020 subsection in Table 6. With the exception of one retailer, the positive relationship between the size of online and offline price changes across categories prevails. Retailer 6 is the one exhibiting the greatest increase from its pre-2020 figure, from 0.2 to 1.5. The largest decrease is reported by Retailer 5, from 0.2 to -0.7. Retailer 2 also flipped sign from -0.2 to 0.2.

Table 13 takes a closer look across periods within sales channels. The average across retailers of the difference between the 2020 and the pre-2020 data for non-food categories is -0.8 p.p. and 1.7 p.p. for the online and offline channel, respectively. The decrease in the average size of online adjustments is mainly explained by Retailer 2, which transitioned from 24.3 in the pre-2020 data to 9.8 in 2020, a decrease of 14.5 p.p. The remaining retailers

[27]The slope of Retailer 5 is statistically significant different from zero but negative.

exhibit small increases on their average size of online adjustments from pre-2020 to 2020. With respect to the offline channel, retailers' offline channel reported a moderate increase on the average size of adjustment in all but one retailer.

Moving on to the size of food-related categories in 2020, Table 14 suggests that online prices variations are larger than offline price variations in all retailers considered in this study. The three retailers in question report a statistically significant difference in favor of larger online price chances than those observed offline. This finding is similar to the one found in the pre-2020 period.

Table 15 presents evidence on the change in sizes of price changes from pre-2020 to 2020. Retailer 1 and Retailer 5 exhibit report stable figures in the size of price adjustments in both, online and offline channels. Retailer 2 shows a 19 p.p. decrease in its average size of online price changes, while a 1.5 p.p. increase in its offline counterparts.

Table 12: Non-Food Categories in 2020

Size of Price Changes

	Size of Price Adjustments				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho=0$	β	Ho: $\beta=0$	Ho: $\beta=1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	12.69	11.78	0.35	15	2	11	2	0.83	0.00	0.45	0.00	0.00
Retailer 2	9.79	8.95	0.40	22	6	13	3	0.46	0.03	0.22	0.49	0.02
Retailer 3	26.71	13.73	0.00	32	29	3	0	0.54	0.00	1.67	0.00	0.10
Retailer 5	17.94	10.97	0.00	37	25	12	0	0.14	0.39	-0.66	0.05	0.00
Retailer 6	18.00	18.05	0.93	32	7	16	9	0.69	0.00	1.45	0.00	0.17
Retailer 7	22.69	18.33	0.00	35	18	12	5	0.38	0.02	0.46	0.20	0.13
Retailer 8	23.84	23.06	0.44	27	6	18	3	0.70	0.00	0.81	0.00	0.24

Note: Prices changes do not consider the sign of adjustment (absolute value). The average size of online price changes comes from the weekday maximizing the Spearman between online and offline prices. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions using online prices as dependent variable, offline prices as the independent variable, plus a constant. The Equality Test columns report the number of categories where, using a two-sided t-test of mean differences, the difference is statistically insignificant at 5% (Equal), greater absolute value mean size of online price changes than offline changes ($On > Off$) or greater offline price adjustments than online changes ($Off > On$) at 5% significance level.

Table 13: Comparison Between 2016-2019 and 2020 for Non-Food Categories

Size of Price Changes by Retailer

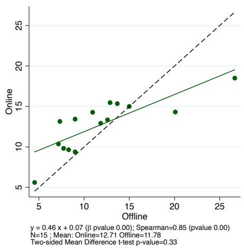
	Data 2016-2019				Data 2020				Difference (p.p.)		
	Average		Ho: Equality	Categories	Average		Ho: Equality	Categories			
	Online	Offline	p-value		Online	Offline	p-value		Online	Offline	Categories
	(a)	(b)	(c)	(d)	(f)	(g)	(h)	(i)	(f) - (a)	(g) - (b)	(i) - (d)
Retailer 1	12.69	10.95	0.01	31	12.69	11.78	0.35	15	0.00	0.83	-16
Retailer 2	24.29	9.72	0.00	33	9.79	8.95	0.40	22	-14.50	-0.77	-11
Retailer 3	22.65	13.47	0.00	41	26.71	13.73	0.00	32	4.06	0.26	-9
Retailer 4	22.22	14.27	0.00	13							
Retailer 5	15.79	9.44	0.00	41	17.94	10.97	0.00	37	2.15	1.53	-4
Retailer 6	19.16	16.85	0.00	48	18.00	18.05	0.93	32	-1.16	1.20	-16
Retailer 7	21.45	14.13	0.00	33	22.69	18.33	0.00	35	1.24	4.20	2
Retailer 8	20.93	18.64	0.10	25	23.84	23.06	0.44	27	2.91	4.42	2

Note: The first and second bloc of columns come from Table 6 and Table 12, respectively. The third set of columns are calculated as the difference of point estimates of the corresponding columns from the first two blocs.

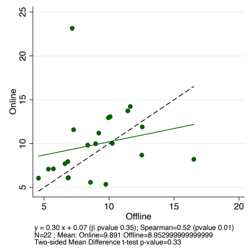
Figure 11: Non-Food Categories in 2020

Size of Price Changes

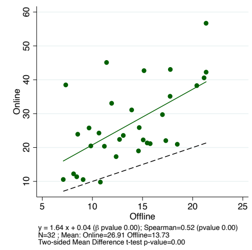
(a) Retailer 1



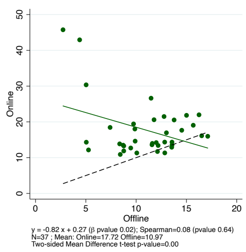
(b) Retailer 2



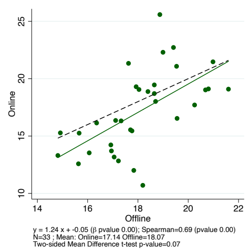
(c) Retailer 3



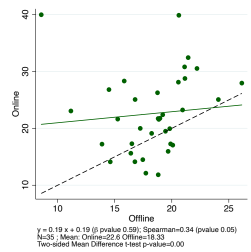
(d) Retailer 5



(e) Retailer 6



(f) Retailer 7



(g) Retailer 8

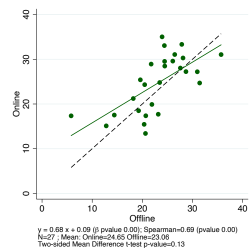


Table 14: Food Categories in 2020

Size of Price Changes

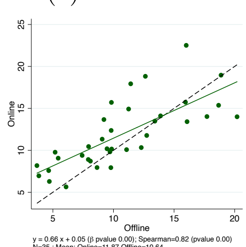
	Size of Price Adjustments				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	12.38	10.90	0.01	35	6	28	1	0.75	0.00	0.69	0.00	0.01
Retailer 2	14.02	12.35	0.06	44	11	27	6	0.54	0.00	0.57	0.00	0.01
Retailer 5	13.36	8.01	0.00	19	12	7	0	0.23	0.34	0.43	0.23	0.12

Note: Prices changes do not consider the sign of adjustment (absolute value). The average size of online price changes comes from the weekday maximizing the Spearman between online and offline prices. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions using online prices as dependent variable, offline prices as the independent variable, plus a constant. The Equality Test columns report the number of categories where, using a two-sided t-test of mean differences, the difference is statistically insignificant at 5% (Equal), greater absolute value mean size of online price changes than offline changes ($On > Off$) or greater offline price adjustments than online changes ($Off > On$) at 5% significance level.

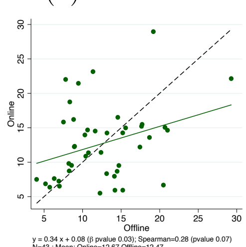
Figure 12: Food Categories

Size of Price Changes in 2020

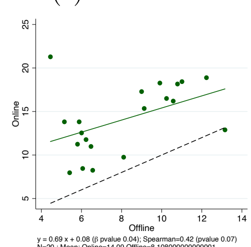
(a) Retailer 1



(b) Retailer 2



(c) Retailer 5



5.3 Distribution of Price Changes in 2020

Figure 13 shows the distribution of price changes for non-food categories. Retailer 1, Retailer 2 and Retailer 5, which are muti-channel retailers offering both food and non-food

Table 15: Comparison Between 2016-2019 and 2020 for Food Categories

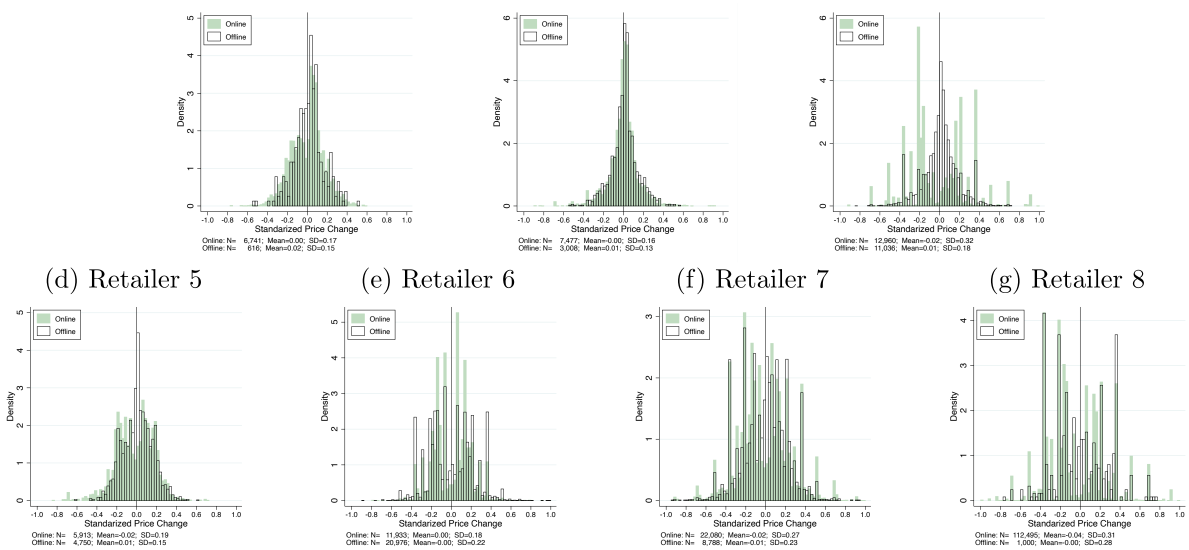
Size of Price Changes by Retailer

	Data 2016-2019				Data 2020				Difference (p.p.)		
	Average		Ho: Equality	Categories	Average		Ho: Equality	Categories			
	Online	Offline	p-value		Online	Offline	p-value		Online	Offline	Categories
	(a)	(b)	(c)	(d)	(f)	(g)	(h)	(i)	(f) - (a)	(g) - (b)	(i) - (d)
Retailer 1	11.61	10.31	0.00	75	12.38	10.90	0.01	35	0.77	0.59	-40
Retailer 2	33.49	10.90	0.00	63	14.02	12.35	0.06	44	-19.47	1.45	-19
Retailer 5	13.44	8.30	0.00	41	13.36	8.01	0.00	19	-0.08	-0.29	-22

Note: The first and second bloc of columns come from Table 7 and Table 14, respectively. The third set of columns are calculated as the difference of point estimates of the corresponding columns from the first two blocs.

Figure 13: Non-Food Categories

Distribution of Non-Zero Price Changes

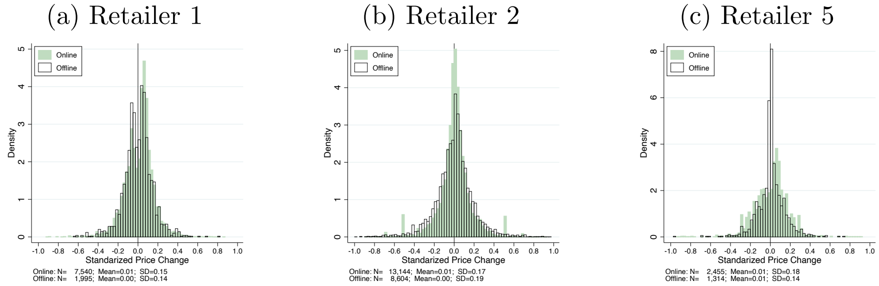


(a) Retailer 1 (b) Retailer 2 (c) Retailer 3

(d) Retailer 5 (e) Retailer 6 (f) Retailer 7 (g) Retailer 8

Figure 14: Food Categories

Distribution of Non-Zero Price Changes



(a) Retailer 1 (b) Retailer 2 (c) Retailer 5

goods, confirm their pattern observed in pre-2020: they do not exhibit large distribution sizes around focal points (multiples of 5). In contrast, the distribution of retailers offering only non-food categories tend to exhibit larger distribution sizes at focal points. Moreover, the distributions of online prices changes exhibit a smaller fraction of small adjustments (±2), while the majority of offline distributions are centered around zero, although this pattern is less pressing than their pre-2020 counterparts. See, for instance, Retailer 6. Furthermore, it seems like focal points in the offline distributions became more relevant in 2020 than they were before. Compare, for instance, Retailer 6 and Retailer 8 in Figure 5 and Figure 13.

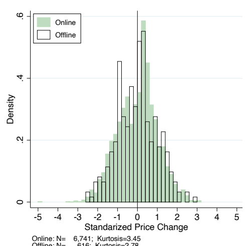
The distribution of food categories, showed in Figure 14, exhibit great overlap between channels compared to non-food categories, specially for Retailer 1 and Retailer 2. Also, note that for Retailer 5 the share of small price changes offline is considerable larger than for online adjustments once as in pre-2020.

5.4 Distribution of Standardized Price Adjustments in 2020

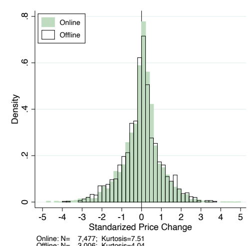
Figure 15: Non-Food Categories

Distribution of Standarized Non-Zero Price Changes

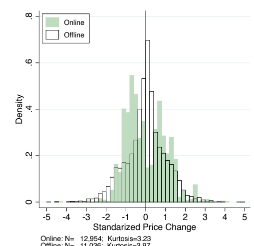
(a) Retailer 1



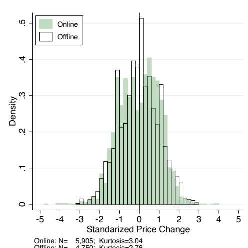
(b) Retailer 2



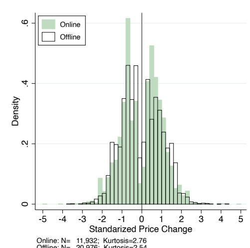
(c) Retailer 3



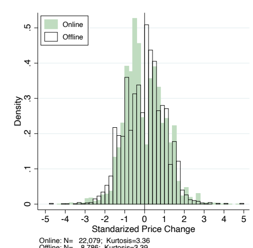
(d) Retailer 5



(e) Retailer 6



(f) Retailer 7



(g) Retailer 8

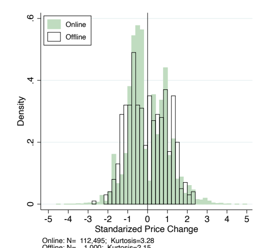
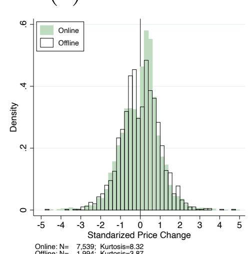


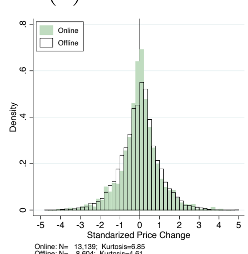
Figure 16: Food Categories

Distribution of Standarized Non-Zero Price Changes

(a) Retailer 1



(b) Retailer 2



(c) Retailer 5

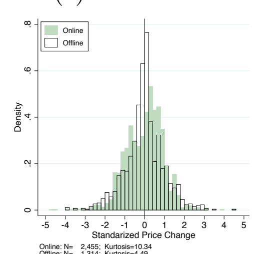


Figure 15 and Figure 16 report the distribution of standardized price changes for non-food and food categories, respectively.

For non-food categories, five out of seven multi-channel retailers report greater kurtosis (point estimate) in the online distribution than in the offline counterpart. In one cases the opposite happens (Retailer 3), while in another case point estimates are about the same (Retailer 7).

Most online and offline distributions report a value close to three, which is similar to that of a normal distribution. A notable exception is Retailer 2, reporting kurtosis of 7.9 in its online distribution. The remaining kurtosis range from 2.2 (offline kurtosis of Retailer 8) to 4.4 (offline kurtosis of Retailer 2).

Moreover, the distribution of standardized price changes in four retailers' website resembles a bimodal distribution. That is, online changes report a smaller fraction of tiny price changes (relative to its mean) in Retailer 3, Retailer 6, Retailer 7 and Retailer 8.[28]

When comparing the kurtosis from the 2020 distributions to the pre-2020 distributions, most of them experience a decrease, regardless the sales channel. For instance, the online kurtosis from Retailer 1 went from 3.9 to 3.5, while its offline counterpart came from 3.9 to 2.8.

Regarding food categories, the kurtosis is considerable different across channels. Kurtosis from the online distribution channel range from 6.9 to 10.3. In contrast, the offline distributions vary from 3.9 to 4.6.[29]

6 Sample Differences Across Sales Channels

As mentioned in the Introduction, the aim of this paper is to shed light on the stylized facts from prices from a sample of goods across different sales channels of the same retailer. Although the sample of goods considered within price categories across channels and retailers are similar, the products within samples are not exactly the same.

For instance, and because of its nature, the offline price survey considers only a sample of products (representative and/or well-known households' brands and varieties most likely). In contrast, the online dataset considers all products displayed on the retailers' websites,

[28] The mean change is close to zero since positive and negative price changes cancel out. Notice the mean of distributions in Figure 5 and Figure 6.

[29] The Laplace distribution has a kurtosis of 6. The normal distribution has a kurtosis of 3.

including not only representative goods but also low-/high-end varieties, special editions and/or temporal goods.

This Section takes a closer look at the product composition within each dataset, which in turn might be indicative about the differences in the stylized facts presented in the previous Section. In particular, this Section presents evidence on the average price, as well as the share of products gone missing from one period to the next one (i.e. product churn) by category, retailer and sales channel.[30] The average price and average share of missing products highlight that, although the price statistics reported above come from the same product categories, the goods across sales channel differ.

Hence, if products included in one dataset but neglected in the other exhibit different price-setting patterns, they could be a source behind the differences in the stylized facts discussed above.

In line with the strategy followed throughout the paper, the following subsections the average price and the average share or missing products are reported by retailer across sales channel using data between 2016 and 2019.[31] For brevity, the results affected by the Covid19 pandemic in 2020 are reported in the Appendix.

6.1 Average Price Level

Regarding the average price of price categories across sales channel, Table 16 shows the share of non-food and food categories exhibiting an average online price greater, equal or less than their offline counterparts.

Most retailers report over 50% of categories with greater average online price than average offline price. That is regardless one focuses on non-food or food categories. The retailer with the greatest proportion of non-food categories favoring greater online average prices relative to average offline prices is Retailer 3 with 80%. In contrast, Retailer 7 is the only retailer reporting less than 50% of non-food categories with online average price greater than offline average prices. Regarding food categories, at least two thirds of the categories in all

[30] In the literature of price indices, mainly stemming from NSO, the term "product churn" is also used to refer the entry/exit of products. This, in turn, arises challenges to construct a balanced panel (fixed basket) of goods required for CPI computations.

[31] Furthermore, the approach of using only one weekday by retailer from the online dataset continues. This day, as explained in detailed above, is chosen as the one that maximizes the ordinal relationship between the frequency of price adjustments across channels.

retailers exhibit an online average price greater than the offline average price.

Surprisingly, all retailers show a small fraction of categories exhibiting statistically insignificant mean difference of average prices across channels. In most retailers, and regardless non-food and food categories, these are one-digit shares. For instance, the share of non-food categories with statistically insignificant mean difference of average prices across channels in Retailer 2, Retailer 4 and Retailer 6 is 5%, 7% and 4%, respectively.

Although this Section merely focuses on the central moment of the price distribution in categories across channels, the fact that very few categories show similar (statistically insignificant mean difference) price averages across channels highlights the heterogeneity in product composition when computing price statistics. The large share of categories showing greater online average price than offline average price could be explained if the online sample considers high-end or special edition products, which in turn are neglected in the offline sample.

The qualitative results regarding greater average online prices than the average offline price hold for the 2020 period, also reported in Table 16. Perhaps the only difference is the increase on the share of categories reporting statistically insignificant mean differences. This is the case for Retailer 1, Retailer 2, Retailer 5 and Retailer 8 for non-food categories. The same is reported by food categories, with Retailer 1 and Retailer 5 with nearly one fifth of categories exhibiting similar average prices across sales channels.

In the Appendix, using data from 2016 to 2019, Table 20 and Table 21 report the (unweighted) average price by retailer and sales channel, the count of categories, as well as the Spearman correlation coefficient and slope across categories. The latter two, perhaps not surprisingly, are positive and close to unity, as shown in Figure 17 and Figure 18 also in the Appendix. Table 20 and Table 21summarize the same statistics for the 2020 period.

Also in the Appendix, Figure 19 and Figure 20 outline the dispersion of standardized price levels across sales channels for non-food and food categories, respectively. Contrary to the histograms analyzing price changes, these histograms show very similar dispersion in terms of the product offer across sales channel. The standardized distributions of price levels in 2020 are depicted in Figure 23 and Figure 24.

Table 16: Average Price Level by Retailer

Share of Caterogies by Outcome of Equality Test

	Data 2016-2019						Data 2020					
	Non Food Categories			Food Categories			Non Food Categories			Food Categories		
	Shares (%)			Shares (%)			Shares (%)			Shares (%)		
	On > Off	Equal	Off > On	On > Off	Equal	Off > On	On > Off	Equal	Off > On	On > Off	Equal	Off > On
Retailer 1	55	16	29	67	7	26	67	15	19	50	22	27
Retailer 2	50	5	45	78	1	21	58	10	32	72	8	20
Retailer 3	80	7	13				80	2	17			
Retailer 4	75	8	17				72	0	28			
Retailer 5	67	12	20	73	4	24	56	16	28	60	19	21
Retailer 6	62	4	34				53	5	43			
Retailer 7	34	0	66				30	7	64			
Retailer 8	54	16	30				46	17	37			

Note: This Table is calculated as follows. First, the average price per category, retailer and sales channel is computed as described in the text. Then, t-tests of mean differences are computed for each category in a given retailer. If the mean difference is statistically significant (10%) in either direction, the category is binned into "On > Off" or "Off > On" depending on the sign of the difference; if the mean difference is statistically insignificant, the product category is binned as "Equal". Finally, the share of categories in each bin is reported in the Table by retailer. For the number of categories per retailer (instead of shares of categories), as well the Spearman correlation coefficient and slope across categories, see Table 20, Table 21, Table 22 and Table 23 in the Appendix.

6.2 Share of Missing Products

This subsection provides statistics regarding the share of missing products from one time vintage to the next one for non-food and food products across sales channels. Products can be reported as missing if, on the one hand, it was not displayed on the website when the robot parsed the website.[32] On the other hand, a product can be reported as missing if the price collector verifies the product is out-of-stock at the time of her visit to the physical store.[33]

If the share of missing products is very different across sales channels, it might be indicative that: (i) sales channels operate differently in terms of inventories/out-of-stocks; or (ii) certain types of goods are more likely to be considered in one dataset but not in the other one (e.g. low-/high-end or temporal varieties), which in turn behave differently. In either case, the share of missing products sheds light on sample differences across sales channels, even if comparing the same categories offered by the same retailers.

The share of missing product is computed in a similar fashion as the frequency of price adjustment. That is, a dummy variable takes the value of 0 if a product is observed in two consecutive time vintages (14 and 7 days apart for non-food and food categories, respectively). The dummy variable takes the value of 1 if the product is observed in the first time wave but not in the second one. Finally, averages are computed by category, retailer and sales channel.

[32]The fact that a product is not displayed could be interpreted as out-of-stock and/or the product disappeared from the market. Unfortunately, it is not possible to distinguish between these two cases with the data at hand.

[33]If the product is repeatedly out-of-stock and/or disappeared from the market, price collectors replace the product with another item belonging to the same price category. These replacements do not affect any of the price statistics in this paper as missing products and replacements are flagged out in the dataset.

Table 17 shows the share of categories exhibiting greater, equal or less fraction of missing products online than offline. First, for non-food categories between 2016 and 2019, it seems that the majority of retailers exhibit greater share of categories reporting a larger fraction of missing products online than offline. That is, more non-food products tend to go missing from one period to the next one in the online channel than in brick and mortar stores. The extreme case is Retailer 8 where all categories report a greater and statistically significant difference in the proportion of products going missing online than offline. The only two instances where there is less than 50% of categories exhibiting greater fraction of online missing products relative to offline missing items are Retailer 1 and Retailer 5 with 26% and 13%, respectively. Although not reported with the same level of detail, **?**, from the UK's ONS, report a similar finding regarding greater product churn online than offline. Moreover, and in contrast to the subsection discussing the price level, there is a greater proportion of categories with similar share of product churn. There are five retailers reporting around 20% of categories where the difference of the share of missing products is statistically insignificant.

The picture is less clear for food-related categories as reported in the second bloc of columns in Table 17. Retailer 1 report 40% of categories showing a similar share of missing products across channels. In contrast, 92% of categories observed in Retailer 2 report a larger fraction of missing products online than offline, while Retailer 5 has 61% of its categories with greater share of missing products offline than online. Hence, there is no clear pattern in terms of missing products for food-related categories. Bear in mind that food categories include some fruits and vegetables (e.g. one category is "Apples", another is "Onions"), which are likely stay stable in the sample with only one observation per category. In contrast, processed food categories offer greater number of varieties per category. Hence, the type of categories (within the food basket) priced in each retailer might explain the heterogeneous patterns in the faction of categories according to the share of missing products.

Data from 2020 behaves differently from the 2016-2019 data. Temporal closures of physical stores could be behind this change in figures. First, the fraction of non-food categories with greater share of offline missing products relative to online missing products goes up. Five retailers report at least a third of their categories in this situation. The fraction goes as high as 86% for Retailer 3. Second, the fraction of categories with roughly equal (statistically insignificant) share of missing products across sales channel also increases. The fraction of categories with equal share of missing products is around 40% or above in five retailers.

Third, in contrast to the 2016-2019, only two retailers exhibit greater fraction of categories with larger share of missing products online than offline (Retailer 6 and Retailer 8).

Finally, with respect to food categories in 2020, there is now a clearer picture that in very few cases online categories report greater share of missing products than their offline counterparts. For all three retailers, around half of the categories report the same share of missing products across channels and around half with greater frequency of missing items offline than online.

The number of categories, as well as the Spearman correlation and slope across categories are reported in the Appendix. Interestingly, the Spearman and slope coefficients across categories is statistically insignificant different from zero for many retailers, type of goods and period under study. Thus, categories reporting greater product churn online do not necessarily exhibit the same pattern offline. As mentioned before, this could be explained either by the different operation retailers give to their physical stores/websites or by the products considered across collection techniques.[34]

Table 17: Missing Products by Retailer

Share of Caterogies by Outcome of Equality Test

	Data 2016-2019						Data 2020					
	Non Food Categories			Food Categories			Non Food Categories			Food Categories		
	Shares (%)			Shares (%)			Shares (%)			Shares (%)		
	On > Off	Equal	Off > On	On > Off	Equal	Off > On	On > Off	Equal	Off > On	On > Off	Equal	Off > On
Retailer 1	26	39	35	20	40	40	0	52	48	0	55	45
Retailer 2	97	3	0	92	8	0	29	19	52	5	45	50
Retailer 3	53	20	27				7	7	86			
Retailer 4	57	26	17				22	61	17			
Retailer 5	13	29	58	7	31	61	22	44	34	0	52	48
Retailer 6	63	22	14				97	3	0			
Retailer 7	74	13	13				15	39	46			
Retailer 8	100	0	0				54	43	3			

Note: This Table is calculated as follows. First, the share of missing products per category, retailer and sales channel is computed as described in the text. Then, z-tests in difference of proportions is computed for each category in a given retailer. If the difference in proportion is statistically significant (10%) in either direction, the category is binned into "On > Off" or "Off > On" depending on the sign of the difference; if the difference in proportion is statistically insignificant, the product category is binned as "Equal". Finally, the share of categories in each bin is reported in the Table by retailer. For the number of categories per retailer (instead of shares of categories), as well the Spearman correlation coefficient and slope across categories, see Table 24, Table 25, Table 26 and Table 27 in the Appendix.

[34] For more, see Table 24, Table 25, Table 26 and Table 27 in the Appendix.

7 Conclusions

Nominal rigidities are a key ingredient in macroeconomic models. This paper characterizes the frequency, size and dispersion of price changes stemming from the websites of eight large multi-channel retailers in Mexico, which are then compared with price statistics computed using data from brick and mortar stores of the same retailers.

To that end, this study analyses two main data sources from 2016 to 2020. The first one is gathered by web scraping techniques and compiled by Banco de México. The online dataset comprehends over 14 million price quotes from more than 150 thousand different products across the eight retailers. The second one is a subset of the CPI price survey undertaken by INEGI in brick and mortar stores. The observations in the offline dataset considers products priced in same eight retail chains for which online prices are available. A little less than one million price quotes from about 22 thousand different products observed in brick and mortar stores are considered in this dataset.

The evidence suggests that prices observed in brick and mortar stores (offline) change more frequently than those observed on websites (online). However, given a price change, online prices tend to change by larger amounts than offline prices. Furthermore, for most retailers, product categories changing more frequently online prices are also those adjusting offline more often. These patterns are true when analyzing data from 2016 to 2019, as well as from data compiled during the Covid19 pandemic in 2020.

Moreover, the results indicate that, for the product categories and retailers in the study, the frequency of price changes increased on average by around 5 p.p. in both online and offline sales channels in 2020 relative to previous years. In contrast, the average size of price adjustment in 2020 do not seem to have changed with respect to the 2016 to 2019 period.

Regarding the distribution of price changes, this study shows that online price changes are more centered at focal points (multiples of 5% in the $\pm$20% range) than offline price changes for the retailers in the sample. When standardizing price changes by product category and retailer, the distributions of online prices changes for the majority of the retailers report a minor fraction of small price changes, while this is not the case in the distributions drawn from offline price changes.

Results from this paper highlight that importance of recognizing the differences between survey and web scraped data. For instance, this study shows that, for the vast majority of retailers in the sample, more than half of their product categories report greater average price and greater share of missing products (turnover) in their online sample than in their offline counterpart.

Thus, the sample versus census-like approaches in price collection might have not trivial implications on measures of price stickiness, specially if goods considered (neglected) in one collection technique but excluded (included) in the other exhibit different price-setting patterns. This is particularly important as metrics on price rigidities are key elements in monetary policy models.

As digital consumption continues growing over time, the results of this study have implications for areas in economics employing price data, which have traditionally used survey data gathered at brick and mortar stores. These include, among others, parameters in monetary policy models, measuring the cost of living, computing deflators, welfare analysis and metrics on market concentration. Further research is needed as big data sources are ever more prevalent in policy work.

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A Appendix

A.1 Descriptive Statistics

Table 18: Non-Food Items

	Database Description				Online				Offline			
	Start date	End date	Days	Fortnights	Observations (Thousands)	Products (Thousands)	Avg Obs Freq (Days)	Median Obs Freq (Days)	Observations (Thousands)	Products (Thousands)	Outlets	CPI Weight (%)
Retailer 1	01jan2016	01jan2020	1,087	76	1,984.1	4.9	1.3	1	12.2	0.3	11	0.4
Retailer 2	31may2016	01jan2020	1,280	88	2,069.9	4.8	1.0	1	31.2	0.7	30	1.9
Retailer 3	21nov2017	01jan2020	627	48	1,228.1	5.2	1.2	1	168.6	4.8	76	4.6
Retailer 4	21nov2017	01nov2019	440	40	169.2	1.2	1.6	1	3.4	0.1	8	0.1
Retailer 5	21nov2017	27dec2019	511	47	378.5	2.2	1.5	1	31.5	1.2	40	0.4
Retailer 6	21nov2017	06aug2019	91	39	918.6	50.6	6.9	7	133.5	4.7	53	0.6
Retailer 7	11aug2016	29dec2019	320	78	556.8	20.9	3.9	1	91.2	3.5	42	0.5
Retailer 8	12aug2016	01jan2020	561	83	778.0	62.3	2.2	1	14.3	0.6	8	0.1

Note: A fortnight is counted if there is at least one observed day in the fortnight. *Fortnights* are defined from the 1st until the 15th, and from the 16th until the last day of the month. *Observations* are the number of prices in the dataset. *Products* represent the number of unique identifiers in the retailer. *Frequency of Observation* is the mean number of days between price observations. *Outlets Locations* stands for the number of stores in the retail chain encompassed in the CPI survey. *CPI weight* represents the total weight from the individual products priced at the retailer (includes weights from food-categories).

Table 19: Food and Drinks Items

	Database Description				Online				Offline			
	Start date	End date	Days	Fortnights	Observations (Thousands)	Products (Thousands)	Avg Obs Freq (Days)	Median Obs Freq (Days)	Observations (Thousands)	Products (Thousands)	Outlets	CPI Weight (%)
Retailer 1	01jan2016	01jan2020	1,101	76	3,129.6	7.0	1.3	1	80.0	0.9	11	0.4
Retailer 2	31may2016	01jan2020	1,280	88	2,779.9	6.7	1.0	1	219.2	2.6	30	1.9
Retailer 3	21nov2017	01jan2020	605	48	14.5	0.1	1.3	1	103.5	1.4	76	4.6
Retailer 4	21nov2017	01nov2019	438	40	16.7	0.1	1.6	1	2.6	0.0	8	0.1
Retailer 5	21nov2017	06dec2019	508	46	455.6	1.5	1.5	1	42.8	0.8	40	0.4
Retailer 6	21nov2017	06aug2019	90	39	6.7	0.3	7.0	7	0.1	0.0	53	0.6
Retailer 7	11aug2016	29dec2019	309	78	2.4	0.1	4.0	2			42	0.5
Retailer 8	12aug2016	31dec2019	359	81	14.2	0.6	3.5	2			8	0.1

Note: A fortnight is counted if there is at least one observed day in the fortnight. *Fortnights* are defined from the 1st until the 15th, and from the 16th until the last day of the month. *Observations* are the number of prices in the dataset. *Products* represent the number of unique identifiers in the retailer. *Frequency of Observation* is the mean number of days between price observations. *Outlets Locations* stands for the number of stores in the retail chain encompassed in the CPI survey. *CPI weight* represents the total weight from the individual products priced at the retailer (includes weights from non-food categories).

A.2 Average Price Level Between 2016 and 2019

Table 20 shows the number of non-food categories exhibiting a mean average online price greater, equal or less than their offline counterparts.

Surprisingly, all retailers show very few categories exhibiting statistically insignificant mean differences across channels in their categories' averages prices. For instance, out of the 38 categories observed in Retailer 1, six exhibit a statistically insignificant mean difference. Similarly, Retailer 2, Retailer 4 and Retailer 6 report only two categories in this circumstance.

In turn, with the exception of Retailer 7, the average prices of most online categories is above the offline average price. For example, Retailer 1 report 21 categories where the average online price is statistically significant greater than the average offline price, 6 instances where the averages are not statistically different across channels, while in 11 cases the categories' offline averages are above online averages. The retailer with the greatest proportion of categories favoring greater online average prices relative to average offline prices is Retailer 3. Out of its 60 categories, 48 show greater average price online than offline, 4 exhibit similar averages across sales channels and in 8 cases the offline sample reported greater average price than online. In contrast, Retailer 7 is the only retailer reporting a larger number of offline categories with greater average price than online categories. The online average price was greater than the offline average price in 14 instances, while in 27 cases the opposite is found.

A clearer picture emerge for the case of food categories. Table 21 reports that the vast majority of online categories show greater average price relative to the offline sample. For example, 60 out of 89 price categories report greater average price online than offline (statistically significant different at 10%), while only 23 report greater offline average price.

Table 20: Non-Food Categories

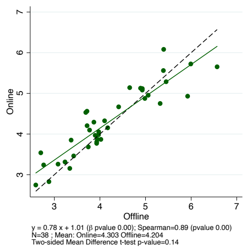
Average Price Level by Retailer

	Average Price Level				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	4.30	4.20	0.14	38	21	6	11	0.89	0.00	0.78	0.00	0.00
Retailer 2	4.28	4.42	0.25	40	20	2	18	0.66	0.00	0.63	0.00	0.00
Retailer 3	5.89	5.34	0.00	60	48	4	8	0.95	0.00	0.89	0.00	0.01
Retailer 4	6.98	6.42	0.00	24	18	2	4	0.81	0.00	0.77	0.00	0.02
Retailer 5	6.39	6.27	0.17	49	33	6	10	0.90	0.00	0.86	0.00	0.01
Retailer 6	6.94	6.77	0.09	50	31	2	17	0.90	0.00	0.79	0.00	0.00
Retailer 7	6.72	6.98	0.01	41	14	0	27	0.87	0.00	1.01	0.00	0.95
Retailer 8	7.76	7.53	0.04	37	20	6	11	0.86	0.00	0.80	0.00	0.01

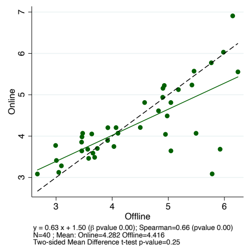
Figure 17: Non-Food Categories

Average Price Level by Retailer

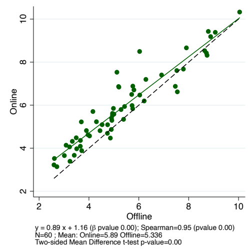
(a) Retailer 1



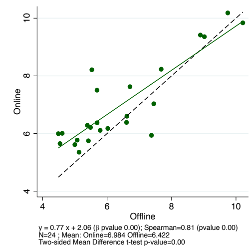
(b) Retailer 2



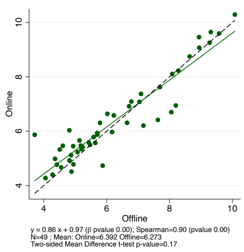
(c) Retailer 3



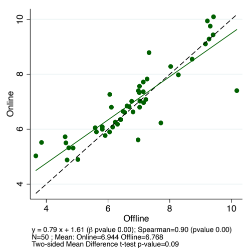
(d) Retailer 4



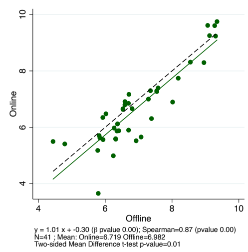
(e) Retailer 5



(f) Retailer 6



(g) Retailer 7



(h) Retailer 8

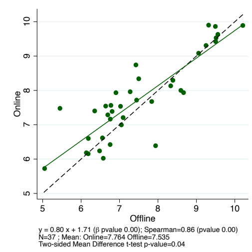


Table 21: Food Categories

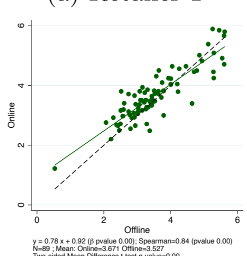
Average Price Level by Retailer

	Average Price Level				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	3.67	3.53	0.00	89	60	6	23	0.84	0.00	0.78	0.00	0.00
Retailer 2	3.62	3.36	0.00	73	57	1	15	0.85	0.00	0.79	0.00	0.00
Retailer 5	4.81	4.53	0.00	55	40	2	13	0.69	0.00	0.61	0.00	0.00

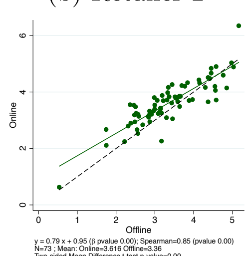
Figure 18: Food Categories

Average Price Level by Retailer

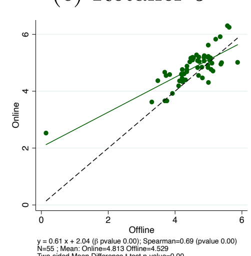
(a) Retailer 1



(b) Retailer 2



(c) Retailer 5



A.3 Average Price Level Between in 2020

Figure 19: Non-Food Categories

Distribution of Standardized Price Level from 2016 to 2019

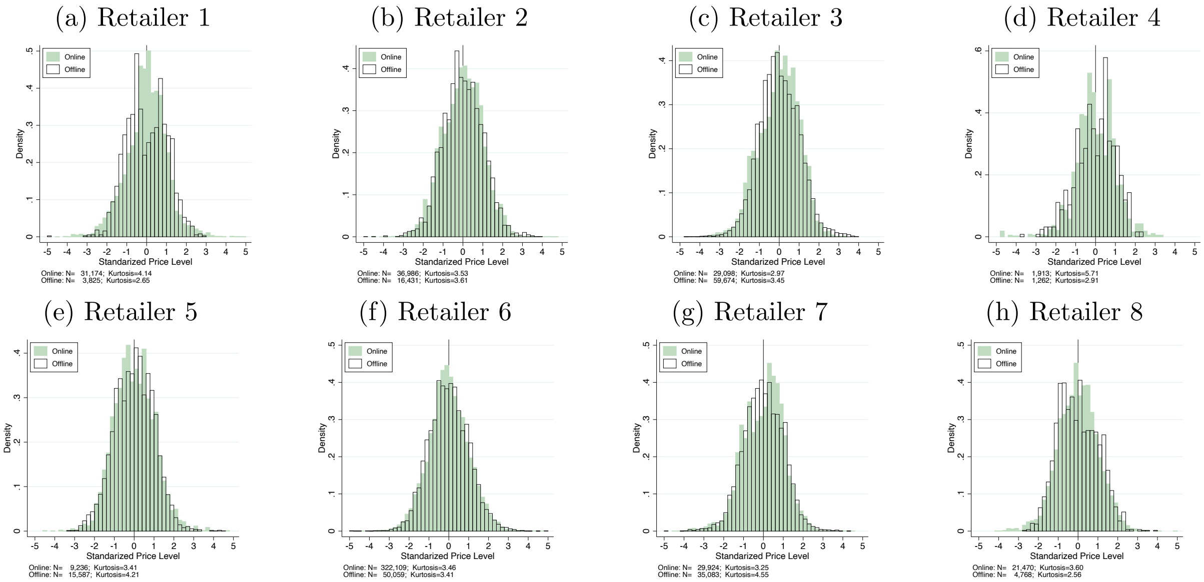


Figure 20: Food Categories

Distribution of Standardized Price Level from 2016 to 2019

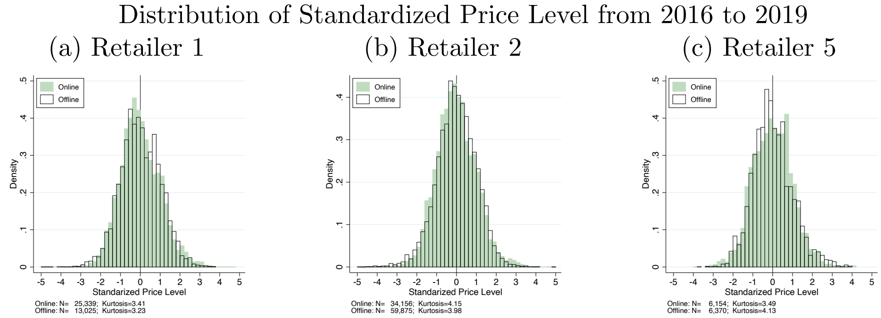


Table 22: Non-Food Categories

Average Price Level by Retailer

	Average Price Level				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	4.25	3.99	0.01	27	18	4	5	0.79	0.00	0.78	0.00	0.06
Retailer 2	4.36	4.33	0.68	31	18	3	10	0.88	0.00	0.73	0.00	0.00
Retailer 3	6.13	5.71	0.00	46	37	1	8	0.92	0.00	0.84	0.00	0.01
Retailer 4	7.41	6.97	0.11	18	13	0	5	0.81	0.00	0.79	0.00	0.17
Retailer 5	6.33	6.34	0.91	50	28	8	14	0.85	0.00	0.90	0.00	0.13
Retailer 6	7.03	6.97	0.51	40	21	2	17	0.87	0.00	0.87	0.00	0.05
Retailer 7	6.86	7.03	0.06	44	13	3	28	0.86	0.00	0.96	0.00	0.53
Retailer 8	7.47	7.36	0.28	35	16	6	13	0.85	0.00	0.84	0.00	0.04

Figure 21: Non-Food Categories

Average Price Level by Retailer

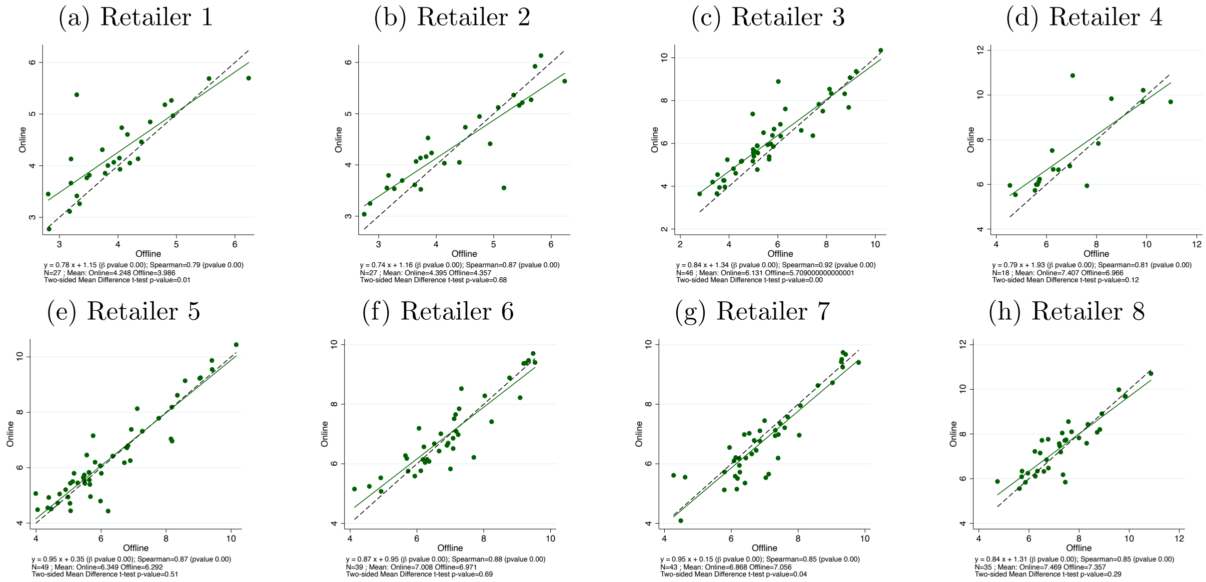


Table 23: Food Categories

Average Price Level by Retailer

	Average Price Level				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	3.83	3.72	0.05	74	37	16	20	0.87	0.00	0.74	0.00	0.00
Retailer 2	3.65	3.44	0.00	61	44	5	12	0.77	0.00	0.62	0.00	0.00
Retailer 5	5.01	4.80	0.00	42	25	8	9	0.68	0.00	0.67	0.00	0.00

Figure 22: Food Categories

Average Price Level by Retailer

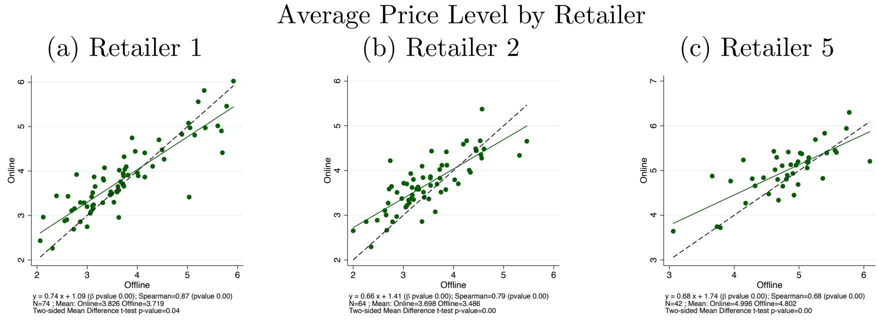
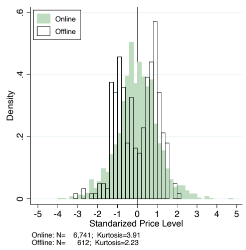


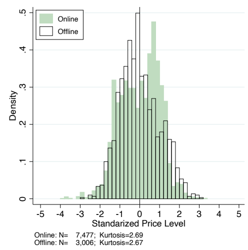
Figure 23: Non-Food Categories in 2020

Distribution of Standardized Price Level

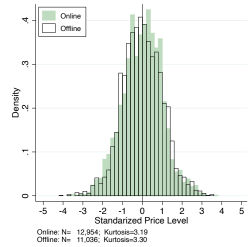
(a) Retailer 1



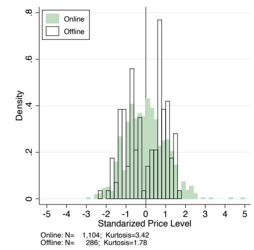
(b) Retailer 2



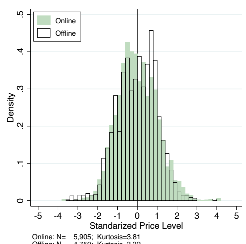
(c) Retailer 3



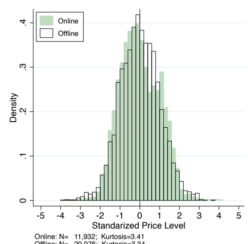
(d) Retailer 4



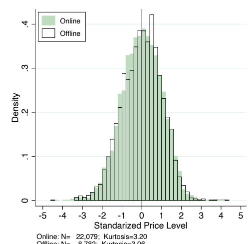
(e) Retailer 5



(f) Retailer 6



(g) Retailer 7



(h) Retailer 8

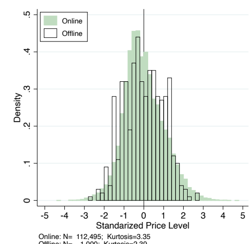
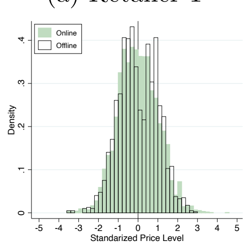


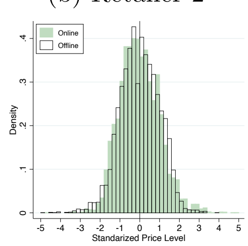
Figure 24: Food Categories in 2020

Distribution of Standardized Price Level

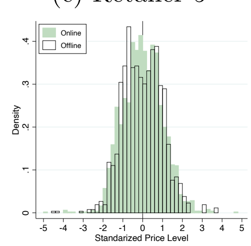
(a) Retailer 1



(b) Retailer 2



(c) Retailer 5



A.4 Share of Missing Products Between 2016 and 2019

Similar to previous tables, the first bloc of columns report the unweighted average of missing products for online and offline categories, as well as the p-values of mean difference tests comparing these averages; the second bloc reports the number of categories with statistically significant differences from proportion difference tests; the third and forth set of columns describe the Spearman and slope coefficients, respectively, of the categories within the retailer.

For non-food categories, on average, six out of the eight retailers exhibit greater product churn online than offline, one shows statistically insignificant difference (Retailer 1), while one reports greater share of product missing offline than online (Retailer 5). However, in contrast to the subsection discussing the price level, there is a greater proportion of categories with similar share of product churn. More than 10 categories in Retailer 1, Retailer 3, Retailer 5 and Retailer 6 the difference of the share of missing products is statistically insignificant.

It is also worth mentioning that the Spearman correlation and slope across categories is statistically insignificant different from zero in six out of the eight retailers in the sample. In other words, those categories reporting greater product churn online do not necessarily exhibit the same pattern offline. As mentioned before, this could be explained either by the different operation retailers give to their physical stores/websites or by the products considered across collection techniques.

For food categories, two of the three retailers favor greater product churn average offline than online. Strikingly, the shares of missing products for food categories is considerably lower than those for non-food categories.

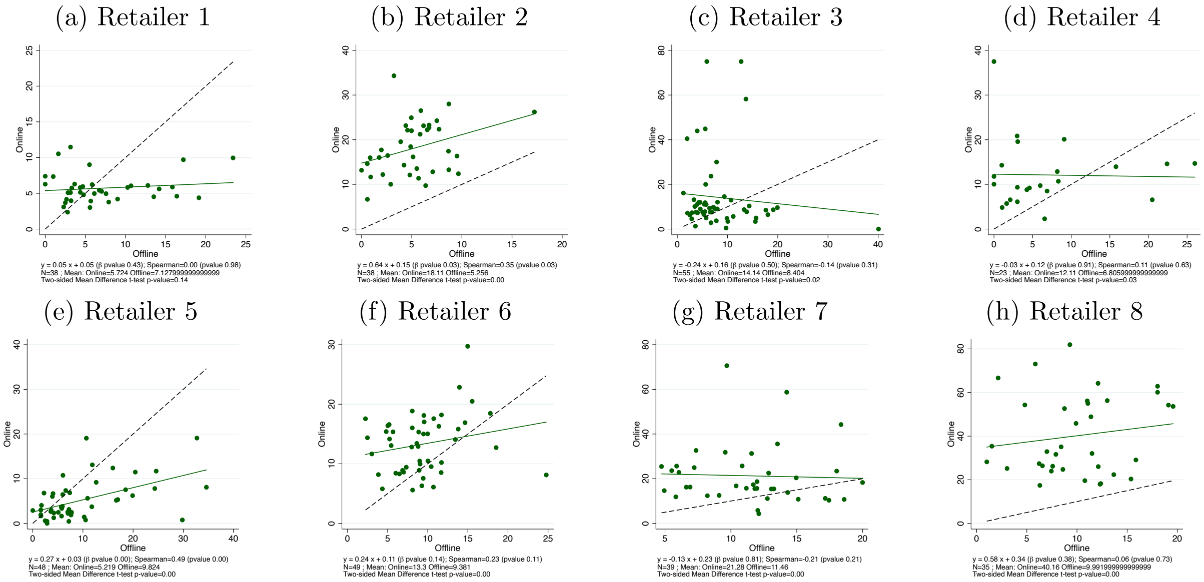
Table 24: Non-Food Categories

Share of Missing Products by Retailer

	Share of Missing Observations				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	5.72	7.13	0.14	38	10	15	13	0.00	0.98	0.05	0.43	0.00
Retailer 2	18.11	5.26	0.00	38	37	1	0	0.35	0.03	0.64	0.03	0.22
Retailer 3	14.14	8.40	0.02	55	29	11	15	-0.14	0.31	-0.24	0.50	0.00
Retailer 4	12.11	6.81	0.03	23	13	6	4	0.11	0.63	-0.03	0.91	0.00
Retailer 5	5.22	9.82	0.00	48	6	14	28	0.49	0.00	0.27	0.00	0.00
Retailer 6	13.30	9.38	0.00	49	31	11	7	0.23	0.11	0.24	0.14	0.00
Retailer 7	21.28	11.46	0.00	39	29	5	5	-0.21	0.21	-0.13	0.81	0.04
Retailer 8	40.16	9.99	0.00	35	35	0	0	0.06	0.73	0.58	0.38	0.52

Figure 25: Non-Food Categories

Share of Missing Products by Retailer



(a) Retailer 1 (b) Retailer 2 (c) Retailer 3 (d) Retailer 4 (e) Retailer 5 (f) Retailer 6 (g) Retailer 7 (h) Retailer 8

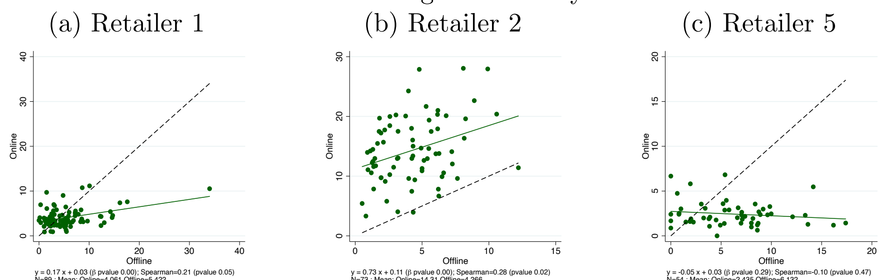
Table 25: Food Categories

Share of Missing Products by Retailer

	Share of Missing Observations				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho = 0$	β	Ho: $\beta = 0$	Ho: $\beta = 1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	4.06	5.42	0.01	89	17	36	36	0.21	0.05	0.17	0.00	0.00
Retailer 2	14.31	4.27	0.00	73	67	6	0	0.28	0.02	0.73	0.00	0.25
Retailer 5	2.43	6.13	0.00	54	4	17	33	-0.10	0.47	-0.05	0.29	0.00

Figure 26: Food Categories

Share of Missing Products by Retailer



(a) Retailer 1 (b) Retailer 2 (c) Retailer 5

A.5 Share of Missing Products in 2020

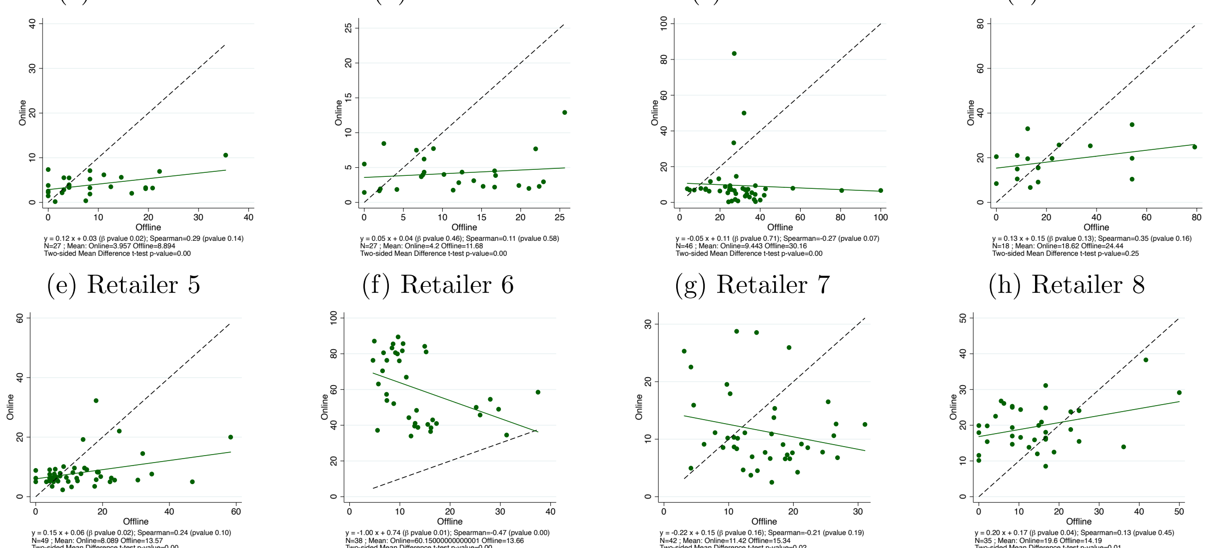
Table 26: Non-Food Categories

Share of Missing Products by Retailer

	Share of Missing Observations				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho=0$	β	Ho: $\beta=0$	Ho: $\beta=1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	3.49	8.89	0.00	27	0	14	13	0.35	0.07	0.09	0.02	0.00
Retailer 2	20.48	12.63	0.18	31	9	6	16	0.07	0.70	0.70	0.28	0.65
Retailer 3	9.25	27.43	0.00	44	3	3	38	-0.28	0.07	-0.02	0.93	0.00
Retailer 4	19.30	24.44	0.30	18	4	11	3	0.38	0.12	0.16	0.09	0.00
Retailer 5	10.95	13.86	0.07	50	11	22	17	0.16	0.28	0.22	0.01	0.00
Retailer 6	58.07	13.59	0.00	39	38	1	0	-0.56	0.00	-1.19	0.00	0.00
Retailer 7	11.73	15.20	0.01	41	6	16	19	0.18	0.25	0.10	0.30	0.00
Retailer 8	23.73	14.19	0.00	35	19	15	1	0.23	0.17	0.25	0.01	0.00

Figure 27: Non-Food Categories

Share of Missing Products by Retailer



(a) Retailer 1 (b) Retailer 2 (c) Retailer 3 (d) Retailer 4

(e) Retailer 5 (f) Retailer 6 (g) Retailer 7 (h) Retailer 8

Table 27: Food Categories

Share of Missing Products by Retailer

	Share of Missing Observations				Equality Test			Spearman		Linear Fit		
	Average		Ho:Equality	Categories	Categories			ρ	Ho: $\rho=0$	β	Ho: $\beta=0$	Ho: $\beta=1$
	Online	Offline	p-value		On > Off	Equal	Off > On		p-value		p-value	p-value
Retailer 1	2.43	6.48	0.00	74	0	41	33	0.12	0.29	0.15	0.00	0.00
Retailer 2	3.46	8.16	0.00	60	3	27	30	0.12	0.36	0.03	0.54	0.00
Retailer 5	4.02	10.75	0.00	42	0	22	20	0.22	0.16	0.03	0.23	0.00

Figure 28: Food Categories

Share of Missing Products by Retailer

(a) Retailer 1 (b) Retailer 2 (c) Retailer 5