Banco de México

Working Papers

N° 2023-09

Stylized Facts From Prices at Multi-Channel Retailers in Mexico

Diego Solórzano
Banco de México

September 2023

La serie de Documentos de Investigación del Banco de México divulga resultados preliminares de trabajos de investigación económica realizados en el Banco de México con la finalidad de propiciar el intercambio y debate de ideas. El contenido de los Documentos de Investigación, así como las conclusiones que de ellos se derivan, son responsabilidad exclusiva de los autores y no reflejan necesariamente las del Banco de México.

The Working Papers series of Banco de México disseminates preliminary results of economic research conducted at Banco de México in order to promote the exchange and debate of ideas. The views and conclusions presented in the Working Papers are exclusively the responsibility of the authors and do not necessarily reflect those of Banco de México.

Documento de Investigación
2023-09

Working Paper
2023-09

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

Diego Solórzano†
Banco de México

Abstract: Using data gathered through web scraping techniques, this paper characterizes product categories' frequency, size and dispersion of price changes in eight retail chains in Mexico, and compare them with price statistics stemming from brick and mortar stores data of the same retailers. Notably, between 2016 and 2019, 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. In 2020, period affected by the pandemic, the above relationship across sales channel holds, while 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 the importance of recognizing the differences between survey and web scraped data.
Keywords: Nominal rigidities; Consumer prices; Web scraped data; Survey microdata
JEL Classification: E31; L16

Resumen: Utilizando precios recopilados mediante técnicas de extracción de contenido de sitios web (*web scraping*), este artículo caracteriza la frecuencia, magnitud y dispersión de los cambios de precios para grupos de bienes en ocho cadenas minoristas en México, y se comparan con las estadísticas de precios calculadas con datos captados en las tiendas físicas de los mismos minoristas. Se encuentra que entre 2016 y 2019 los precios observados en las tiendas físicas (*offline*) cambian más frecuentemente que aquellos en los sitios web (*online*); no obstante, dado un cambio de precio, los precios *online* muestran cambios de precios más grandes que sus contrapartes *offline*. En 2020, período afectado por la pandemia, la relación arriba mencionada entre canales de venta se mantiene, pero la frecuencia de cambios de precios aumentó cerca de la misma magnitud en ambos canales, al tiempo que la magnitud promedio de los ajustes no varió con respecto a los años anteriores. Los resultados llaman a resaltar la importancia de reconocer las diferencias entre los datos provenientes de encuestas y de sitios web.
Palabras Clave: Rigideces nominales; Precios consumidor; Datos de web scraping; Microdatos de encuestas

*I would like to thank Alejandrina Salcedo, Josué Cortés and participants at CEMLA-Banco de España Seminar in Big Data for their useful comments. Data accessed through Banco de México's EconLab. The EconLab processed the data as part of its efforts to promote evidence-based research and foster ties between Banco de México's research staff and the academic community. Inquiries regarding the data should be directed to econlab@banxico.org.mx. All errors are my own.

† Dirección General de Investigación Económica. Email: jsolorzano@banxico.org.mx.

1 Introduction

Do prices displayed on retailers' websites change as often as they do in their brick and mortar stores? Given a price change, is the size of adjustment similar between websites and the physical outlets of the same stores? 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 to the same price moments using data from brick and mortar stores of the same retailers. As they offer their clients multiple consumption channels, in this case websites (online) and brick and mortar stores (offline), these outlets are commonly known as "multi-channel" retailers.[1]

Price moments are calculated for fairly homogeneous product categories and for each of the sales channels (online and offline) within a given retailer.[2] 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, e.g. milk, butter, soap, dish washer, women trousers, men trousers, etc., known as *genéricos* by Mexico's National Statistical Institute (INEGI). As the retailers in our sample include supermarkets, price clubs and departmental stores, this paper follows the literature by focusing on prices in the goods sector, e.g. Cavallo (2018) and Peña and Prades (2021).[3] Additionally, this paper sheds light on the extent to which the Covid-19 pandemic in 2020 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 Covid-19 pandemic. To that end, price statistics are reported for two periods of time, from 2016 to 2019 and during the 2020 Covid-19 pandemic.

As one transitions from CPI micro data to web scraped data sources for measuring

[1]Retailers offering their products through different sales channels are also known as multi-channel retailers. 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.

[2]Price moments in this paper encompass, for the frequency of price changes, the first moment; for the size/dispersion of prices changes, the first, second and fourth moments.

[3]Notable exception focusing on an industry in the service sector is Solórzano (2023).

nominal rigidities, the comparison across sales channels on price setting presented in this paper is long overdue. On the one hand, there is a growing literature analyzing the frequency of price changes, as well as the size of price adjustments, using microdata collected at brick and mortar stores as part of the CPI survey.[4] On the other hand, as consumption habits have changed and web scraping has become ever more prevalent as a data source in economics, there has been a renewed interest on price setting and its behaviour on websites.[5] By following the same methodology benchmarked by papers using survey data, it is important to recognize if changing the scope of price collection and data sources (i.e. all prices on websites) might or might not reflect the same degree of price stickiness as found in survey data. Further research is needed as big data sources are ever more prevalent in policy-oriented work.

The results suggest that, between 2016 and 2019 prices observed in brick and mortar stores (offline) change more frequently than those observed on websites (online). This is particularly true for food and personal care categories; apparel changes more frequently online than offline; while product categories related to medicines, furniture and recreation adjust at similar frequencies across sales channels. However, given a price change, online prices tend to change by larger amounts than offline prices. That seems to be the case in all retailers and type of goods in the sample. For most retailers, the categories' extensive margins of price adjustments across channels exhibit a positive relationship. That is, product categories changing online prices more frequently 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 $\pm 20\%$ range) than offline price adjustments. When standardizing price changes by product category and retailer, the majority of retailers exhibit a minor 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,

[4]Among others, using US CPI microdata: Bils and Klenow (2004), Nakamura and Steinsson (2008), Álvarez et al. (2016); EU CPI microdata: Dhyne et al. (2006), Aucremanne and Dhyne (2004), Veronese et al. (2005), Baumgartner et al. (2005), Costa Dias et al. (2008); UK CPI: Dixon and Tian (2017); Japan CPI: Higo and Saita (2007); Brazil CPI: Gouvea (2007); Colombia CPI: Julio and Zárate (2008); and Mexico CPI: Solórzano and Dixon (2020), Gagnon (2009), Kochen and Sámano (2016).

[5]Cavallo (2018) and Gorodnichenko et al. (2018) using data from few countries and Peña and Prades (2021) with data from Chile, among others.

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 percentage points (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 23 million price quotes from more than 210 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 23 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. It is also worth highlighting that I use posted prices for the price moments reported in the paper. In other words, sales prices are included and not filtered out.[6]

Rationalizing sample differences across sales channels is fundamental for understanding and drawing conclusions from price statistics stemming from these two different

[6]Recent studies such as Kryvtsov and Vincent (2021) and Coibion et al. (2015) suggest sales prices are informative for macro analysis. Including sales prices is complementary to the exclusion of high frequency price changes (i.e. sales), as in Nakamura and Steinsson (2008) or Eichenbaum et al. (2011).

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.[7]

This paper contributes to three strands in the literature on price rigidities. First, this research contributes to the comparison of stylized facts of goods' price adjustments across sales channels of the same retailers. Cavallo (2017) is perhaps the most representative example in this strand.[8] However, in contrast to Cavallo (2017), this paper's aim is not to provide a product-to-product comparison across sales channels. Instead, I focus on price statistics (across sales channels) benchmarked by the macroeconomic literature when measuring nominal rigidities. That is, I look into the frequency and size of price changes of product categories.[9] 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.

Second, 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.

[7]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.

[8]Cavallo (2017) is part of the initiative "One billion prices project". It provides a proxy for official price indexes for few countries. Providing an alternative price index is not of this paper's objective.

[9] Although not matching online and offline individual products might be seen as a step back from an industrial organization perspective, price moments in this paper stemming from product categories have been proven informative to calibrate macroeconomic models, particularly once high frequency price changes which are orthogonal to the business cycle are accurately treated. See, among others, Galí (2015), Smets and Wouters (2007) Álvarez et al. (2016) and Woodford and Walsh (2005).

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.[10] 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 intra-year averages. 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.

Third, 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 and Stelmasiak (2019) and Hull et al. (2017) evaluate the use of web scraped data for improving their nowcast and short-term inflation forecasts, respectively. Another line of research in this literature comes from National Statistical Offices. 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. (2022); Van Loon and Roels (2018); Griffioen and Ten Bosch (2016); Rafael and Reyes (2019); Auer and Boettcher (2017); Glassock and Holt (2019). 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.[11] See, among others, Bils and Klenow (2004), Nakamura and Steinsson (2008), Dhyne et al. (2006). 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 present in policy-oriented work.

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 price

[10]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 checks for keeping measurement errors to a minimum. Hence, this should be less of a problem generating small price changes.

[11]See footnote 9.

setting comparison across channels. Section 5 discusses sample differences potentially explaining why price moments are different online and offline. Section 6 concludes.

2 Data

In this section, I outline both data sets analyzed 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 only. These outlets are commonly known as "multi-channel" retailers as they offer their clients multiple consumption channels, in this case online and offline.

2.1 Online

The online price collection, compiled by Banco de México, is carried out by a robot parsing out the website of eight retailers with online presence in Mexico. They are a mix of supermarkets, price clubs and departmental 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.[12] Per product, it 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.[13] After the price collection is completed, goods are classified using deterministic keywords in the products' descriptions 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

[12]Price collection is carried out in the retail chains' generic websites (i.e. before being assigned to any specific branch) if feasible. In some cases, the robot is automatically directed to the Mexico City's area/branch website or, if asked, the robot enters Mexico City's downtown zip code. Therefore, online prices are mostly from Mexico City.

[13]Posted prices are considered those paid by consumers, including sales, although they are not flagged out by a sales indicator. Also, as it is common practice in Mexico, posted and normal prices include any applicable tax depending on the type of good (e.g. some are subject to VAT tax). No service nor delivery fees are included in the online price collection.

classification.[14] 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 provide a point of comparison between online (websites) and offline (brick and mortar) price setting without having to match products across sale channels, 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.[15]

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.[16] As shown in Table 1, the earliest price gathering took place for one retailer in January 2016, three started in 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 data-collection days 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 shown in Table 1.[17] As there are 24 fortnights in one year, there is more than two years of data for every retailer except Retailer 6, for which there are 39 fortnights available.

[14]COICOP stands for Classification Of Individual Consumption by Purpose. It is a classification developed by the United Nations Statistics Division to classify and analyze individual consumption expenditures incurred by households, non-profit institutions serving households and general government according to their purpose.

[15]One might be concerned on whether retailers offer the same, or at least similar, set of goods on their website and 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.

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

[17]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).

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 23 million price quotes from more than 209.8 thousand different products across the eight retailers.

Table 1: Online Data by Retailer from 2016 to 2020

	Start date	End date	Days	Fortnights	Observations (Thousands)	Products (Thousands)	Frequency of Observation (Days)
Retailer 1	01 Jan 2016	05 Oct 2020	1,367	94	6,464.2	12.6	1.3
Retailer 2	31 May 2016	05 Oct 2020	1,546	106	5,961.1	12.4	1.0
Retailer 3	21 Nov 2017	31 Dec 2020	987	71	1,999.7	5.6	1.2
Retailer 4	21 Nov 2017	30 Dec 2020	730	61	322.0	1.6	1.6
Retailer 5	21 Nov 2017	31 Dec 2020	823	71	1,314.3	4.2	1.4
Retailer 6	21 Nov 2017	31 Dec 2020	344	57	1,377.9	64.0	3.3
Retailer 7	11 Aug 2016	31 Dec 2020	672	102	1,057.0	23.7	2.4
Retailer 8	12 Aug 2016	31 Dec 2020	921	106	4,528.3	85.7	1.7
Total					23,024.5	209.8	

Note: As the analysis centers at items in product categories appearing in both sales channels, the table does not necessarily reflect the retailers' size in terms of the number of items they offer to the public. Furthermore, statistics in this table encompass food and non-food items. In the following sections, results from food items are reported using lettered retailers (as instead of numbers) in order to further ensure confidentiality. Though, they are not reported using letters here as it would reveal their overlap (retailers in numbers and retailers in letters) through the start and end dates of recollections. 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 product identifiers in the retailer. *Frequency of Observation* is the mean number of days between price observations. Table 23 in the Appendix summarizes the data set under analysis from 2016 to 2019 only. Source: Author's own calculations based on data gathered by Banco de México.

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.[18]

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 price 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 (2019) and Nakamura et al. (2011) document uniform prices across different branches of the same retailer.

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.[19] However, in contrast to the online price survey, price collectors do not register the normal price in addition to the sales price.

Fourth, 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,

[18] 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.

[19] 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.

all non-food categories are priced on a fortnightly fashion.[20] 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 Álvarez et al. (2016) attribute averages prices or imputations to biases toward more frequent and smaller in magnitude prices changes. Thus, this paper is not subject to this source of bias when measuring how frequent and by how much prices adjust.

Sixth, I use data from the 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 Covid-19 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 when the online data is available.

Seventh, product categories can be clustered into COICOP Divisions. The COICOP Division *Apparel* considers product categories like men's jumpers, women's trousers, infants' footwear, among others. Such clustering adds another dimension on the comparison across sales channels along with the retailer dimension.

All in all, the offline price survey comprehends a little less than one million price quotes from about 22.6 thousand different products.

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 constitutes 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

[20]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.

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:

$$FreqPriceChange^{v}_{j,r} = \frac{\sum_{i \in \Theta^{v}_{j,r}} \mathbb{1}\left(p_{i,j,r,t} \neq p_{i,j,r,t-k}\right)}{\sum_{i \in \Theta^{v}_{j,r}} \mathbb{1}\left(p_{i,j,r,t} \text{ and } p_{i,j,r,t-k} \text{ observed}\right)} \tag{1}$$

where, $p_{i,j,r,t}$ is the price (in logs) of product i, which belongs to product category j, offered by retailer r on day t; and $\mathbb{1}(statement)$ are indicators equal to one if $statement$ is true and zero otherwise. 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 the difference in 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).

In order to further make both types of price collection comparable, I opt keeping 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.[21] 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 a given product category changing more often in brick and mortar stores is associated with a 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 summarized 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. 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 uses all days, it turns out to be lower 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.[22]

For non-food categories, Table 2 shows that for some retailers it is inconsequential the day of the week selected in the online data for the analysis when comparing them to the offline data; while for some other retailers the day of the week chosen matters. For instance, the Spearman coefficients of Retailer 1 and Retailer 2 are around 0.75 and 0.65, respectively, regardless the day of the week. In contrast, Retailer 5 exhibits a closer qualitatively relationship between the online and offline frequency of price adjustments on Wednesdays (0.67) than, for instance, Fridays (0.55). Also, for Retailer 6 the maximum correlation is calculated using Friday (0.66) data, whilst the minimum

[21] 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 than that.

[22] While the greatest point estimate of the Spearman correlation on a given day might or might not be statistically different to any other day's Spearman correlation coefficient for the same retailer, the goal is to select one day of the week per retailer. Ideally, if the greatest point estimate would not be statistically different to other day(s), all of the paper's results would have to be computed for these other days (e.g. pairs of online-Wednesday v offline; online-Friday v offline; and so on). For brevity, I simply select the day with the greatest point estimate; and just assume it is likely that results would hold if any other day with statistically insignificant difference would have been selected for the analysis.

is Wednesday (-0.54).[23] 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.[24] Retailer A and Retailer B, there are not big differences on the day chosen for the analysis. Retailer C reports no statistically significant coefficient but I use Friday nevertheless.

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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's own calculations based on data from INEGI and Banco de México.

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 A	0.85 ***	0.85 ***	0.86 ***	0.87 ***	0.87 ***	0.85 ***	0.85 ***	0.86 ***	Thursday
Retailer B	0.62 ***	0.64 ***	0.61 ***	0.61 ***	0.62 ***	0.61 ***	0.61 ***	0.62 ***	Monday
Retailer C	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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's own calculations based on data from INEGI and Banco de México.

[23] 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.

[24] Note, non-food categories retailers are numbered 1-8, while food-related categories retailers are listed A-C. This is due to confidentiality concerns (not to disclose what retailers sell either food or non-food or both types of goods) and at the request of the data steward.

Having discussed how this study uses only one day of the week by retailer in the online dataset for calculating price moments, 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.

The size of (non-zero) price adjustment of a given product is calculated as the (log) difference of $p_{i,j,c,t}$ and $p_{i,j,c,t-k}$. Following the literature on nominal rigidities, like Dhyne et al. (2006), aggregates at retailer-product category level are computed using the absolute value of prices (non-zero) 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 (non-zero) price adjustments, conditional a price change, for product category j in retailer r and distribution channel $v \in \{\text{Offline, Online}\}$ is calculated as:

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

where $\Delta^{(k)} p_{i,j,r,t}$ 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; and $\mathbb{1}(statement)$ is the indicator equal to one if $statement$ is true and zero otherwise. 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 $i \in \Theta^{v}_{j,r}$.

As part of the analysis relating the online price changes to offline price adjustments, I use a parsimonious econometric framework for shedding further light on whether those categories adjusting prices more frequently (by a larger margin) online are those changing more often (by a greater size) offline as well. Also, the econometric framework would allow to revise what dimension, either retailer or COICOP, better explains the heterogeneity in the dataset. To that end, I run the following expression,

$$X^{online}_{j,r,t} = X^{offline}_{j,r,t} \times Covid19_{2020} + Covid19_{2020} + \theta_r + \theta_d + \alpha + \varepsilon_{j,r,t} \tag{3}$$

where X is either $FreqPriceChange$ (Expression 1) or $SizePriceChange$ (Expression 2), j represents a product category, $t \in \{pre-2020, 2020\}$ highlights if the observation comes from the 2016-2019 or the 2020 period, $Covid19_{2020}$ is a dummy that takes the value of one if $t = 2020$ and zero otherwise; θ_r are retailer fixed effects, while θ_d

are COICOP Division fixed effects encompassing various product categories. Standard errors are clustered at the retailer-COICOP Division level.

Finally, I study how likely it is to observe extreme price changes, given a price adjustment, across distribution channels by looking at 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,

$$z_{i,j,r,t} = \frac{\Delta^{(k)} p_{i,j,r,t} - \mu_{j,r}}{\sigma_{j,r}} \tag{4}$$

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 4 standarizes prices changes regardless their distribution channel.

4 Stylized Facts From Online and Offline Price Setting

4.1 Frequency of Price Adjustments

In this section, I first present the stylized facts on the frequency of price changes using data from the 2016-2019 period. I then move on to discuss the results in 2020 data and how they compare to the previous period. As discussed above, the analysis by retailer is primarily motivated by Cavallo (2017) results. The author calls for caution when contrasting online and offline pricing patters in the presence of few sources of data (i.e. number retailers) as there is high degree of heterogeneity across them. Furthermore, the study by type of goods is followed as (i) some goods are more susceptible to be purchased online than offline and (ii) widely documented price setting heterogeneity across product categories when using survey or web scraped data.[25] For brevity, I report in the Appendix the list of product categories under study and price

[25]For instance, Dhyne et al. (2006) using survey data, and Cavallo (2017) using web scraped prices.

first moments abstracting from the retailer dimension.[26]

Table 4 reports the benchmark results on the frequency of price changes for non-food and food categories by retailer using data from 2016 to 2019. As summarized in Panel A, most retailers' non-food categories exhibit statistically significant differences between the frequency of price changes on their online and offline channels.[27] Notably, Retailers 1 to 5 favor the idea of more frequent price adjustments offline than online. 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.

Thus, five out of the eight retailers in the sample exhibit more frequent price changes offline than online in their non-food categories. However, when pooling categories across retailers altogether, it seems that there is a statistically significant difference at 10% in favor of more frequent price adjustments online than offline. Though, this result is mainly driven by Retailer 6, which is one with a great number of categories and a disproportionate online price flexibility. This again shows the heterogeneity across data sources, as Cavallo (2017) pointed out.

In order to check that few categories are not driving the retailers' averages, columns (e) to (g) in Table 4 focus on comparing the frequency of price changes of individual price categories.[28] On the one hand, Retailers 1 to 5 show a great number of individual categories reporting more frequent price changes through their offline channel than on their online platforms. On the other hand, Retailers 6 and 8 have more price categories adjusting more often their online prices than their offline prices. Hence, it seems that the conclusion based on averages is not due to outliers. Though, despite favoring one sales channel or the other, about a quarter of all product categories seems to change at

[26]See Table 24 and Table 25, where price statistics are calculated as unweighted averages across retailers. Product categories by retailer are not reported (other than in the scatter plots) to ensure confidentiality.

[27]Columns (a) and (b) report the average frequency of price adjustments across categories in each retailer, while column (c) is the p-value of a mean equality t-test between the online and offline average frequency. As mentioned in Section 2, price moments are calculated using categories in both online and offline datasets simultaneously. Thus, the number of categories in both online and offline datasets is the same (column d).

[28]In particular, I run z-tests on the equality of proportions of price changes for each product category and count how many of them are statistically different (5%) in favor of more changes on a given sales channel. Column (e) reports the number of categories where the online dataset exhibits greater proportion of price changes, column (f) shows the number of categories where the null-hypothesis of equality is not rejected, and column (g) highlights the number of categories with greater frequency of price changes offline than online.

similar frequencies across channels.[29]

Columns (h) and (i) report the Spearman correlation coefficient and its p-value, respectively, across retailers.[30] Lastly, column (j) shows the slope from an OLS regression, while columns (k) and (l) detail the p-values of a null equal to zero and equal to one, respectively.[31] Apart from Retailer 3, all coefficients in column (j) are positive and statistically significant different from zero. Thus, categories changing more frequently on retailers' websites are also adjusting more frequently in brick and mortar stores. In fact, for Retailer 7 and Retailer 8 the view that the OLS slope is different from one is not rejected (column l). This result might be indicative that, although the overall average frequency of price changes is different, retailers might use price setting strategies shifting the frequencies of adjustments from one sales channel relative to the other one by a constant factor. I elaborate further on this relationship using a less parsimonious regression below.

Panel B in Table 4 reports the results of food and beverages categories at retailer level.[32] Either looking retailer by retailer or by pooling categories altogether, 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.[33] Moreover, the OLS slope from the three retailers also show a positive relationship between the frequency of price changes across their channels. Though, the slope from Retailer C is not statistically significant different from zero.

As some non-food categories are more likely to be purchased online than offline, Table 5 takes a closer look at them and provides the same analysis rearranging retailers' product categories by COICOP Division. The difference on the averages across sales channels is not statistically significant for Furnishings, Health, and Recreation

[29]That is, for 77 out of 320 categories it cannot be rejected at 5% the equality on their proportion of price changes across channels, again with a great deal of heterogeneity across retailers (19 out of 48 for Retailer 5, while 0 out of 48 in Retailer 6).

[30]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 across different days of the week.

[31]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.

[32]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. A threshold of 10 categories per retailer is put in place for calculating averages. Letters, as instead of numbers, are used in order to unsure greater confidentiality on which retailers sell both food and non-food items or just one of them.

[33]E.g. 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.

and Transport. Importantly, the OLS slope is not different from 1 for Furnishings, and Recreation and Transport, posing the idea that in fact they change at somewhat similar frequencies. In contrast, Apparel changes more frequently online than offline, while for Personal Care the opposite happens. Thus, it seems that the type of goods also plays a role on the pricing-patterns across sales channels. Below in this subsection, through the lens of an econometric framework, I discuss whether the retailer dimension or the COICOP Division better explains the variation in the dataset.

Before moving on into the results using the 2020 data, Figure 1 pools all product categories under study in Table 4 and Table 5.[34] Consistent with the previous discussion, most scatters lie below the 45 degree line. In the Appendix, Figure 9 and Figure 10 break down the scatter by retailer; while Figure 11 by COICOP Divisions.

Table 4: Frequency of Price Adjustments by Retailer
Data from 2016 and 2019

	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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
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
Pooled	23.57	21.74	0.09	320	103	77	140	0.38	0.00	0.58	0.00	0.00
B. Food												
Retailer A	12.91	20.23	0.00	88	1	29	58	0.87	0.00	0.72	0.00	0.00
Retailer B	13.51	30.98	0.00	73	2	7	64	0.64	0.00	0.32	0.00	0.00
Retailer C	8.83	17.78	0.00	53	3	16	34	0.13	0.36	0.07	0.37	0.00
Pooled	12.10	23.29	0.00	214	6	52	156	0.67	0.00	0.41	0.00	0.00

Note: Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average frequency of online price changes is computed using the day of the week that maximizes the Spearman between online and offline prices. The frequency of price changes is computed on a fortnightly basis for non-food goods (Panel A), while calculated on a weekly basis for food-related items (Panel B). For more on the methodology, see Section 3. Columns (a) and (b) report averages across unweighted product categories. Column (c) reports the p-value from a two-sided t-test of mean differences. Product categories are the same across sales channels within the retailer, but might differ across retailers. Columns (e) to (g) report the number of categories that, using two-sided z-test of proportion differences, exhibit greater fraction of online price changes than offline changes at 5% significance level ($On > Off$), the difference is statistically insignificant at 5% (Equal), and greater proportion of offline price changes than online adjustments at 5% significance level ($Off > On$). Beta coefficients come from regressions using online prices as dependent variable, offline prices as the independent variable, plus a constant. Source: Author's own calculations based on data from INEGI and Banco de México.

Table 6 reports the average frequency of price changes by retailer using data from 2020. As before, it seems that for both non-food and food categories (Panels A and B) the majority of retailers change their prices more frequently offline than online.[35]

[34]Each scatter represents one price category. 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. The OLS slope, reported in column (j), and the 45 degree line are depicted as solid and dashed lines, respectively.

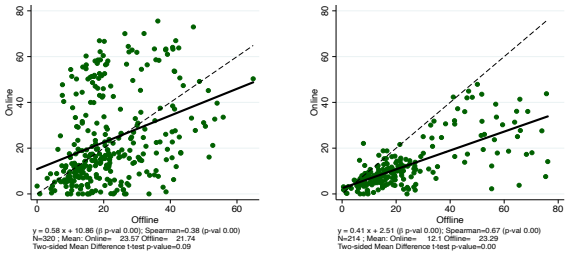
[35]In Panel A, four retailers report greater average frequency of price changes offline (column b) than online (column a), while the opposite happens in three cases, and in one case the difference is

Table 5: Frequency of Price Adjustments by COICOP Division
Data from 2016 and 2019

	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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
Apparel	30.55	16.60	0.00	59	34	3	22	0.23	0.09	1.03	0.17	0.97
Furnishings	25.33	24.27	0.48	122	40	36	46	0.58	0.00	0.86	0.00	0.26
Health	13.84	14.89	0.54	35	4	19	12	0.28	0.11	0.01	0.99	0.00
Recreation and Transport	23.22	21.92	0.57	39	13	8	18	0.73	0.00	0.99	0.00	0.96
Personal Care and Others	19.37	25.25	0.01	65	12	11	42	0.07	0.56	0.02	0.91	0.00
Pooled	23.57	21.74	0.09	320	103	77	140	0.38	0.00	0.58	0.00	0.00

Note: Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average frequency of online price changes is computed using the day of the week that maximizes the Spearman between online and offline prices. Columns (a) and (b) report averages calculated across unweighted product categories. Column (c) reports the p-value from a two-sided t-test of mean differences. Product categories are the same across sales channel within COICOP Division. Columns (e) to (g) report the number of categories that, using two-sided z-test of proportion differences, exhibit greater fraction of online price changes than offline changes at 5% significance level ($On > Off$), the difference is statistically insignificant at 5% (Equal), and greater proportion of offline price changes than online adjustments at 5% significance level ($Off > On$). Beta coefficients come from regressions using online prices as dependent variable, offline prices as the independent variable, plus a constant. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 1: Frequency of Price Adjustments from 2016 to 2019
Each scatter represents a product category from a given retailer
(a) Non-Food (b) Food



Note: These figures pool all product categories reported in Table 4 and Table 5. Each scatter represents one price category in a given retailer. 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. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. In the Appendix, Figure 9 and Figure 10 break down the scatter by retailer; while Figure 11 depicts the categories by COICOP Division. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average frequency of online price changes is computed using the day of the week that maximizes the Spearman between online and offline prices. The frequency of price changes is computed on a fortnightly basis for non-food goods, while calculated on a weekly basis for food-related items. For more on the methodology, see Section 3. Source: INEGI and Banco de México.

Though, when pooling the categories altogether, the difference in the average is statistically insignificant for non-food categories, but it remains significant for food-related categories also in favor of more often offline price variations than online price changes. In terms of the OLS slope relating the frequencies of online and offline price changes, six are positive and statistically significant different from zero in Panel A and two out of three in Panel B. Hence, categories changing more frequently offline are those adjusting online more often as well as in the the 2016-2019 period.

statistically insignificant.

Regarding the type of products, as defined by the COICOP Division classification, Table 7 also confirms the results found in the 2016-2019 data. In other words, Furnishings, Health, and Recreation and Transport seem to change at same frequencies across sales channel; Apparel reports greater frequency of adjustment online than offline; whilst Personal Care the opposite. Notably, the OLS slope in four out of five divisions is not different from the unity.

Figure 2 depicts all product categories used in Table 6 and Table 7. Compared to the 2016-2019 period, it is less clear that most scatters lay below the 45 degree line, specially for non-food categories. In the Appendix, Figure 12, Figure 13 and Figure 14 illustrate frequency of price changes in 2020 across product categories by retailer and COICOP Division. All in all, it seems that the qualitative conclusion from the 2016-2019 period, i.e. more frequent price changes in brick and mortar stores than in websites, persists in the 2020.

Table 6: Frequency of Price Adjustments by Retailer
Data from 2020

	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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
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
Pooled	28.08	27.67	0.65	261	79	100	82	0.61	0.00	0.84	0.00	0.02
B. Food												
Retailer A	10.39	17.55	0.00	74	0	39	35	0.71	0.00	0.57	0.00	0.00
Retailer B	17.74	28.09	0.00	60	4	15	41	0.72	0.00	0.60	0.00	0.00
Retailer C	7.50	19.50	0.00	42	0	10	32	0.39	0.01	0.12	0.16	0.00
Pooled	12.21	21.61	0.00	176	4	64	108	0.65	0.00	0.58	0.00	0.00

Note: Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average frequency of online price changes is computed using the day of the week that maximizes the Spearman between online and offline prices in the 2016/19 period. The frequency of price changes is computed on a fortnightly basis for non-food goods (Panel A), while calculated on a weekly basis for food-related items (Panel B). For more on the methodology, see Section 3. Columns (a) and (b) report averages across unweighted product categories. Column (c) reports the p-value from a two-sided t-test of mean differences. Product categories are the same across sales channels within the retailer, but might differ across retailers. Columns (e) to (g) report the number of categories that, using two-sided z-test of proportion differences, exhibit greater fraction of online price changes than offline changes at 5% significance level ($On > Off$), the difference is statistically insignificant at 5% (Equal), and greater proportion of offline price changes than online adjustments at 5% significance level ($Off > On$). Beta coefficients come from regressions using online prices as dependent variable, offline prices as the independent variable, plus a constant. Source: Author's own calculations based on data from INEGI and Banco de México.

4.1.1 Comparison Pre-2020 and 2020

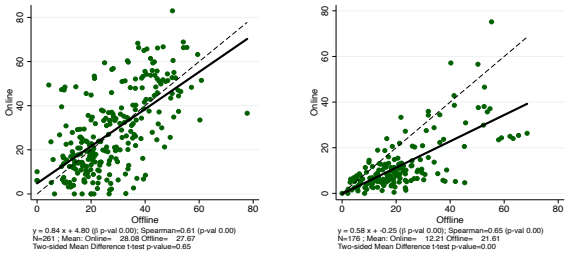
As it is mentioned above, the main reason to compute the stylized facts of price adjustments in two different periods stemms from the fact that in 2020, as a result of

Table 7: Frequency of Price Adjustments by COICOP Division
Data from 2020

	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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
Apparel	36.80	27.58	0.00	52	33	15	4	0.62	0.00	0.97	0.00	0.87
Furnishings	29.18	28.65	0.66	103	31	41	31	0.75	0.00	1.02	0.00	0.81
Health	17.04	18.28	0.64	27	3	15	9	0.06	0.76	0.66	0.03	0.27
Recreation and Transport	30.10	30.22	0.97	31	7	15	9	0.79	0.00	0.89	0.00	0.52
Personal Care and Others	21.17	29.27	0.00	48	5	14	29	0.29	0.05	0.24	0.12	0.00
Pooled	28.08	27.67	0.65	261	79	100	82	0.61	0.00	0.84	0.00	0.02

Note: Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average frequency of online price changes is computed using the day of the week that maximizes the Spearman between online and offline prices in the 2016/2019 period. Columns (a) and (b) report averages calculated across unweighted product categories. Column (c) reports the p-value from a two-sided t-test of mean differences. Product categories are the same across sales channel within COICOP Division. Columns (e) to (g) report the number of categories that, using two-sided z-test of proportion differences, exhibit greater fraction of online price changes than offline changes at 5% significance level ($On > Off$), the difference is statistically insignificant at 5% (Equal), and greater proportion of offline price changes than online adjustments at 5% significance level ($Off > On$). Beta coefficients come from regressions using online prices as dependent variable, offline prices as the independent variable, plus a constant. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 2: Frequency of Price Adjustments in 2020
Each scatter represents a product category from a given retailer
(a) Non-Food (b) Food



Note: These figures pool all product categories reported in Table 6 and Table 7. Each scatter represents one price category. 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. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. In the Appendix, Figure 12, Figure 13 and Figure 14 illustrate frequency of price changes in 2020 across product categories by retailer and COICOP Division. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average frequency of online price changes is computed using the day of the week that maximizes the Spearman between online and offline prices. The frequency of price changes is computed on a fortnightly basis for non-food goods, while calculated on a weekly basis for food-related items. For more on the methodology, see Section 3. Source: INEGI and Banco de México.

the Covid-19 pandemic, price-setters might have given a step forward in terms of their website operations. Hence, I analyze whether the frequency of price changes varies on either of their sales channels in 2020 relative to 2016-2019 data.

Table 8 offers a comparison between periods, 2016-2019 and 2020. It shows that, in general for non-food categories, both online and offline sales channels exhibit an increase on the frequency prices change in 2020 relative to the 2016/19 period.[36] In

[36]For non-food categories, four out of the five retailers that displayed a statistically significant difference between periods in the online channel favor more often price changes in 2020 (Panel A, columns d and e). Moreover, for non-food categories in the offline channel, five out of the five retailers

contrast, food-related categories see a decrease on how often they see a price change in 2020 relative to pre-2020.[37]

Table 9 repeats the exercise on comparing time periods by sales channel and COICOP Division. All differences in both sales channels suggest an increase in 2020. In the case of the online channel (column e), they are statistically significant different from zero for Apparel and Furnishings. In the offline channel (column i), they all but Health increased.

Table 8: Comparison Between 2016-2019 and 2020 by Retailer
Frequency of Price Adjustments for Non-Food and Food Categories

	Product Categories	Online				Offline			
		Average		Difference	Ho: Equality p-value	Average		Difference	Ho: Equality p-value
		2016/19	2020			2016/19	2020		
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
A. Non-Food									
Retailer 1	27	12.12	12.10	-0.02	0.98	16.35	16.16	-0.19	0.89
Retailer 2	26	17.38	17.76	0.37	0.71	24.80	24.13	-0.67	0.60
Retailer 3	38	16.64	14.10	-2.54	0.16	18.41	21.44	3.03	0.00
Retailer 4	10	15.86	24.98	9.12	0.02	22.34	24.23	1.89	0.56
Retailer 5	43	19.18	23.93	4.76	0.00	26.99	30.16	3.17	0.09
Retailer 6	33	56.64	53.05	-3.58	0.05	25.55	42.74	17.19	0.00
Retailer 7	36	24.32	35.13	10.81	0.00	20.29	25.03	4.74	0.00
Retailer 8	27	30.35	40.30	9.96	0.01	24.51	36.04	11.53	0.00
B. Food									
Retailer A	74	12.32	10.39	-1.93	0.01	19.46	17.55	-1.92	0.07
Retailer B	59	15.04	17.99	2.95	0.01	34.56	28.47	-6.09	0.00
Retailer C	42	8.77	7.50	-1.27	0.08	17.55	19.50	1.96	0.09

Note: The number of categories, column (a), is less than those reported in Table 4 and Table 6 as it restricts the sample to product categories appearing in both time periods and sales channels. Thus, averages in columns (b), (c), (f) and (g) might also differ to those in the aforementioned Tables. Columns (d) and (h) are calculated as the unweighted average difference across categories, while columns (e) and (i) report the p-value from a two-sided t-test of mean differences. Source: Author's own calculations based on data from INEGI and Banco de México.

In general, it seems that, (i) prices tend to change more frequently in brick and mortar stores (offline) than on websites, (ii) product categories changing more often in one sales channel tend to do so as well in the other one i.e. positive relationship on the frequency of price changes across channels, (iii) this is particularly clear for food categories and Personal Care, while it is less clear for the rest of non-food categories, (iv) such price patterns hold in both 2016-2019 and 2020 periods and (v) the frequency of price adjustment increased in 2020 relative to 2016-2019 for non-food categories, whilst for food-related categories the frequency decreased.

Lastly, results from Equation 3 are reported in Table 10. First, by looking at the

with a statistically significant difference between periods favor greater frequency of adjustment in 2020 (Panel A, columns h and i).

[37]Two out of three retailers decrease their frequency of price changes in 2020 relative to 2016/19 in both sales channels (Panel B, columns d and i), and such decrease is statistically significant (10%).

Table 9: Comparison Between 2016-2019 and 2020 by COICOP Division
Frequency of Price Adjustments for Non-Food Categories

	Product Categories	Online				Offline			
		Average		Difference	Ho: Equality p-value	Average		Difference	Ho: Equality p-value
		2016/19	2020			2016/19	2020		
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
A. Non-Food									
Apparel	41	27.84	36.13	8.29	0.00	16.56	28.67	12.10	0.00
Furnishings	99	26.86	29.24	2.38	0.05	24.46	28.63	4.17	0.00
Health	21	17.15	18.15	0.99	0.59	14.73	16.73	2.00	0.31
Recreation and Transport	31	27.19	30.10	2.91	0.17	23.25	30.22	6.97	0.00
Personal Care and Others	48	19.90	21.17	1.28	0.37	26.54	29.27	2.73	0.08

Note: The number of categories, column (a), is less than those reported in Table 5 and Table 7 as it restricts the sample to product categories appearing in both time periods and sales channels. Thus, averages in columns (b), (c), (f) and (g) might also differ to those in the aforementioned Tables. Columns (d) and (h) are calculated as the unweighted average difference across categories, while columns (e) and (i) report the p-value from a two-sided t-test of mean differences. Source: INEGI and Banco de México.

R-squared and the coefficient of interest in columns (2) and (3), it seems that the retailer fixed effects tend to capture more the variation in the dataset than the COICOP Division fixed effects. Second, column (5) suggests an increase in online price changes in 2020 relative to the pre-2020 period. Finally, as column (6) illustrates, the slope between the online and offline frequency of price changes does not seem to have changed between periods.

Table 10: Frequency of Price Adjustments

	Online Frequency					
	(1)	(2)	(3)	(4)	(5)	(6)
Offline Frequency	0.617***	0.480***	0.599***	0.473***	0.468***	0.439***
	(0.120)	(0.0573)	(0.0821)	(0.0575)	(0.0588)	(0.0844)
Covid 2020					1.414**	-0.181
					(1.403)	(1.897)
Covid × Offline Fq						0.0663
						(0.108)
Observations	971	971	971	971	971	971
R-squared	0.252	0.635	0.428	0.649	0.651	0.652
Retailer FE	.	Yes	.	Yes	Yes	Yes
COICOP Div FE	.	.	Yes	Yes	Yes	Yes

Standard errors clustered at Retailer-COICOP Div in parentheses.
Source: INEGI and Banco de México.
*** p<0.01, ** p<0.05, * p<0.1

4.2 Absolute Size of Price Adjustments

Table 11 reports the average size of price changes for non-food and food categories as defined by Equation 2 for the 2016-2019 period. It seems that for both non-food

and food categories the size of non-zero price changes in the online channel are greater, on average, than the offline price changes in all retailers.[38] In turn, the difference is statistically significant at the 10% in all cases (column c in Panels A and B). That is also confirmed by the great number of individual categories where the size of price changes is greater online than offline (column e).[39] 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 seems to be greater for prices observed online than those seen offline. Qualitatively, that is also the case when pooling retailers' categories altogether in the 2016-2019 period.

In most cases the OLS slopes are positive as column (j) in Table 11 shows. However, with the exception of four out of 11 instances, they are not statistically significant different from zero.[40] For Retailers 4 and 7, the hypothesis of a 1-to-1 relationship between the magnitudes of prices changes online and offline is not rejected (see p-value in column l). Thus, although it persists the positive relationship for the case of the size of price changes across categories within retailers, as found on the frequency of price changes, the relationship is weaker and statistically insignificant in most cases.

Table 12 analyses the size of price changes by COICOP Division of non-food categories for the 2016-2019 period. Consistent with Table 11, all divisions favor the idea of greater magnitude of price changes online than offline, given a non-zero price change. Differences range from about 9 p.p. (Personal Care) to nearly 5 p.p. (Health). Moreover, Furnishings is the only division where the slope is positive and statistically significant.

Figure 3 depicts the size of price changes across sales channels for all price categories in the 2016-2019 period. As expected, most scatters lay above the 45 degree line. In the Appendix, Figure 15 and Figure 16 break down the scatters by retailer, whilst Figure 17 highlights the scatters by COICOP Division.

Regarding the size of price adjustments in 2020, as reported in Panels A and B from Table 13, six out of ten cases online prices change by a larger magnitude than

[38]For instance, point differences in non-food categories range from nearly 2 p.p. (Retailer 1) to about 15 p.p. (Retailer 2) in favor of greater online price changes than offline price adjustments. In food-related categories, the range spans from around 1 p.p (Retailer A) to nearly 23 p.p. (Retailer B).

[39]Note, however, it is not uncommon to find few categories reporting not statistically significant differences across channels, nor reporting greater price variations offline than online (columns f and g).

[40]The exceptions with a p-value less than 0.10 in column (k) are Retailers 1, 4 A and C. Similarly, the Spearman correlation coefficients of Retailers 1, 5, A and C are positive and statistically different from zero.

Table 11: Size of Price Adjustments by Retailer
Data from 2016 and 2019

	Size 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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
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
Pooled	19.66	13.31	0.00	265	176	59	30	0.24	0.00	0.28	0.00	0.00
B. Food												
Retailer A	11.61	10.31	0.00	75	24	45	6	0.63	0.00	0.59	0.00	0.00
Retailer B	33.49	10.90	0.00	63	55	5	3	-0.10	0.42	-0.16	0.72	0.01
Retailer C	13.44	8.30	0.00	41	29	11	1	0.48	0.00	0.55	0.00	0.01
Pooled	19.73	10.06	0.00	179	108	61	10	0.23	0.00	0.55	0.03	0.09

Note: Using data from 2016 to 2019 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. Source: INEGI and Banco de México.

Table 12: Size of Price Adjustments by COICOP Division
Data from 2016 and 2019

	Size 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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
Apparel	23.15	17.72	0.00	43	30	11	2	-0.13	0.40	-0.06	0.75	0.00
Furnishings	18.46	13.37	0.00	103	61	24	18	0.21	0.04	0.24	0.07	0.00
Health	15.77	10.93	0.00	29	13	12	4	-0.04	0.82	0.10	0.71	0.00
Recreation and Transport	21.10	12.41	0.00	32	24	4	4	0.23	0.20	0.36	0.41	0.14
Personal Care and Others	20.35	11.61	0.00	58	48	8	2	0.07	0.62	0.27	0.29	0.01
Pooled	19.66	13.31	0.00	265	176	59	30	0.24	0.00	0.28	0.00	0.00

Note: Using data from 2016 to 2019 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. Source: INEGI and Banco de México.

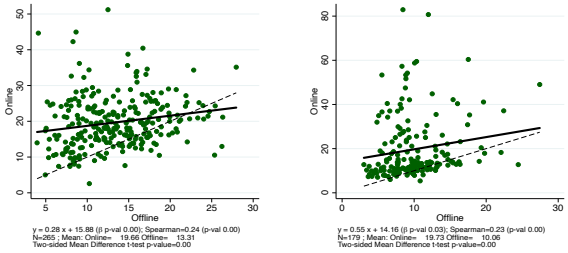
offline prices at the 10% significance.[41] In contrast, three instances do not exhibit a statistically significant differences on their averages. The OLS slope, relating the size of price changes across sales channels, is positive and statistically significant in six out of 10 cases. In fact, Retailers 3, 6 and 8 report a slope not statistically significant

[41]Retailer 4 is omitted for the analysis on the size of price changes in 2020 due to small sample issues in 2020. The six cases are Retailers 3, 5, 7, as well as Retailers A, B and C.

Figure 3: Size of Price Adjustments from 2016 to 2019

Each scatter represents a product category from a given retailer

(a) Non-Food (b) Food



Note: These figures depict the size of price changes across sales channels for all price categories in the 2016-2019 period. Each scatter represents one price category in a given retailer. The size of price changes from the online channel is highlighted in the vertical axis, while the horizontal axis comes from the offline price survey. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. In the Appendix, Figure 15 and Figure 16 break down the scatters by retailer, whilst Figure 17 highlights the scatters by COICOP Division. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average size of non-zero price changes is computed using the day of the week that maximizes the Spearman between the frequency of adjustments of online and offline prices. Statistics computed on a fortnightly basis for non-food goods, while calculated on a weekly basis for food-related items. For more on the methodology, see Section 3. Source: INEGI and Banco de México.

different from one, implying a one to one relationship (plus a constant) on the size of adjustments between sales channels.

Table 14 takes a closer look at non-food categories in 2020. In contrast to the pre-2020 data, where all divisions favor greater size of price changes online than offline, in 2020 there is one exception (Health). Though, similar to the previous period, only one category (Personal Care) exhibits a statistically significant OLS slope across sales channels.

Figure 4 depicts the size of price changes across sales channels for all price categories in 2020. In contrast to the pre-2020 period, it is less clear that most scatters lay above the 45 degree line, while the slope is somewhat steeper. In the Appendix, the break down by retailer is illustrated in Figure 18 and Figure 19; and by COICOP Division in Figure 20.

All in all, it seems that the size of prices changes is different between channels. The evidence suggests greater price changes online than offline, specially in the 2016-2019 period.

4.2.1 Comparison Pre-2020 and 2020

Table 15 compares the size of price adjustments across periods within sales channels. It shows that in four out of 11 instances the average size of online price changes in 2020 decreased relative to the average size of online price adjustments from 2016 to 2019,

Table 13: Size of Price Adjustments
Data in 2020

	Size 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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
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	0.10	0.56	-0.79	0.03	0.00
Retailer 6	17.14	18.07	0.07	33	4	17	12	0.69	0.00	1.24	0.00	0.43
Retailer 7	24.02	18.33	0.00	35	19	11	5	0.27	0.12	0.27	0.55	0.11
Retailer 8	23.84	23.06	0.44	27	6	18	3	0.70	0.00	0.81	0.00	0.24
Pooled	19.77	15.32	0.00	201	91	85	25	0.54	0.00	0.65	0.00	0.00
B. Food												
Retailer A	12.38	10.90	0.01	35	6	28	1	0.75	0.00	0.69	0.00	0.01
Retailer B	14.02	12.35	0.06	44	11	27	6	0.54	0.00	0.57	0.00	0.01
Retailer C	13.36	8.01	0.00	19	12	7	0	0.23	0.34	0.43	0.23	0.12
Pooled	13.31	10.99	0.00	98	29	62	7	0.57	0.00	0.55	0.00	0.00

Note: Using data from 2020 only. Retailer 4 is omitted due to small sample issues (less than 10 categories). 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. Source: INEGI and Banco de México.

Table 14: Size of Price Adjustments by COICOP Division
Data in 2020

	Size 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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
Apparel	27.62	21.80	0.00	43	23	16	4	0.39	0.01	0.27	0.37	0.02
Furnishings	18.12	14.28	0.00	83	34	38	11	0.38	0.00	0.25	0.17	0.00
Health	8.07	7.44	0.66	10	2	6	2	0.18	0.63	0.02	0.94	0.00
Recreation and Transport	21.31	14.68	0.01	26	14	8	4	-0.06	0.77	-0.07	0.85	0.01
Personal Care and Others	16.61	12.83	0.00	39	18	17	4	0.56	0.00	0.53	0.03	0.05
Pooled	19.77	15.32	0.00	201	91	85	25	0.54	0.00	0.65	0.00	0.00

Note: Using data from 2020 categories only. Prices changes do not consider the sign of adjustment (absolute value). Categories from Retailer 4 are not considered due to small sample issues (less than 10 categories). 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. Source: INEGI and Banco de México.

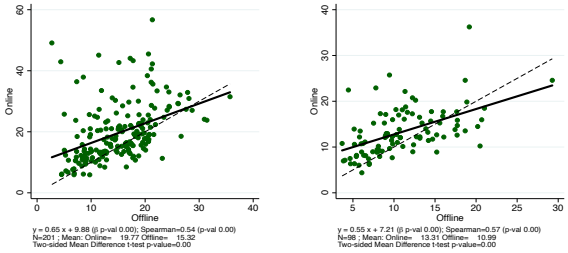
and such decreases are statistically significant. Out of these four cases, three come from non-food categories (Retailers 1, 2 and 6) and one from food-related categories (Retailer B). In contrast, only in one case an increase was observed (Retailer 7), while the remaining five there are no meaningful differences across periods for the online channel.

The offline channel exhibits a different pattern. The three instances where the difference between averages are statistically significant across periods (Retailers 5, 6 and

Figure 4: Size of Price Adjustments in 2020

Each scatter represents a product category from a given retailer

(a) Non-Food (b) Food



Note: These figures depict the size of price changes across sales channels for all price categories in tin 2020. Each scatter represents one price category in a given retailer. The size of price changes from the online channel is highlighted in the vertical axis, while the horizontal axis comes from the offline price survey. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. In the Appendix, the break down by retailer is illustrated in Figure 18 and Figure 19; and by COICOP Division in Figure 20. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average size of non-zero price changes is computed using the day of the week that maximizes the Spearman between the frequency of adjustments of online and offline prices. Statistics computed on a fortnightly basis for non-food goods, while calculated on a weekly basis for food-related items. For more on the methodology, see Section 3. Source: INEGI and Banco de México.

7), they favor an increase in the magnitude of price changes in 2020 with respect to the pre-2020 period.[42]

These findings are confirmed by Table 16 when rearranging non-food product categories by COICOP Division. That is, there is some evidence that online price changes decrease their size of adjustment in 2020 relative to pre-2020, while in the offline channel there seems to be an increase in the order of their variations.

Lastly, estimates from Equation 3 using the size of price adjustments are reported in Table 17. Results suggest that, in general, product categories changing by a larger margin online are also those adjusting by a larger size offline. The R-squared seems to recognize the retailer-dimension as a greater source of heterogeneity over the COICOP Division in the dataset. This is shown in column (2) and column (3), and it is a similar result to the one found for the frequency of price changes in Table 10. Moreover, the point estimate of the Covid dummy in column (5) is negative but not statistically significant, in line with some of the decreases reported in Table 15. Surprisingly, the most saturated model, column (6), does not report any slope (pre-2020 and 2020) statistically significant. Although positive, results from column (6) confirm that the relationship across sales channels on the size of price changes is less clearer than for the frequency of price variations.

[42]In five out of the seven remaining retailers also favor an increase in 2020 with respect to pre-2020, though the differences are not statistically significant.

Table 15: Comparison Between 2016-2019 and 2020
Size of Price Adjustments by Retailer

	Product Categories	Online				Offline			
		Average		Difference	Ho: Equality p-value	Average		Difference	Ho: Equality p-value
		2016/19	2020			2016/19	2020		
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
A. Non-Food									
Retailer 1	15	14.03	12.69	-1.34	0.05	11.14	11.78	0.64	0.63
Retailer 2	22	24.64	9.79	-14.86	0.00	9.33	8.95	-0.38	0.54
Retailer 3	28	22.23	25.81	3.58	0.11	13.59	13.41	-0.17	0.81
Retailer 5	33	15.66	17.31	1.65	0.13	9.71	11.36	1.65	0.00
Retailer 6	33	18.27	17.14	-1.13	0.03	16.46	18.07	1.61	0.00
Retailer 7	31	20.94	23.40	2.45	0.10	14.34	18.14	3.80	0.00
Retailer 8	14	20.94	20.16	-0.78	0.41	19.46	21.17	1.70	0.34
B. Food									
Retailer A	35	11.57	12.38	0.81	0.18	10.80	10.90	0.10	0.85
Retailer B	44	28.44	14.02	-14.42	0.00	11.94	12.35	0.40	0.31
Retailer C	19	13.59	13.36	-0.23	0.89	7.44	8.01	0.57	0.33

Note: The number of categories, column (a), is less than those reported in Table 11 and Table 13 as it restricts the sample to product categories appearing in both time periods and sales channels. Thus, averages in columns (b), (c), (f) and (g) might also differ to those in the aforementioned Tables. Columns (d) and (h) are calculated as the unweighted average difference across categories, while columns (e) and (i) report the p-value from a two-sided t-test of mean differences. Retailer 4 is omitted due to small sample issues in 2020 (less than 10 categories). Source: Author's own calculations based on data from INEGI and Banco de México.

Table 16: Comparison Between 2016-2019 and 2020 for Non-Food Categories
Size of Price Adjustments by COICOP Division

	Product Categories	Online				Offline			
		Average		Difference	Ho: Equality p-value	Average		Difference	Ho: Equality p-value
		2016/19	2020			2016/19	2020		
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
A. Non-Food									
Apparel	27	23.64	24.77	1.13	0.56	17.73	20.56	2.83	0.00
Furnishings	78	18.20	17.83	-0.37	0.70	13.15	14.46	1.31	0.01
Health	8	19.48	7.02	-12.45	0.00	9.25	7.78	-1.47	0.34
Recreation and Transport	26	19.03	21.31	2.28	0.08	12.91	14.68	1.77	0.05
Personal Care and Others	37	19.69	16.30	-3.40	0.04	11.33	12.21	0.88	0.03

Note: The number of categories, column (a), is less than those reported in Table 12 and Table 14 as it restricts the sample to product categories appearing in both time periods and sales channels. Thus, averages in columns (b), (c), (f) and (g) might also differ to those in the aforementioned Tables. Columns (d) and (h) are calculated as the unweighted average difference across categories, while columns (e) and (i) report the p-value from a two-sided t-test of mean differences. Retailer 4 is omitted due to small sample issues in 2020 (less than 10 categories). Source: Author's own calculations based on data from INEGI and Banco de México.

4.3 Distribution of Price Changes

Having presented the average size of price changes, this section turns into the distribution of price changes. In contrast to the previous subsection, where the sign of price variations are neglected by calculating the absolute value of price adjustments, the distribution of price changes encompasses information on price hikes (positive changes) or price drops (negative adjustments). These distributions (i) only consider non-zero price changes, (ii) price changes are calculated as the first difference of log prices and (iii) the

Table 17: Size of Price Adjustments

	Online Size					
	(1)	(2)	(3)	(4)	(5)	(6)
Offline Size	0.480***	0.417***	0.318***	0.310***	0.380***	0.199
	(0.148)	(0.101)	(0.0739)	(0.0976)	(0.0686)	(0.143)
Covid 2020					-3.660	-8.465
					(2.625)	(5.201)
Covid × Offline Sz						0.373
						(0.229)
Observations	743	743	743	743	743	743
R-squared	0.068	0.246	0.100	0.291	0.321	0.331
Retailer FE	.	Yes	.	Yes	Yes	Yes
COICOP Div FE	.	.	Yes	Yes	Yes	Yes

Standard errors clustered at Retailer-COICOP Division in parentheses.
Source: Author's own calculations based on data from INEGI and Banco de México.
*** p<0.01, ** p<0.05, * p<0.1

distributions pool all price changes in any given retailer by sales channel. Figure 5 and Figure 6 depict the pre-2020 distribution of price adjustments for non-food and food-related categories, respectively. Figure 7 and Figure 8 illustrate the distribution of price changes using the 2020 data. 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.

An interesting pattern standing out is the size of the distributions around zero (small prices changes) between sales channel. The distribution of online prices changes exhibits a minor fraction of small price adjustments (± 2.5), while the offline distribution is centered around these small price variations. See, for instance, Retailer 3 in Figure 5.[43]

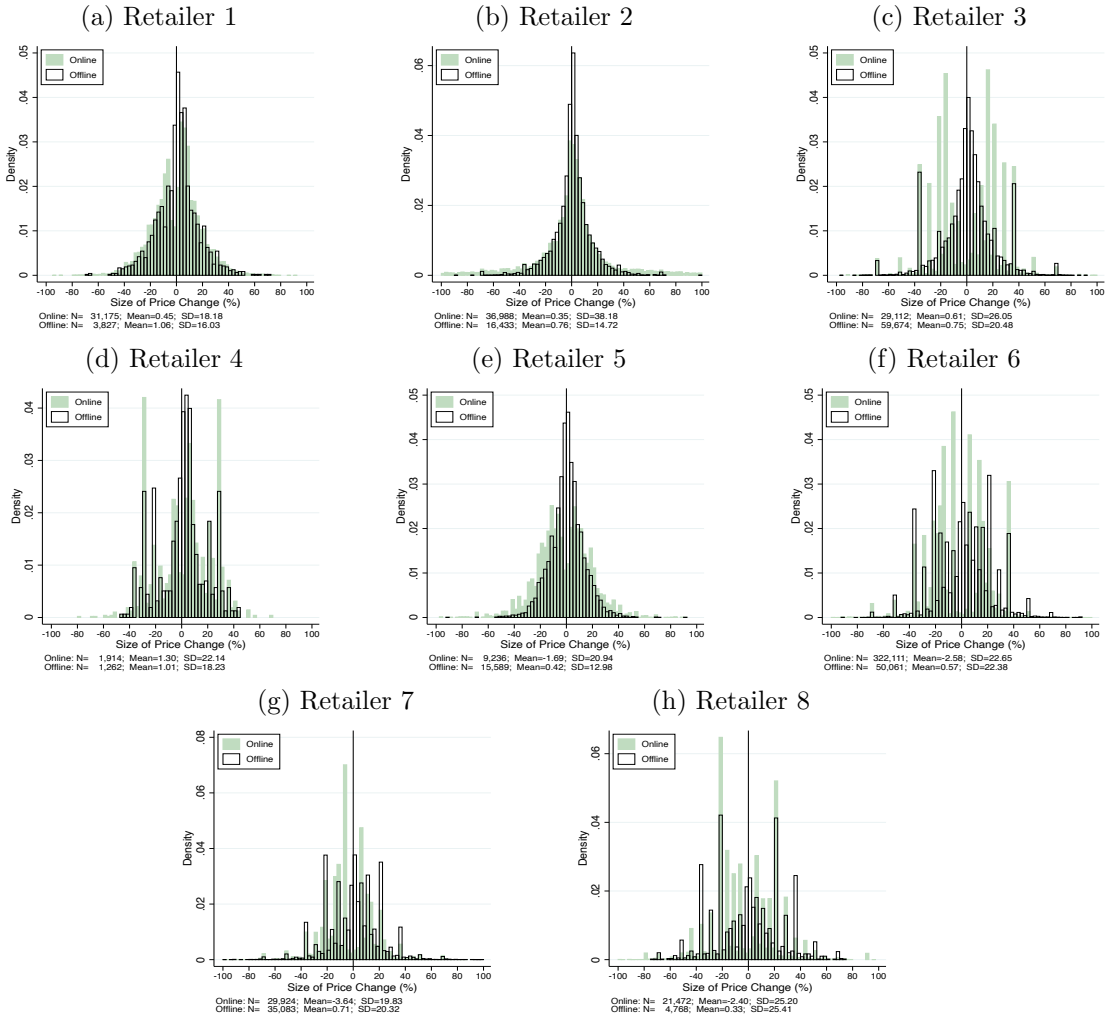
Álvarez et al. (2016) and Cavallo (2017) attribute the non-trivial size of small price changes to imputations and use of average prices commonly used in CPI surveys. These two factors are not a source of bias in calculating offline price changes in this paper.[44]

Moreover, it seems that, on the one hand, some multi-channel retailers seem to set their price variations mainly at focal points (multiples of 5 between ± 20); and in the other hand, some muti-channel retailers report changes along the continuous horizontal

[43]In fact, all but Retailers 2, B and C exhibit a distribution with a "crater-like" pattern in both pre-2020 and 2020 periods. Hence, it seems that the discrepancy between the distribution size around zero is more pressing for non-food products than for food items.

[44]As mentioned in Section 2 and Section 3, for this research (i) observed prices are employed as instead of average prices and (ii) imputations are filtered out (the dataset includes an indicator flagging out these cases). Note, however, imputations and average prices are indeed used by INEGI when computing the CPI.

Figure 5: Distribution of Non-Zero Price Changes in Non-Food Categories in 2016-2019



Note: These distributions (i) only consider non-zero price changes, (ii) price changes are calculated as the first difference of log prices and (iii) the distributions pool all price changes in any given retailer by sales channel. They depict the pre-2020 distribution of price adjustments for non-food categories. 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 bins price changes in multiples of 2.5 p.p. The area in each histogram adds up to one. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

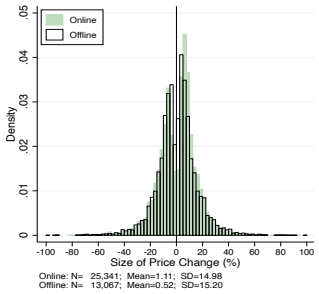
axis in both sales channels.[45] The focal points are clearer in the distribution of online price changes, though they are also present in the offline distribution (specially in the 2020 period).

All in all, the distributions of online price changes show a smaller fraction of price changes around zero (small price changes), as well as a greater share of prices changes at focal points, relative to their offline counterparts. These findings align well with the

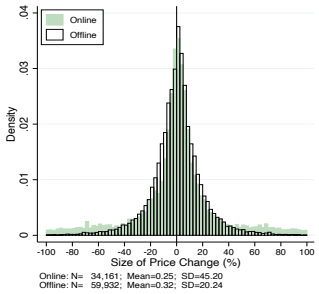
[45]See, for instance, the focal points at Retailers 3, 4, 6 and 8 in both periods, while the absent of them at Retailers 1, 2, A and B in both periods

Figure 6: Distribution of Non-Zero Price Changes in Food Categories in 2016-2019

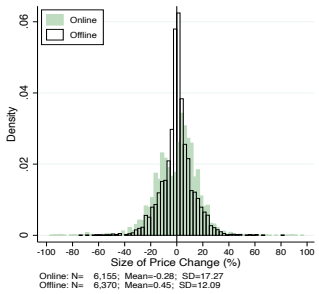
(a) Retailer A



(b) Retailer B



(c) Retailer C



Note: These distributions (i) only consider non-zero price changes, (ii) price changes are calculated as the first difference of log prices and (iii) the distributions pool all price changes in any given retailer by sales channel. They depict the pre-2020 distribution of price adjustments for food-related categories. 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 bins price changes in multiples of 2.5 p.p. The area in each histogram adds up to one. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

fact that, on average, online prices change by a greater margin (absolute value) than those in physical stores.

4.4 Kurtosis of Price Changes

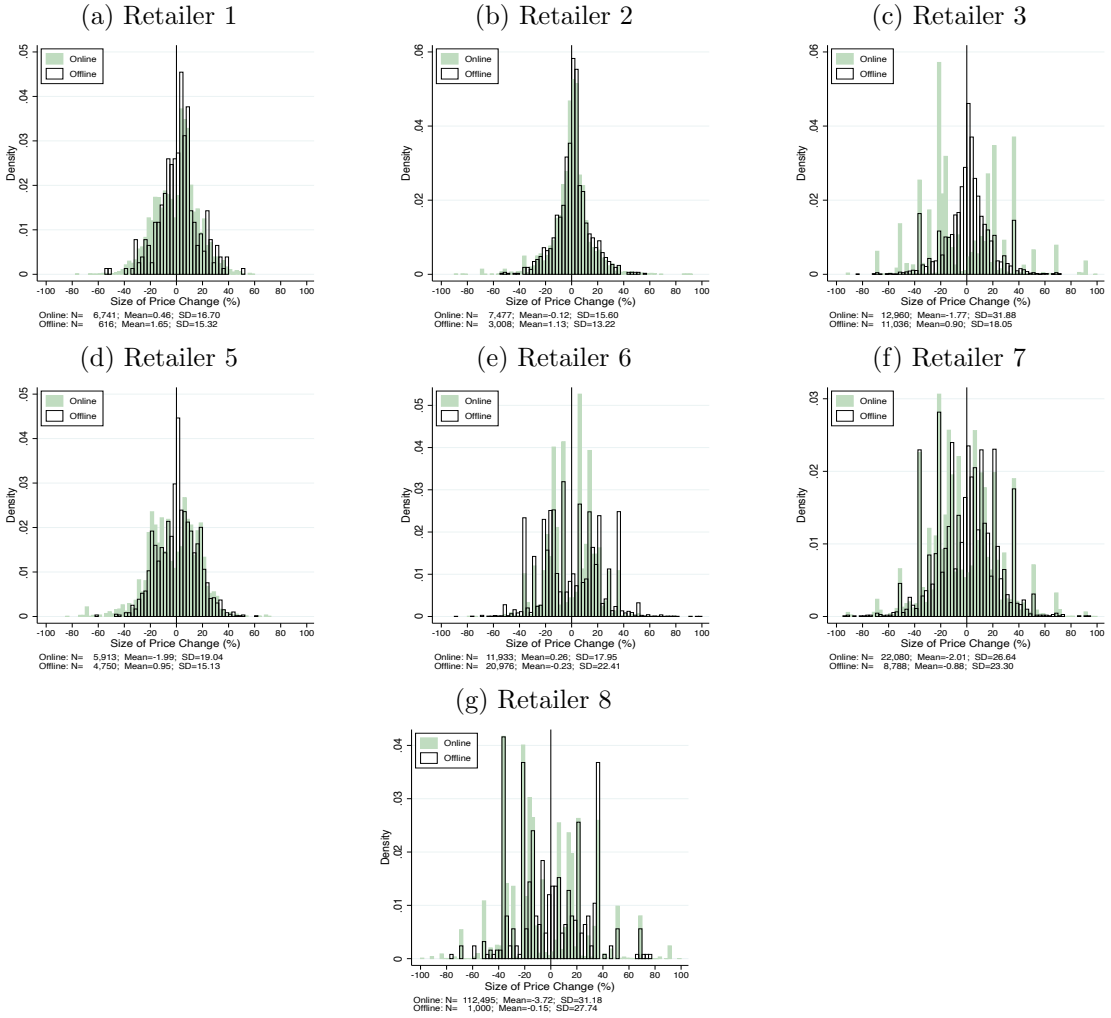
Continuing with the comparison on the size of price changes across sales channels, I study the kurtosis of the distribution of standardized prices changes.[46] The kurtosis summarizes the share of extreme values at the tails (large price changes) relative to its mean and standard deviation. Since leading pricing models in the New Keynesian literature imply different shapes of the distribution of prices changes, the kurtosis has attracted researchers' attention.[47]

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. Moreover, costs associated with price changes might be also different across sales

[46] As detailed in Section 3, Álvarez et al. (2016) highlight that calculating the kurtosis from a distribution that comes from heterogeneous distributions might bias estimates of the kurtosis.

[47] On the one hand, price-setters facing a menu-cost when adjusting their prices would imply a minor share of small 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. The kurtosis as a sufficient statistic for rationalizing the real effects of monetary policy by different models is studied by Álvarez et al. (2016).

Figure 7: Distribution of Non-Zero Price Changes in Non-Food Categories in 2020



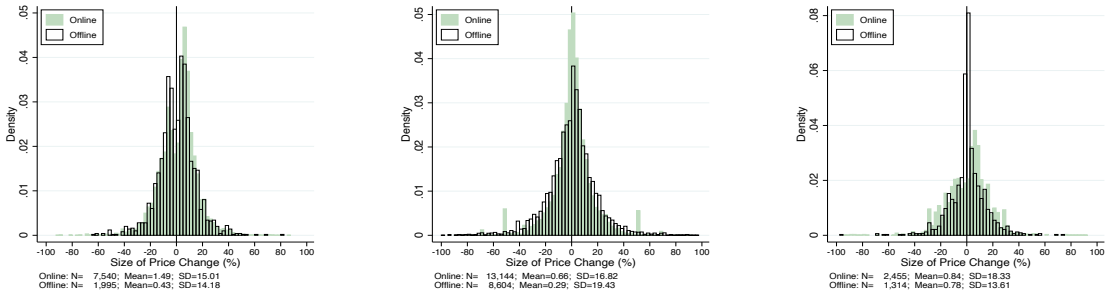
Note: These distributions (i) only consider non-zero price changes, (ii) price changes are calculated as the first difference of log prices and (iii) the distributions pool all price changes in any given retailer by sales channel. They depict the 2020 distribution of price adjustments for non-food categories. Retailer 4 is omitted in 2020 due to small sample issues. 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 bins price changes in multiples of 2.5 p.p. The area in each histogram adds up to one. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

platforms. Bear in mind the retailers under study are multi-channel and multi-product. Thus, when resetting their prices, they might opt to change a lot (perhaps all) of them, resulting in many small price adjustments across both sales channels.

Table 18 summarizes the kurtosis in the distribution of standardized price changes, as defined in Equation 4, for non-food and food categories across sales channels and periods. In the Appendix, Figure 21 depicts the distribution of standardized price changes in the pre-2020 period for non-food and food categories, respectively; whereas

Figure 8: Distribution of Non-Zero Price Changes in Food Categories in 2020

(a) Retailer A (b) Retailer B (c) Retailer C



Note: These distributions (i) only consider non-zero price changes, (ii) price changes are calculated as the first difference of log prices and (iii) the distributions pool all price changes in any given retailer by sales channel. They depict the 2020 distribution of price adjustments for food-related categories. 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 bins price changes in multiples of 2.5 p.p. The area in each histogram adds up to one. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 22 does the same for the 2020 data.

First, Panel A shows that for non-food categories between 2016 and 2019 the kurtosis is greater in the offline distribution of standardized price changes than in the online distribution.[48] The opposite happens for food categories over this period in all retailers i.e. the distribution of online standardized price changes report a greater share of large price changes (fatter tails) than the offline distribution.[49] Second, in 2020 the kurtosis seems to be greater in the online channel relative to the offline channel for both non-food and food categories (panel B).[50] Third, when comparing the kurtosis from the 2020 to the pre-2020 non-food categories distributions, most of them experience a decrease, regardless the sales channel. See Panel C.

In the Appendix, it is shown that the distributions of non-food online price changes resemble a bimodal distribution, while the offline distributions are centered at zero

[48]That is, four out of eight multi-channel retailers report greater kurtosis (point estimate) in their offline distribution than in their online counterpart. Note, most online and offline distributions report a value close to three (similar to a standard normal distribution). A notable exception is Retailer 2, reporting kurtosis of 7.96 and 5.64 for its online and offline distributions, respectively (Laplace distribution has a kurtosis of six).

[49]Notably, the kurtosis is considerable different across sales channels for food categories: it ranges from 5.4 to 10.3 in the online distributions and from 3.9 to 5.8 in the offline distributions.

[50]For non-food categories, five out of seven retailers exhibit greater kurtosis in their online price changes than in their offline analogs. As in pre-2020, most online and offline distributions report a value close to three. A notable exception is Retailer 2. The remaining kurtosis range from 2.2 (offline kurtosis of Retailer 8) to 4.0 (offline kurtosis of Retailer 2). Similar to Cavallo (2017) findings, it seems that retailers tend to exhibit very heterogeneous price setting strategies across their sales channels.

Table 18: Kurtosis of Standardized Non-Zero Price Changes
By Retailer and Sales Channel

	Non-Food Categories								Food Categories		
	Retailer 1	Retailer 2	Retailer 3	Retailer 4	Retailer 5	Reteailer 6	Retailer 7	Retailer 8	Retailer A	Retailer B	Retailer C
A. Data from 2016 to 2019											
(a) Online	3.86	7.96	2.82	3.00	3.24	2.92	3.56	2.99	5.47	6.85	6.60
(b) Offline	3.98	5.64	3.93	3.00	4.00	2.92	4.68	2.53	4.58	5.75	4.80
Difference (b) - (a)	0.12	-2.32	1.11	0.00	0.76	0.00	1.12	-0.46	-0.89	-1.10	-1.80
B. Data in 2020											
(c) Online	3.45	7.51	3.23		3.04	2.76	3.36	3.28	8.32	6.85	10.34
(d) Offline	2.78	4.04	3.97		2.76	2.54	3.39	2.15	3.87	4.61	4.49
Difference (d) - (c)	-0.67	-3.47	0.74		-0.28	-0.22	0.03	-1.13	-4.45	-2.24	-5.85
C. Difference Between Periods											
Online (c) - (a)	-0.41	-0.45	0.41		-0.20	-0.16	-0.20	0.29	2.85	0.00	3.74
Offline (d) - (b)	-1.20	-1.60	0.04		-1.24	-0.38	-1.29	-0.38	-0.71	-1.14	-0.31

Note: This table summarizes the kurtosis in the distribution of standardized price changes, as defined in Equation 4, for non-food and food categories across sales channels and periods. Retailer 4 is omitted in 2020 due to small sample issues. In the Appendix, Figure 21 depicts the distribution of standardized price changes in the pre-2020 period for non-food and food categories; while Figure 22 does the same with the 2020 data. Source: Author's own calculations based on data from INEGI and Banco de México.

in both pre-2020 and 2020 periods.[51] 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 (the mean change is close to zero since positive and negative changes cancel out as reported across figures). For food categories, the distribution of standardized online price changes report a greater share of large price changes (fatter tails) than the offline distribution.[52]

5 Sample Differences Across Sales Channels

As mentioned in the Introduction, the aim of this paper is to shed light on the stylized facts of prices stemming from different sales channels of the same retailers. Although, the sample of goods considered within product categories across sales 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, including not only representative goods but also low-/high-end varieties, special editions and/or temporal goods.

[51] Retailers 6, 7 and 8 exemplify these cases in Figure 21; Retailers 3, 6, 7 and 8 do so in Figure 22.

[52] See Figure 21 and Figure 22 where Retailer A and Retailer C exhibit not many small price changes online, while in their offline channel small price changes are more common. The opposite happens for Retailer B.

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, I present 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 retailer and COICOP division across sales channels.[53] The average price level and share of missing products highlight that, despite coming from the same product categories and retailers, price moments are calculated using a different set of goods across sales channels. If products included in one dataset, but neglected in the other, exhibit different price setting patterns, they are a likely source behind the differences in the stylized facts discussed above.

In line with the strategy followed throughout the paper, the average price level and share of missing products are reported by retailer and COICOP division across sales channels; as well as for the two separate periods, 2016 to 2019 and in 2020.[54]

5.1 Average Price Level

Regarding the average price level of product categories across sales channel, Table 19 provides a summary on the fraction of product categories in each retailer that report a statistically significant difference on their average price level.[55]

It shows that across retailers, either selling non-food or food categories between 2016 and 2019, over 50% of their product categories exhibit greater average price in the online channel relative to their offline counterparts, with the exception of Retailer 7.[56] Surprisingly, all retailers show a small fraction of categories exhibiting statistically

[53]In the literature of price indices, mainly stemming from National Statistical Offices, the term "product churn" is also used to refer the entry/exit of products. In this study, missing products are those not observed in the current period, given they were observed in the previous period. I do not distinguish between temporal or permanent exit.

[54]The use of only one weekday by retailer from the online dataset continues as before. That is, the weekday is chosen as the one that maximizes the ordinal relationship between the frequency of price adjustments across channels and reported in Table 2 and Table 3.

[55]Specifically, first, I compute the average price per category, retailer and sales channel. 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. Tables 26-29 in the Appendix complements this Table by reporting the number of categories, Spearman correlation coefficients and OLS slopes by retailer and COICOP Division. The scatter plots from these Tables are depicted in Figure 23, Figure 24, Figure 26 and Figure 27.

[56]The retailer with the greatest proportion of non-food categories favoring greater online average

insignificant mean difference of average prices across channels.[57] The qualitative results regarding greater average online prices than the average offline price hold for the 2020 period, reported in the second bloc of columns in Table 19.

Although this Section merely focuses on the central moment of the price level distribution in categories across channels in the same retailers, the fact that very few categories show similar (statistically insignificant) average prices 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 former considers high-end or special edition products, which in turn are neglected in the latter sample.

Table 20 provides the analysis by COICOP Division. It seems that about two thirds of product categories in Apparel, Furnishings and Personal goods report a greater online average price than the offline average price. In turn, Health and Recreation and transport seem to be more evenly spread between greater online or offline average prices across categories. For the 2020 data, more COICOP Divisions spread their categories favoring greater average price level on either sales channel, with the exception of Personal goods (with over 70% of categories with greater online average price than offline average price).

In the Appendix, Figure 25 outlines the dispersion of standardized price levels across sales channels for non-food and food categories, respectively, in the pre-2020 period. Contrary to the histograms analyzing price changes, these histograms show very similar dispersion in terms of the product offer across sales channels. The standardized distributions of price levels in 2020 are depicted in Figure 28.

5.2 Share of Missing Products

A product can be reported as missing if, on the one hand, it was not displayed when the robot parsed the website or, on the other hand, the price collector verifies the product is out-of-stock at the time of her visit to the physical store.[58] If the share of

prices relative to average offline prices is Retailer 3 with 80%. Regarding food categories, at least two thirds of the categories in all retailers exhibit a greater average price online than offline.

[57]Regardless non-food or food categories, these are one-digit shares. For instance, for Retailers 2 and 7, they are 5.3% and 0.0%, respectively.

[58]A product not displayed can be interpreted as out-of-stock and/or it disappeared from the market. Unfortunately, it is not possible to distinguish between these two cases with the data at hand. If the product is repeatedly out-of-stock and/or disappeared from the market, price collectors replace the

Table 19: Average Price Level by Retailer

Share of Categories by Outcome of Equality Test

	Data 2016-2019				Data 2020			
	Categories	Shares (%)			Categories	Shares (%)		
		On > Off	Equal	Off > On		On > Off	Equal	Off > On
A. Non-Food								
Retailer 1	38	55.3	15.8	28.9	27	66.7	14.8	18.5
Retailer 2	38	52.6	5.3	42.1	31	58.1	9.7	32.3
Retailer 3	55	80.0	5.5	14.5	44	79.5	2.3	18.2
Retailer 4	23	73.9	8.7	17.4				
Retailer 5	48	68.8	10.4	20.8	49	61.2	10.2	28.6
Retailer 6	49	61.2	4.1	34.7	38	52.6	2.6	44.7
Retailer 7	39	33.3	0.0	66.7	42	33.3	9.5	57.1
Retailer 8	35	54.3	17.1	28.6	35	45.7	17.1	37.1
B. Food								
Retailer A	89	67.4	6.7	25.8	74	50.0	21.6	27.0
Retailer B	73	78.1	1.4	20.5	60	71.7	8.3	20.0
Retailer C	54	74.1	1.9	24.1	42	59.5	19.0	21.4

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. For the Spearman correlation coefficients and slopes across categories, see Table 26 and Table 28 in the Appendix. Retailer 4 is omitted in 2020 due to small sample issues. Source: Author's own calculations based on data from INEGI and Banco de México.

Table 20: Average Price Level by COICOP Division

Share of Categories by Outcome of Equality Test

	Data 2016-2019				Data 2020			
	Categories	Shares (%)			Categories	Shares (%)		
		On > Off	Equal	Off > On		On > Off	Equal	Off > On
A. Non-Food								
Apparel	61	62.3	4.9	32.8	58	48.3	8.6	43.1
Furnishings	124	64.5	8.1	27.4	100	58.0	10.0	32.0
Health	36	38.9	19.4	41.7	25	44.0	12.0	44.0
Personal Care and Others	65	72.3	4.6	23.1	50	76.0	6.0	18.0
Recreation and Transport	39	46.2	7.7	46.2	33	48.5	9.1	42.4

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. For the Spearman correlation coefficients and slopes across categories, see Table 27 and Table 29 in the Appendix. Source: Author's own calculations based on data from INEGI and Banco de México.

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

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 terms of turn out. Inventories and turn out can influence price-setters decisions and therefore the stylized facts analyzed in this paper. Thus, the share of missing products sheds light on sample differences across sales channels even if the product categories are the same within a given retailer.

The share of missing products is computed in a similar fashion as the frequency of price adjustment. That is, a dummy variable takes the value of zero 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 one if the product is observed in the previous time wave but not in the current time wave. Finally, averages are computed by category and sales channel. As in the rest of the paper, statistics are reported by retailer, by COICOP Division and for two separate episodes (2016-2019 and 2020).

Table 21 shows the fraction of categories exhibiting greater, equal or lower share of online missing products than offline missing products. First, between 2016 and 2019, it seems that the majority of retailers (seven out of 11) exhibit greater share of categories reporting a larger fraction of missing products online than offline. That is, more products tend to go missing from one period to the next one in the online channel than in brick and mortar stores.[59] Although not reported with the same level of detail, Flower (2019) from the UK's Office of National Statistics finds a similar result regarding greater product churn online than offline.

There is a greater proportion of categories with similar share of product churn relative to the proportion of categories with similar price levels across sales channels.[60]

offline dataset.

[59]Extreme cases are Retailers 2, 8 and B, where more than 90% of product categories report statistically significant greater proportion of products going missing online than offline. The instances with less than 50% of categories exhibiting greater fraction of online missing products relative to offline missing items are Retailers 1, 5, A and C.

[60]There are seven retailers, including two offering non-food categories, reporting 20% or more categories where the difference on the share of missing products is statistically insignificant across sales channels. Bear in mind that food categories include some fruits and vegetables (e.g. one category is "Apples", another is "Onions"), likely to stay stable in the sample. In contrast, processed food categories offer greater number of varieties per category. Hence, the type of categories priced in each retailer might also explain the heterogeneous patterns regarding the share of missing products.

Second, findings from the data from 2020 contrast sharply with those from 2016-2019 data. Temporal closures of physical stores is the most likely explanation behind this change in figures. In only two out of the 11 retailers (non-food and food panels) report more than 50% of categories with greater share of missing products online than offline on average, while in most cases the *Equal* or *Off>On* columns increase relative to the 2016-2019 period.

Qualitatively, COICOP Divisions exhibit similar patterns, as reported in Table 22. That is, there are more categories reporting greater shares of products gone missing online than offline between 2016 and 2019 and such dynamics are partially reversed in 2020 by an increase on the share of categories with similar or more products gone missing 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, COICOP Divisions and periods 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 and/or by the products considered across collection techniques.

6 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 23 million price quotes from more than 210 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 23 thousand different products observed in brick and mortar stores are considered in this dataset.

Table 21: Missing Products by Retailer

Share of Categories by Outcome of Equality Test

	Data 2016-2019				Data 2020			
	Categories	Shares (%)			Categories	Shares (%)		
		On > Off	Equal	Off > On		On > Off	Equal	Off > On
A. Non-Food								
Retailer 1	38	26.3	39.5	34.2	27	0.0	51.9	48.1
Retailer 2	38	97.4	2.6	0.0	31	29.0	19.4	51.6
Retailer 3	55	52.7	20.0	27.3	44	6.8	6.8	86.4
Retailer 4	23	56.5	26.1	17.4				
Retailer 5	48	12.5	29.2	58.3	50	22.0	44.0	34.0
Retailer 6	49	63.3	22.4	14.3	39	97.4	2.6	0.0
Retailer 7	39	74.4	12.8	12.8	41	14.6	39.0	46.3
Retailer 8	35	100.0	0.0	0.0	35	54.3	42.9	2.9
B. Food								
Retailer A	89	19.1	40.4	40.4	74	0.0	55.4	44.6
Retailer B	73	91.8	8.2	0.0	60	5.0	45.0	50.0
Retailer C	54	7.4	31.5	61.1	42	0.0	52.4	47.6

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. For the Spearman correlation coefficients and slopes across categories, see Table 30 and Table 32 in the Appendix. Retailer 4 is omitted in 2020 due to small sample issues. Source: Author's own calculations based on data from INEGI and Banco de México.

Table 22: Missing Products by COICOP Division

Share of Categories by Outcome of Equality Test

	Data 2016-2019				Data 2020			
	Categories	Shares (%)			Categories	Shares (%)		
		On > Off	Equal	Off > On		On > Off	Equal	Off > On
A. Non-Food								
Apparel	61	78.7	16.4	4.9	59	52.5	30.5	16.9
Furnishings	124	54.0	21.0	25.0	110	28.2	26.4	45.5
Health	36	58.3	19.4	22.2	28	3.6	42.9	53.6
Personal Care and Others	65	55.4	20.0	24.6	55	32.7	30.9	36.4
Recreation and Transport	39	46.2	17.9	35.9	33	27.3	36.4	36.4

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. For the Spearman correlation coefficients and slopes across categories, see Table 31 and Table 33 in the Appendix. Source: Author's own calculations based on data from INEGI and Banco de México.

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 in aggregate, although not on a retailer by retailer basis. 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 Covid-19 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 does 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 the 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. Moreover, this document's findings suggest that the treatment of high frequency price changes which are orthogonal to the business cycle may differ depending on the data source.

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-oriented work.

References

Álvarez, F., H. Le Bihan, and F. Lippi (2016): "The real effects of monetary shocks in sticky price models: A sufficient statistic approach," *American Economic Review*, 106, 2817–51.

Aucremanne, L. and E. Dhyne (2004): "How frequently do prices change? Evidence based on the micro data underlying the Belgian CPI," *Evidence Based on the Micro Data Underlying the Belgian CPI (April 2004)*.

Auer, J. and I. Boettcher (2017): "From price collection to price data analytics," *Statistics Austria presentation at the 2017 Ottawa Group*.

Baumgartner, J., E. Glatzer, F. Rumler, and A. Stiglbauer (2005): "How frequently do consumer prices change in Austria? Evidence from micro CPI data," *ECB Working Paper No. 523*.

Bils, M. and P. J. Klenow (2004): "Some evidence on the importance of sticky prices," *Journal of Political Economy*, 112, 947–985.

Cavallo, A. (2017): "Are online and offline prices similar? Evidence from large multi-channel retailers," *American Economic Review*, 107, 283–303.

——— (2018): "Scraped data and sticky prices," *Review of Economics and Statistics*, 100, 105–119.

Coibion, O., Y. Gorodnichenko, and G. H. Hong (2015): "The cyclicality of sales, regular and effective prices: Business cycle and policy implications," *American Economic Review*, 105, 993–1029.

Coronado, H., E. Lahura, and M. Vega (2020): "¿Qué tan rígidos son los precios en línea? Evidencia para Perú usando big data," *Banco Central de Reserva del Perú DT. No. 2020-018*.

Costa Dias, M., D. A. Dias, and P. Duarte Neves (2008): "Stylised features of consumer price setting behaviour in Portugal: 1992–2001," *Portuguese Economic Journal*, 7, 75–99.

DellaVigna, S. and M. Gentzkow (2019): "Uniform pricing in US retail chains," *The Quarterly Journal of Economics*, 134, 2011–2084.

Dhyne, E., L. J. Alvarez, H. L. Bihan, G. Veronese, D. Dias, J. Hoffmann, N. Jonker, P. Lunnemann, F. Rumler, and J. Vilmunen (2006): "Price changes in the Euro Area and the United States: Some facts from individual consumer price data," *Journal of Economic Perspectives*, 20, 171–192.

Dixon, H. D. and K. Tian (2017): "What we can learn about the behaviour of firms from the average monthly frequency of price-changes: An application to the UK CPI data," *Oxford Bulletin of Economics and Statistics*, 79, 907–932.

Eichenbaum, M., N. Jaimovich, and S. Rebelo (2011): "Reference prices, costs, and nominal rigidities," *American Economic Review*, 101, 234–262.

Flower, T. (2019): "Using alternative data sources in consumer prices, UK," Office for National Statistics.

Gagnon, E. (2009): "Price setting during low and high inflation: Evidence from Mexico," *The Quarterly Journal of Economics*, 124, 1221–1263.

Galí, J. (2015): *Monetary policy, inflation, and the business cycle: an introduction to the new Keynesian framework and its applications*, Princeton University Press.

Glassock, A. and M. Holt (2019): "Experimental clothing indexes using Australian web scraped data," in *Papers presented at the International Meeting of the Group of Experts on Consumer Price Indices.*

Gorodnichenko, Y., V. Sheremirov, and O. Talavera (2018): "Price setting in online markets: Does IT click?" *Journal of the European Economic Association*, 16, 1764–1811.

Gouvea, S. (2007): "Price rigidity in Brazil: Evidence from CPI micro data," *Banco Central de Brasil Working Paper.*

Griffioen, A. and O. Ten Bosch (2016): "On the use of internet data for the Dutch CPI," in *Papers presented at the Meeting of the Group of Experts on Consumer Price Indices.*, Statistics Netherlands.

Higo, M. and Y. Saita (2007): "Price setting in Japan: Evidence from CPI micro data," in *Bank of Japan Working Paper Series E-20.*

Hull, I., M. Löf, and M. Tibblin (2017): "Price information collected online and short-term inflation forecasts," in *Big Data*, Bank for International Settlements, vol. 44.

Julio, J. M. and H. Zárate (2008): "The price setting behavior in Colombia: Evidence from micro data," *Ensayos sobre Política Económica*, 26, 12–44.

Kochen, F. and D. Sámano (2016): "Price-setting and exchange rate pass-through in the Mexican economy: Evidence from CPI micro data," *Banco de México, Working Papers Series.*

Konny, C. G., B. K. Williams, and D. M. Friedman (2022): "Big data in the US consumer price index: Experiences and plans," in *Big Data for 21st Century Economic Statistics*, University of Chicago Press, 69–98.

Kryvtsov, O. and N. Vincent (2021): "The cyclicality of sales and aggregate price flexibility," *The Review of Economic Studies*, 88, 334–377.

Macias, P. and D. Stelmasiak (2019): "Food inflation nowcasting with web scraped data," *NBP Working Papers 302, Narodowy Bank Polski.*

Nakamura, A. O., E. Nakamura, and L. I. Nakamura (2011): "Price dynamics, retail chains and inflation measurement," *Journal of Econometrics*, 161, 47–55.

Nakamura, E. and J. Steinsson (2008): "Five facts about prices: A reevaluation of menu cost models," *The Quarterly Journal of Economics*, 1415–1464.

Peña, J. and E. Prades (2021): "Price setting in Chile: Micro evidence from consumer on-line prices during the social outbreak and Covid-19," *Working Papers 2112, Banco de España.*

Rafael, P. and J. Reyes (2019): "Use of big data in modern markets coexisting with traditional markets data," in *Papers presented at the Meeting of the Group of Experts on Consumer Price Indices.*, INEGI.

Smets, F. and R. Wouters (2007): "Shocks and frictions in US business cycles: A Bayesian DSGE approach," *American Economic Review*, 97, 586–606.

Solórzano, D. (2023): "Grab a bite? Prices in the food away from home industry during the COVID-19 pandemic," *Forthcoming in Banco de México's Working Papers Series.*

Solórzano, D. and H. Dixon (2020): "The relationship between nominal wage and price flexibility: New evidence," *Working Papers 2020-20, Banco de México.*

Van Loon, K. and D. Roels (2018): "Integrating big data in the Belgian CPI," in *Papers presented at the Meeting of the Group of Experts on Consumer Price Indices*, Statistics Belgium.

Veronese, G., S. Fabiani, A. Gattulli, and R. Sabbatini (2005): "Consumer price behaviour in Italy: Evidence from micro CPI data," *Available at SSRN 668249.*

Woodford, M. and C. E. Walsh (2005): "Interest and prices: Foundations of a theory of monetary policy," *Macroeconomic Dynamics*, 9, 462–468.

A Appendix

A.1 Descriptive Statistics

Table 23: Online Data by Retailer from 2016 to 2019

	Online						
	Start date	End date	Days	Fortnights	Observations (Thousands)	Products (Thousands)	Frequency of Observation (Days)
Retailer 1	01 Jan 2016	01 Jan 2020	1,101	76	5,113.7	11.9	1.3
Retailer 2	31 May 2016	01 Jan 2020	1,280	88	4,849.7	11.6	1.0
Retailer 3	21 Nov 2017	01 Jan 2020	627	48	1,242.6	5.4	1.2
Retailer 4	21 Nov 2017	01 Nov 2019	440	40	185.9	1.3	1.6
Retailer 5	21 Nov 2017	27 Dec 2019	511	47	834.1	3.7	1.5
Retailer 6	21 Nov 2017	06 Aug 2019	91	39	925.2	50.9	6.9
Retailer 7	11 Aug 2016	29 Dec 2019	320	78	559.2	21.0	3.9
Retailer 8	12 Aug 2016	01 Jan 2020	561	83	792.1	62.9	2.2
Total					14,502.5	168.7	

Note: As the analysis centers at items in product categories appearing in both sales channels, the table does not necessarily reflect the retailers' size in terms of the number of items they offer to the public. Furthermore, statistics in this table encompass food and non-food items. In the following sections, results from food items are reported using lettered retailers (as instead of numbers) in order to further ensure confidentiality. Though, they are not reported using letters here as it would reveal their overlap (retailers in numbers and retailers in letters) through the start and end dates of recollections. 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 product identifiers in the retailer. *Frequency of Observation* is the mean number of days between price observations. Source: Author's own calculations based on data gathered by Banco de México.

In the main text, price statistics are reported by retailer (e.g. Table 4) or by COICOP Division (i.e. clustering product categories as in Table 5). In what follows, Table 24 and Table 25 summarize price first moments per product category. They are calculated as unweighted averages across retailers. Product categories by retailer are not reported to ensure confidentiality. Throughout the paper I only use product categories observed in both sales channels within a given retailer.

Table 24: Non-Food Items by Product Category and Sales Channel

Product Category	2016-2019						2020					
	Observations		Frequency		Size		Observations		Frequency		Size	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline	Online	Offline	Online	Offline
I. Apparel												
Accessories for footwear	1,211	3,628	5.26	13.95	10.90	7.00	201	96	4.98	10.42		
Babies' garments	10,083	6,210	62.13	18.92	23.61	15.78	1,866	2,364	30.74	25.74	34.14	17.01
Baby T-shirts	6,448	15,953	50.22	17.96	16.73	19.92	3,173	3,356	43.72	27.89	31.41	19.70
Boys' trousers	12,161	14,447	53.37	17.02	23.78	20.94	700	3,106	51.79	28.96	27.82	24.46
Children's T-shirts	46,894	20,153	43.43	16.53	23.48	19.87	6,786	3,129	39.00	33.53	25.50	20.06
Children's socks	2,384	6,549	58.10	21.24	19.49	17.88	448	1,228	49.25	29.77	22.95	23.55
Footwear for infants and children	9,021	5,854	60.64	14.40	20.57	20.49	2,092	920	42.36	31.42	34.80	25.79
Footwear for men	129	9,711	29.27	15.99	24.04	15.70	102	674	4.90	22.55		
Footwear for women	221	8,778	29.29	17.12	25.80	18.23	54	680	7.41	22.94		
Girls' skirts, dresses and trousers	30,268	14,472	50.80	19.36	20.58	20.72	3,449	2,540	49.77	28.86	20.81	20.20
Ladies' blouses and T-shirts	29,018	12,702	22.14	18.08	26.34	19.78	25,649	2,624	35.76	27.57	22.14	17.41
Ladies' other garments	5,570	10,423	20.74	20.64	26.60	16.53	5,307	728	31.38	30.63	28.98	23.61
Ladies' skirt and dress	9,326	37,392	20.81	19.07	30.22	18.91	29,134	324	36.19	30.86	34.67	23.94
Ladies' trousers and jeans	3,966	23,510	19.91	17.31	20.45	19.93	8,059	996	27.95	29.54	24.41	23.98
Men's other garments	17,201	15,204	22.02	22.15	23.54	19.94	12,875	2,504	40.60	34.03	28.48	25.70
Men's shirts and T-shirts	24,478	20,141	17.74	16.64	25.02	16.37	37,058	2,642	39.30	36.95	27.77	23.67
Men's socks	200	7,362	50.50	18.50	16.76	17.44	3,247	1,104	47.92	29.71	26.91	22.51
Men's trousers and jeans	6,691	34,694	21.19	14.74	26.55	18.51	5,705	2,320	24.41	23.18	28.51	22.67
Other footwear	566	5,938	36.93	12.70	27.94	17.80	233	428	45.92	27.57	35.63	21.44
Sport shoes	118,548	9,795	31.76	10.38	21.41	11.04	3,051	1,974	30.03	20.81	19.23	17.41
Stockings, socks and tights	281	13,997	19.37	11.67	16.47	16.83	79	92	27.85	13.04		
Underwear for ladies	2,167	14,529	22.22	18.98	24.95	18.47	4,305	176	37.98	23.86	32.07	26.47
Winter garments	79,559	44,946	26.11	13.15	25.09	13.89	25,466	11,468	37.30	17.36	26.58	18.87
II. Furnishings												
Air conditioner	6,706	8,577	32.62	23.92	15.21	13.94	2,544	1,990	45.37	34.15	15.56	12.18
Batteries	3,519	3,123	9.05	16.12	13.26	9.87	1,149	620	14.14	14.70	21.93	8.99
Bedlinen	21,712	10,178	29.77	17.88	18.19	18.49	12,096	1,882	25.15	30.63	22.66	19.59
Bleaches	8,028	8,829	15.10	35.42	18.02	9.81	2,404	630	16.20	27.68	10.46	9.49
Candles	7,040	2,665	4.42	13.85	14.85	11.77	1,323	544	4.74	13.27	9.82	9.87
Carpets and other floor coverings	30	66	0.00	15.15								
Coffee machines and others	15,715	7,105	23.99	27.87	18.37	11.92	7,532	3,930	24.88	26.28	17.89	14.64
Detergents	31,101	14,111	17.12	34.32	26.20	11.50	9,860	848	20.11	32.84	13.66	10.46
Dining table	557	735	36.49	25.72	17.37	15.48	268	928	18.51	16.85	21.84	19.21
Disposable household goods	22,674	3,238	13.39	12.78	21.64	7.28	5,653	1,744	13.28	11.32	29.45	9.37
Duvets and blankets	22,354	15,805	34.82	24.81	20.93	19.28	8,751	4,496	32.00	32.18	23.34	17.70
Fabric softener	9,205	12,431	16.29	33.71	20.39	12.34	2,783	520	30.53	31.70	14.54	14.97
Glassware, cutlery and cookware	5,313	8,704	32.38	16.97	18.77	15.34	1,811	582	35.17	16.32	22.44	16.51
Kitchen furniture	470	918	19.57	12.31	11.51	14.27	680	240	5.29	10.00	10.54	9.07
Light bulb	11,028	3,537	7.73	11.59	20.34	9.46	1,080	160	12.57	13.39	18.45	7.41
Living room sets	900	160	17.22	21.25	13.97	3.96	347	44	39.48	9.09		
Microwave oven	2,078	8,255	40.84	28.42	16.99	12.41	1,578	2,804	41.61	39.81	13.84	14.33
Napkins	7,290	10,646	10.86	23.19	21.80	7.85	2,560	1,008	17.27	28.40	11.13	10.12
Non-electric kitchen utensils	1,384	1,690	17.56	9.70	21.75	14.36						
Pesticides	5,093	2,634	19.99	39.32	15.20	10.25	1,219	498	16.88	29.78	7.90	7.92
Plastic cutlery	138	5,917	7.25	9.73			70	1,086	17.14	9.58		
Pocket spring mattress	13,680	7,157	39.43	23.72	23.87	18.88	6,182	2,336	33.20	32.43	24.56	16.55
Pottery	17,794	9,155	25.76	18.10	20.67	16.08	5,058	1,894	27.69	29.53	18.33	17.93
Refrigerators	12,464	9,091	42.17	42.43	14.27	12.53	4,612	2,966	53.29	46.04	16.35	15.15
Small tools and accessories	6,622	734	5.46	4.61	18.51	9.98	2,555	200	9.49	17.14	29.72	16.99
Soap	1,988	1,786	9.77	20.45	12.45	14.57	765	366	4.26	11.16		
Stoves	6,578	5,786	38.23	33.79	14.85	14.30	2,493	1,738	51.48	44.46	16.78	14.90
Table lamp	26,553	3,330	28.28	16.78	20.32	16.11	8,154	1,996	29.34	25.91	20.76	16.66
Towels	350	2,478	7.37	10.82			184	500	9.24	18.40	11.87	8.42
Vacuum cleaner	6,385	3,294	30.78	26.91	20.19	13.48	2,234	2,180	36.66	29.52	18.08	15.62
Washing machine	10,463	8,179	41.82	38.11	16.00	14.07	4,272	2,838	54.40	45.67	16.43	18.35
III. Health												
Allergy medications	6,734	890	12.35	14.54	11.35	9.93	913	102	6.46	13.73		
Anti-inflammatories medicines	11,967	1,494	14.11	18.48	14.70	11.87	2,506	164	13.05	15.15	6.74	5.71
Cardiovascular	8,320	1,044	18.55	19.65	16.85	8.01	1,071	280	14.83	19.55	10.57	5.19
Dermatological	1,030	4,090	8.46	18.08	20.99	10.18	157	402	8.92	17.91		
Diabetes medications	8,917	1,219	14.74	14.89	9.06	8.14	1,910	162	13.20	12.17	5.89	9.75
Expectorants and decongestants	10,779	1,118	12.10	15.63	15.56	7.43	1,592	160	15.89	20.00	8.47	16.52
First aid materials	14,234	2,276	9.75	11.05	11.59	10.09	2,832	1,304	5.59	17.66	9.39	8.97
Flu medicines	6,776	970	15.51	16.91	22.07	16.71	890	80	27.85	19.79		
Gastrointestinal medicines	19,621	784	13.83	11.49	13.98	8.43	2,610	92	15.44	10.87		
Homeopathic and naturopathic medicines	3,882	1,202	8.36	10.51	16.22	10.20	832	74	7.81	18.92		
Lenses, hearing aids and others	14,708	2,014	19.65	12.23	17.50	17.44	3,653	188	34.53	19.13		
Nutritionals	12,105	5,353	12.76	13.54	18.97	9.38	3,688	1,348	12.17	23.43	8.37	5.83
Other medical products	5,886	5,436	17.62	18.75	16.56	8.18	1,289	2,700	22.35	18.21	6.16	5.70
IV. Recreation and Transport												
Audio players	26,364	14,623	24.78	28.25	17.46	15.95	11,350	3,218	30.64	41.01	22.74	15.35
Bicycles	4,338	4,270	26.27	19.91	20.67	9.80	1,373	2,442	21.86	22.99	26.32	12.44
Equipment for sport	25,583	10,954	16.35	11.97	27.14	15.40	3,871	2,706	28.80	24.68	26.84	17.39
Lubricants	238	680	12.61	20.88	13.70	8.13	380	138	20.79	15.94	12.33	5.27
Magazines	6,467	476	0.22	2.58			894	62	0.00	6.45		
Motor cycles	2,002	554	42.22	35.79	7.42	5.14	606	332	47.34	36.15	12.58	8.79
Other books	2,122	576	2.21	4.17	44.65	4.11	83	72	0.00	16.67		
Other school materials	259	1,070	11.97	15.89	14.97	5.43	154	206	22.08	19.42	25.76	5.03
Pet food	297	3,968	9.68	29.95	8.70	8.44	138	730	8.70	26.85		
Television	9,085	13,393	49.53	44.04	14.73	15.32	3,415	2,824	64.48	49.09	13.59	17.45
Toys and board games	11,115	16,767	23.18	15.82	23.21	13.92	3,227	3,012	29.03	27.36	22.10	17.94
Video games	6,345	2,160	9.05	18.87	42.78	11.36	885	260	6.33	30.00	21.74	16.25
V. Personal Care and Others												
Body cream	1,480	8,974	12.23	36.50	14.16	13.75	326	1,640	7.06	36.95	31.10	13.92
Deodorant	64,422	9,194	19.26	31.50	20.28	10.61	18,364	2,262	20.57	37.66	15.24	10.41
Disposable nappies	21,237	10,604	19.47	33.64	17.08	9.16	7,798	2,268	23.91	35.84	13.69	9.57
Electric razor and cartridges	19,061	9,060	14.13	22.10	21.47	8.85	4,595	1,640	11.29	28.53	16.17	10.61
Electrical appliances for personal care	3,185	3,706	26.07	19.06	23.20	12.99	1,406	2,184	34.42	30.10	21.79	16.92
Handbags and belts	4,186	22,932	29.04	20.44	25.06	14.23	6,023	2,720	21.17	17.34	26.75	21.13
Makeup and cosmetics	26,245	12,486	29.39	10.72	19.28	10.62	4,107	272	48.45	10.29	37.91	8.56
Other toiletries	11,400	11,438	16.21	16.78	16.94	11.78	3,222	2,684	25.85	19.81	16.74	13.48
Sanitary pads	16,347	9,925	17.99	28.60	21.15	10.57	4,112	2,202	16.46	33.25	14.02	12.49
Shampoo	71,520	10,729	15.40	36.75	19.25	11.32	20,681	2,964	16.41	36.06	14.38	11.21
Toilet paper	10,524	21,709	14.73	23.32	23.57	9.39	4,016	2,368	20.11	30.17	13.56	10.80
Toilet soap	49,151	12,392	15.00	29.30	24.03	13.13	17,196	2,741	14.53	27.70	14.37	11.86
Tooth paste and toothbrush	29,660	13,713	17.16	34.36	24.11	15.11	8,672	3,226	19.12	30.45	11.65	13.99
Watches, jewelry and others	250,569	10,895	25.29	14.13	15.81	12.10	20,807	2,050	37.41	34.28	14.89	17.20

Note: Product categories observed in both sales channels within a given retailer are reported only. Product categories by retailer are not reported to ensure confidentiality. The number of observations comes from the sum across retailers where the product category is observed. Frequency and size of adjustments reflect fortnightly price changes. Statistics per product category are calculated as unweighted averages across retailers. Source: INEGI and Banco de México.

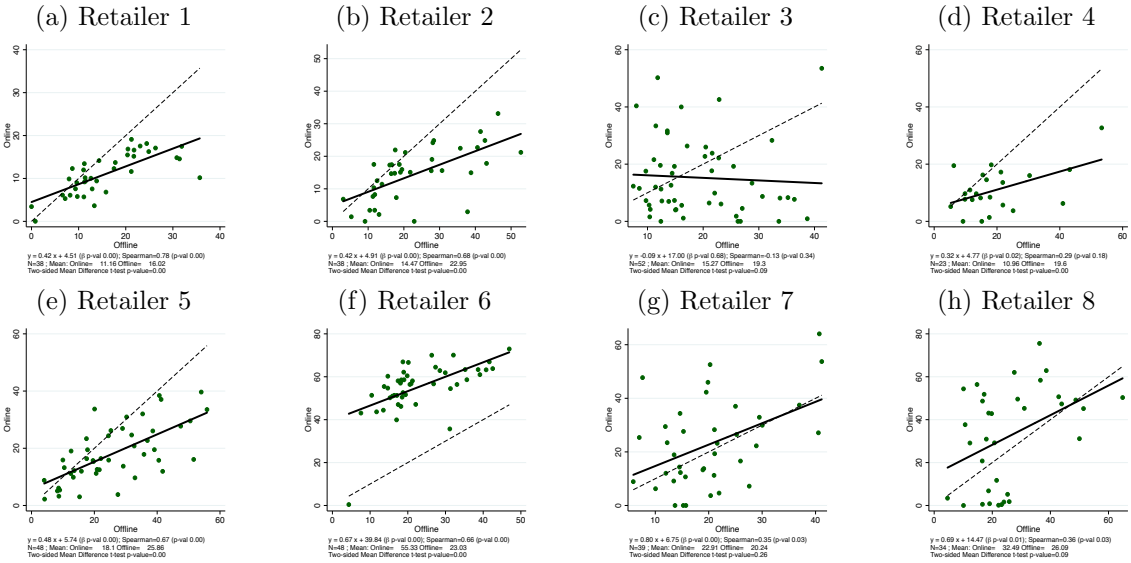
Table 25: Food Items by Product Category and Sales Channel

Product Category	2016-2019						2020					
	Observations		Frequency		Size		Observations		Frequency		Size	
	Online	Offline	Online	Offline	Online	Offline	Online	Offline	Online	Offline	Online	Offline
I. Food												
Apples	2,640	3,454	24.84	50.86	14.03	13.25	1,495	559	24.69	43.91	13.56	12.09
Avocado	666	3,742	30.33	53.93	13.85	10.15	230	667	23.86	50.45	13.76	12.72
Baby food	13,071	2,881	12.22	16.28	22.63	12.20	3,483	651	7.20	15.83	6.96	3.84
Bananas	1,242	3,654	22.19	42.85	19.31	11.51	451	562	17.81	37.88	8.90	15.21
Beacon	2,916	2,492	10.87	15.20	27.71	9.14	669	137	10.19	23.33		
Beans	14,566	4,530	7.16	11.07	15.65	9.98	3,886	618	6.89	11.73	9.10	8.21
Beef	561	15,491	5.41	14.57	7.37	6.41	160	1,151	10.00	18.42	4.38	6.09
Beef viscera	755	2,605	5.12	10.03	80.70	11.97	70	47	8.57	6.38		
Beer	31,704	5,179	8.77	14.12	25.81	5.85	7,283	557	4.68	19.44	17.12	9.00
Biscuits	65,042	6,406	6.94	19.51	20.30	9.31	21,044	1,534	6.26	16.67	13.34	11.48
Bottled water	41,737	2,732	10.64	15.67	23.94	8.11	15,097	233	7.64	8.58	10.99	10.41
Brandy	2,687	3,214	8.26	11.33	11.39	8.09	962	761	8.29	18.43	10.29	7.28
Bread	1,010	730	5.55	8.84	9.32	7.63	116	189	6.03	10.58		
Butter	7,482	3,817	9.44	16.06	17.72	7.17	2,327	648	10.88	17.28	6.35	4.95
Cakes	4,993	2,241	7.68	4.16	30.19	9.54	1,509	440	5.58	5.37		
Cakes (boxed)	1,559	1,479	15.11	14.97	15.37	15.02	388	359	14.81	16.87	6.03	5.74
Canned beans	1,704	1,693	7.82	16.65	18.52	9.75	387	333	8.94	10.23		
Cantaloupes	420	3,135	26.25	61.10	13.38	13.20	128	386	23.15	40.14		
Carrots	2,376	3,253	7.34	48.80	34.96	13.36	867	428	6.51	31.21	17.74	14.57
Cereal snacks	1,286	322	3.02	5.76			148	216	1.98	8.63		
Cheese (americano)	2,193	2,759	16.96	20.10	46.19	9.16	409	573	9.19	18.84	8.96	12.29
Cheese (fresh)	4,697	2,428	9.69	20.75	17.29	9.48	1,311	124	9.47	16.54		
Cheese (manchego)	15,880	3,158	9.94	23.02	25.89	8.66	3,277	266	10.74	25.25	9.11	8.82
Cheese (oaxaca)	1,415	1,829	9.87	21.07	32.21	8.31	409	47	5.62	25.53		
Cheese (others)	4,345	4,272	8.53	12.55	22.86	6.86	774	774	8.80	10.39		
Chicken	636	5,576	5.29	18.03	6.01	6.68	100	378	13.00	21.69		
Chicken eggs	5,463	2,334	19.74	20.72	21.95	9.24	1,523	38	18.91	13.16		
Chicken stock and salt	4,964	2,425	6.66	9.28	36.37	10.89	1,491	466	5.80	8.05	12.48	8.96
Chili (dried)	812	652	4.93	6.60	10.74	8.69	330	88	2.42	4.55		
Chili (others)	1,899	2,414	31.49	43.60	11.76	14.33	923	292	20.56	42.22	14.01	19.44
Chili (poblano)	200	543	32.00	41.62	12.45	10.24	64	47	35.94	31.91	19.83	18.88
Chili (serrano)	137	554	37.23	42.78	12.75	13.18						
Chocolate and confectionery	92,773	1,496	5.73	14.92	21.44	7.96	24,885	875	5.55	13.06	15.05	9.05
Chorizo	8,835	1,483	5.54	9.57	33.59	6.20	1,556	78	10.60	29.49	10.59	5.19
Coffee	1,870	2,461	7.03	11.32	21.43	8.57	982	465	7.20	18.33	17.95	8.78
Coffee (instant)	585	578	15.38	15.57	11.78	10.02	265	85	10.94	21.18	8.92	6.06
Corn	852	545	7.98	7.34	11.74	13.19	198	47	2.53	8.51		
Corn tortillas	3,058	2,573	4.24	3.94	19.65	4.23	271	198	4.43	9.60		
Cornflakes	1,045	3,720	6.99	29.05	15.30	9.57	274	734	8.23	24.64		
Cucumber	1,011	2,445	20.48	62.31	27.03	16.58	587	573	20.35	47.04	15.27	17.72
Dried meat	41	948	4.88	12.97								
Dried vegetables	171	422	8.19	9.00			41	44	9.76	18.18		
Edible oils	25,287	6,328	8.69	18.83	19.55	7.63	9,373	854	8.47	13.35	16.84	7.01
Fresh fish	662	9,322	8.08	18.98	14.62	8.51	81	493	1.23	14.81		
Fresh tomatoes	2,340	4,522	19.83	63.82	15.58	18.96	887	339	27.54	51.27	19.91	21.35
Fried potatoes	2,129	2,011	3.27	20.71	7.87	10.04	157	92	5.10	23.91		
Fruit and vegetables juices	342	244	2.05	24.59								
Grapes	1,305	3,441	25.50	46.45	26.99	16.91	581	627	33.62	39.37	16.83	18.35
Green tomatoes	615	2,784	37.75	63.72	14.93	15.80	153	197	75.16	55.33	17.71	17.65
Guava	205	1,970	28.92	43.35	12.38	11.92	95	270	19.52	29.58	6.20	6.98
Ham	23,473	3,561	10.64	19.75	28.03	9.40	3,119	553	8.20	18.71	9.45	8.10
Ice cream	8,223	1,854	9.70	20.41	28.30	11.36	2,110	368	13.27	22.01	12.66	15.20
Jam, honey and jelly	32,903	1,323	4.97	18.60	16.10	6.15	10,403	883	8.15	16.05	18.85	6.64
Jelly	15,912	2,620	8.52	20.72	10.29	9.95	5,172	528	10.85	19.85	9.49	5.00
Lard	149	184	0.00	8.12			33	47	0.00	0.00		
Lemons	607	582	39.21	56.87	12.50	14.69						
Lettuce	5,129	3,347	13.55	32.10	25.23	14.50	1,896	622	8.85	19.22	9.94	11.47
Mayonnaise and mustard	17,942	3,295	8.73	14.93	19.41	11.21	6,839	551	9.92	19.82	15.42	10.17
Milk (formula)	199	2,080	10.31	14.37			80	414	6.25	16.70		
Milk (powdered)	1,695	304	7.91	13.16	13.82	7.67	643	39	6.69	10.26		
Milk (soy)	833	719	6.22	8.19	17.71	6.85	393	270	14.50	10.00	10.71	6.00
Milk (whole)	39,209	5,256	12.26	12.02	17.70	5.25	14,955	804	11.27	13.98	7.51	4.70
Nopal	514	2,749	5.71	40.99	8.50	9.91	196	283	2.31	20.89		
Onions	1,496	3,467	18.69	61.26	12.92	14.04	633	574	22.97	55.30	15.35	16.88
Oranges	665	3,220	21.15	45.36	25.68	20.74	375	522	22.17	43.87	17.40	19.58
Other	3,225	587	13.11	20.86	19.53	11.89	1,283	352	12.28	22.61	15.79	12.76
Other alcoholic beverages	240	3,668	0.50	16.74								
Other bread	1,612	1,979	1.79	1.90			174	47	0.00	2.13		
Other canned fruits	2,896	3,195	5.01	16.31	31.19	7.47	772	593	5.47	12.79		
Other fresh seafood	3,318	2,461	5.92	15.92	26.69	8.89	642	409	7.25	8.66	22.14	11.35
Other fruits	2,750	12,272	14.11	28.61	23.64	15.90	1,196	3,026	14.61	26.38	13.51	13.81
Other preserved or processed seafood	298	972	1.01	5.66			80	208	2.50	8.65		
Other spices	22,681	3,413	3.74	11.10	13.45	6.74	8,378	785	4.33	18.19	7.92	8.26
Papaya	339	3,219	41.96	59.41	11.97	11.21	165	480	37.58	50.42	20.75	12.25
Pasta products and couscous	2,185	2,038	4.66	10.28	10.40	11.82	744	433	13.58	9.93	12.03	10.76
Peach	456	3,539	36.81	42.26	21.77	14.28	194	728	42.32	35.71	15.25	15.58
Pears	1,324	3,436	29.17	52.15	19.30	10.02	618	615	35.76	45.46	16.73	13.38
Pineapples	411	2,249	37.96	49.15	28.10	15.37	164	377	49.72	45.88	13.20	17.56
Pork	2,922	6,573	8.52	22.68	12.25	8.25	212	1,141	9.30	26.26	11.92	13.16
Potatoes	1,446	3,454	26.23	53.16	14.41	12.04	467	570	23.53	41.07	13.58	11.48
Premix for beverages	628	290	2.87	24.14	7.54	7.57	352	47	2.56	8.51		
Ready-made soups and tomatoed sauce	702	287	6.27	8.36	8.30	3.80	214	46	2.80	19.57		
Rice	17,447	3,345	6.13	19.98	19.00	6.42	2,368	418	6.36	28.09	13.02	8.22
Rum	5,711	2,544	9.15	12.53	12.37	12.38	1,609	435	11.49	24.65	15.16	13.54
Sausage	1,320	380	12.68	23.45	15.06	7.37	477	187	20.19	20.30	13.43	7.18
Shrimps	1,331	518	11.72	18.34	10.23	8.86	552	133	4.35	15.04	9.67	9.47
Soft drinks	46,985	3,650	9.60	12.24	18.76	5.99	20,014	625	9.67	15.05	6.40	6.99
Squash	432	1,533	31.76	59.68	31.54	21.84	149	189	36.44	36.73	36.24	19.18
Sugar	2,669	687	8.22	14.17	8.71	4.76	203	88	9.85	22.73	13.49	5.89
Tea	18,749	321	3.64	4.19			4,871	495	2.44	6.32		
Tequila	11,196	4,761	8.53	16.73	14.22	7.02	3,442	1,196	8.30	18.61	13.80	9.09
Tinned tuna and sardine	7,970	3,811	10.04	21.82	19.02	6.42	3,051	626	14.28	28.76	10.10	7.52
Tinned vegetables	25,513	3,495	5.25	13.06	16.36	9.88	8,981	920	6.30	14.48	16.63	9.08
Tostadas	5,493	2,853	6.90	9.78	16.70	8.29	2,159	495	2.61	8.94	8.97	7.42
Watermelons	213	542	30.52	41.70	14.33	15.11	70	47	5.71	12.77		
Wheat flour	1,134	238	4.23	16.81	7.04	4.93	486	87	5.35	14.94		
Wheat tortillas	5,495	1,754	3.59	18.76	16.56	9.11	1,857	470	2.82	14.52	12.72	10.30
White bread	1,417	2,095	1.01	1.17								
Wine	413	2,618	3.39	15.01			147	803	3.40	15.44		
Yoghurt	60,099	4,642	14.15	31.54	16.26	9.23	19,398	1,272	13.82	14.48	8.13	7.42
Zucchini	206	496	42.23	48.19	13.65	12.43						

Note: Product categories observed in both sales channels within a given retailer are reported only. The product categories sold in each retailer is not reported to ensure confidentiality. The number of observations comes from the sum across retailers where the product category is observed. Frequency and size of adjustments reflect weekly price changes. Statistics per product category are calculated as unweighted averages across retailers.

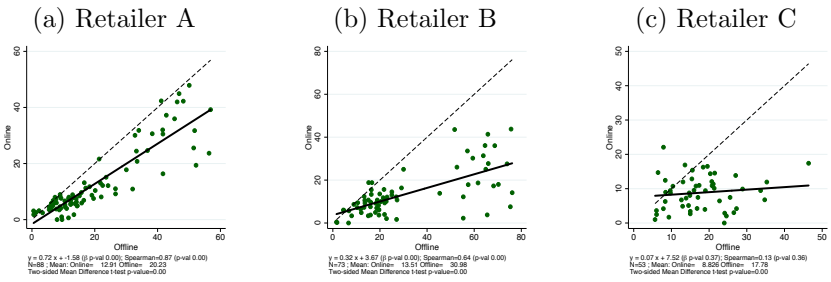
A.2 Frequency of Price Adjustments

Figure 9: Frequency of Price Changes of Non-Food Categories by Retailer in 2016-2019



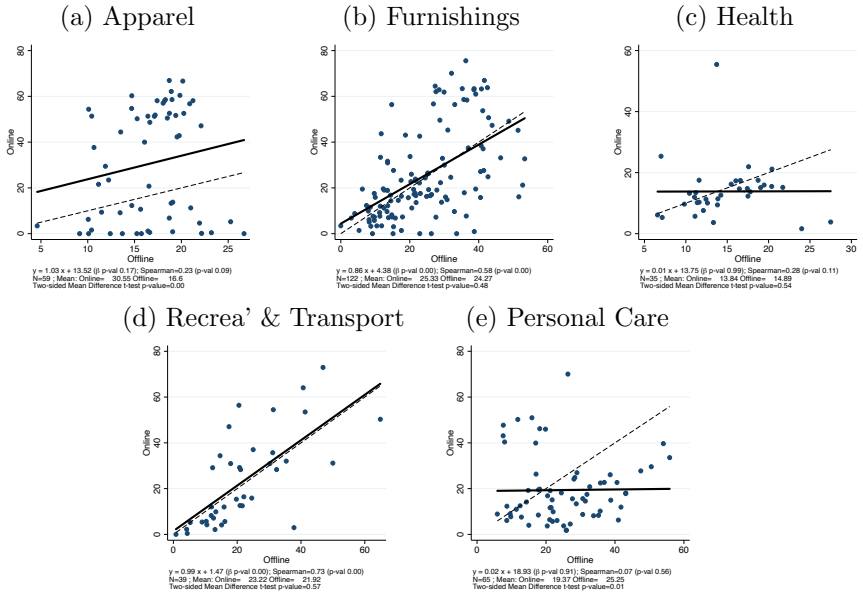
Note: Each scatter represents one price category. The frequency of price changes from the online channel is highlighted in the vertical axis, while the horizontal axis comes from the offline price survey. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 10: Frequency of Price Changes of Food Categories by Retailer in 2016-2019



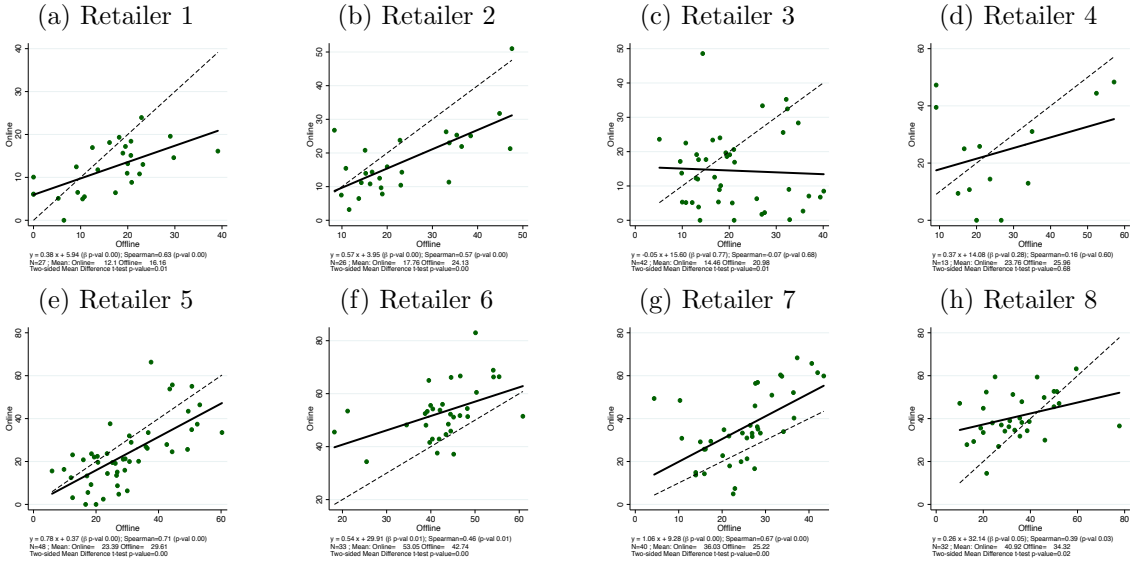
Note: Each scatter represents one price category. The frequency of price changes from the online channel is highlighted in the vertical axis, while the horizontal axis comes from the offline price survey. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 11: Frequency of Price Changes by COICOP Division in 2016-2019



Note: Each scatter represents one price category in a given retailer. 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. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

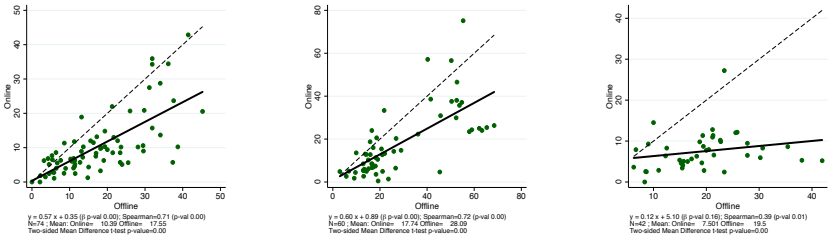
Figure 12: Frequency of Price Changes of Non-Food Categories by Retailer in 2020



Note: Each scatter represents one price category. 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. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 13: Frequency of Price Changes of Food Categories by Retailer in 2020

(a) Retailer A (b) Retailer B (c) Retailer C

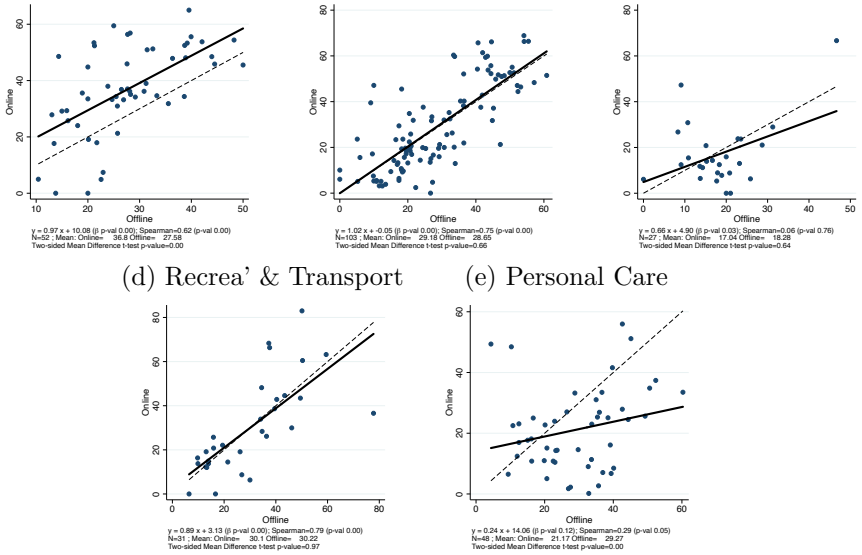


Note: Each scatter represents one price category. The frequency of price changes from the online channel is highlighted in the vertical axis, while the horizontal axis comes from the offline price survey. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 14: Frequency of Price Changes by COICOP Division in 2020

(a) Apparel (b) Furnishings (c) Health

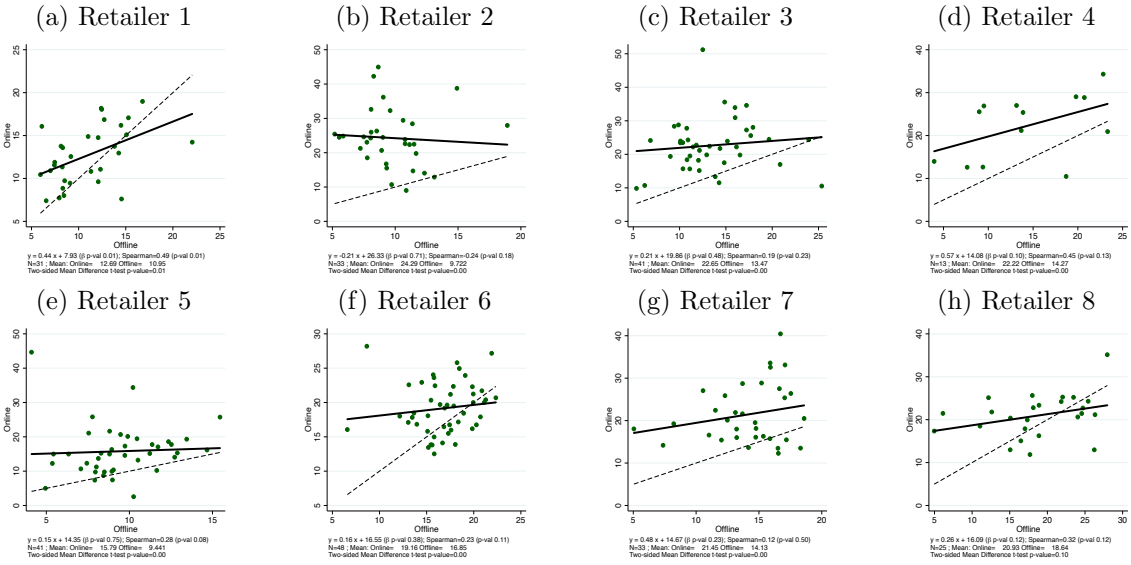
(d) Recrea' & Transport (e) Personal Care



Note: Each scatter represents one price category in a given retailer. 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. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

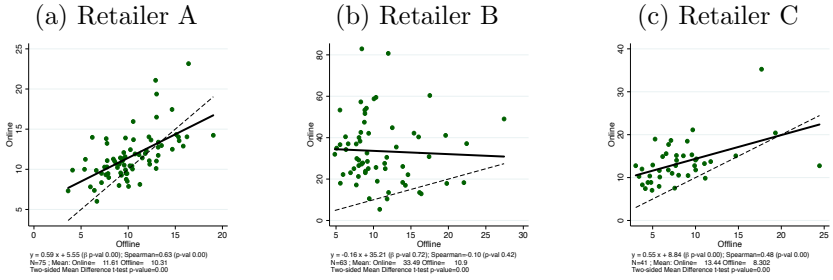
A.3 Size of Price Adjustments

Figure 15: Size of Price Adjustments of Non-Food Categories by Retailer in 2016-2019



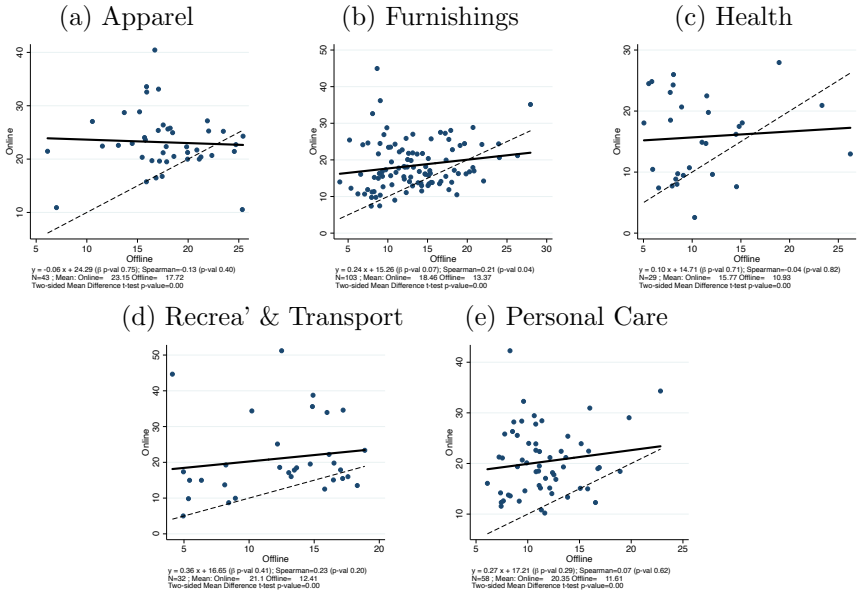
Note: Each scatter represents one price category. The size of price changes from the online channel is highlighted in the vertical axis, while the horizontal axis comes from the offline price survey. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average size of non-zero price changes is computed using the day of the week that maximizes the Spearman between the frequency of adjustments of online and offline prices. Statistics computed on a fortnightly basis for non-food goods. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 16: Size of Price Adjustments of Food Categories by Retailer in 2016-2019



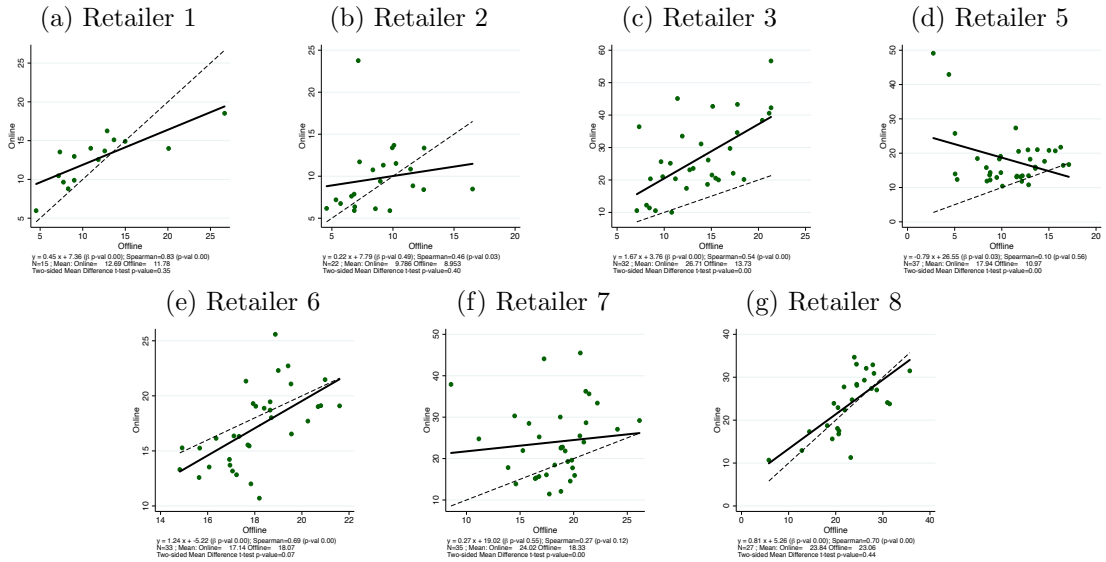
Note: Each scatter represents one price category. The size of price changes from the online channel is highlighted in the vertical axis, while the horizontal axis comes from the offline price survey. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average size of non-zero price changes is computed using the day of the week that maximizes the Spearman between the frequency of adjustments of online and offline prices. Statistics computed on a weekly basis for food-related items. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 17: Size of Price Adjustments by COICOP Division in 2016-2019



Note: Each scatter represents one price category in a given retailer. The size of price changes from the online channel is highlighted in the vertical axis, while the horizontal axis comes from the offline price survey. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average size of non-zero price changes is computed using the day of the week that maximizes the Spearman between the frequency of adjustments of online and offline prices. Statistics computed on a fortnightly basis for non-food goods. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

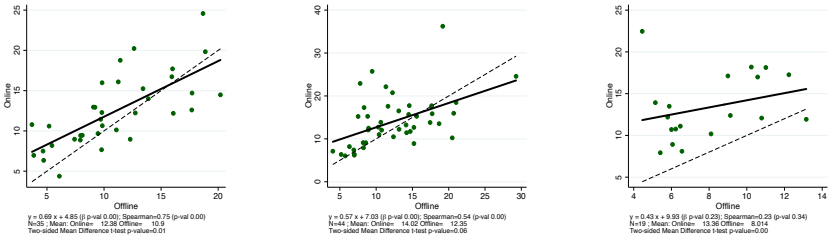
Figure 18: Size of Price Adjustments of Non-Food Categories by Retailer in 2020



Note: Each scatter represents one price category. The size of price changes from the online channel is highlighted in the vertical axis, while the horizontal axis comes from the offline price survey. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average size of non-zero price changes is computed using the day of the week that maximizes the Spearman between the frequency of adjustments of online and offline prices. Statistics computed on a fortnightly basis for non-food goods. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 19: Size of Price Adjustments of Food Categories by Retailer in 2020

(a) Retailer A (b) Retailer B (c) Retailer C

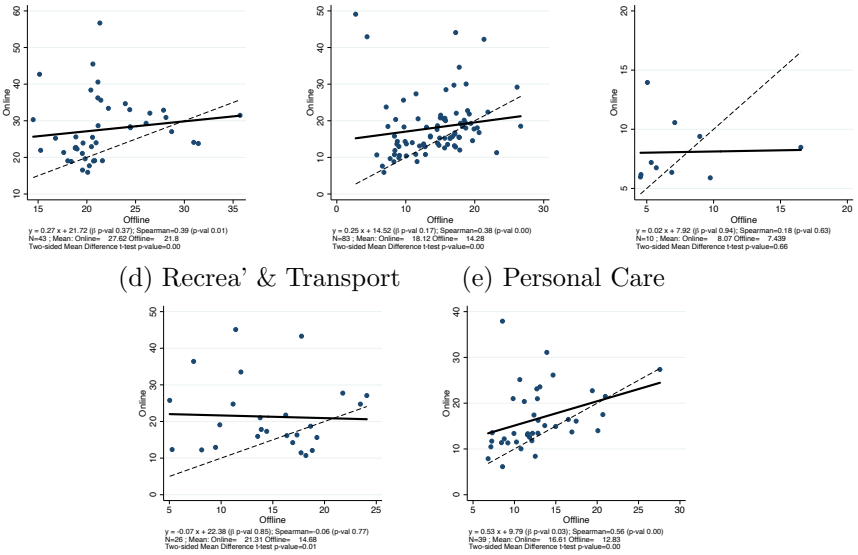


Note: Each scatter represents one price category. The size of price changes from the online channel is highlighted in the vertical axis, while the horizontal axis comes from the offline price survey. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average size of non-zero price changes is computed using the day of the week that maximizes the Spearman between the frequency of adjustments of online and offline prices. Statistics computed on a weekly basis for food goods. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 20: Size of Price Adjustments by COICOP Division in 2020

(a) Apparel (b) Furnishings (c) Health

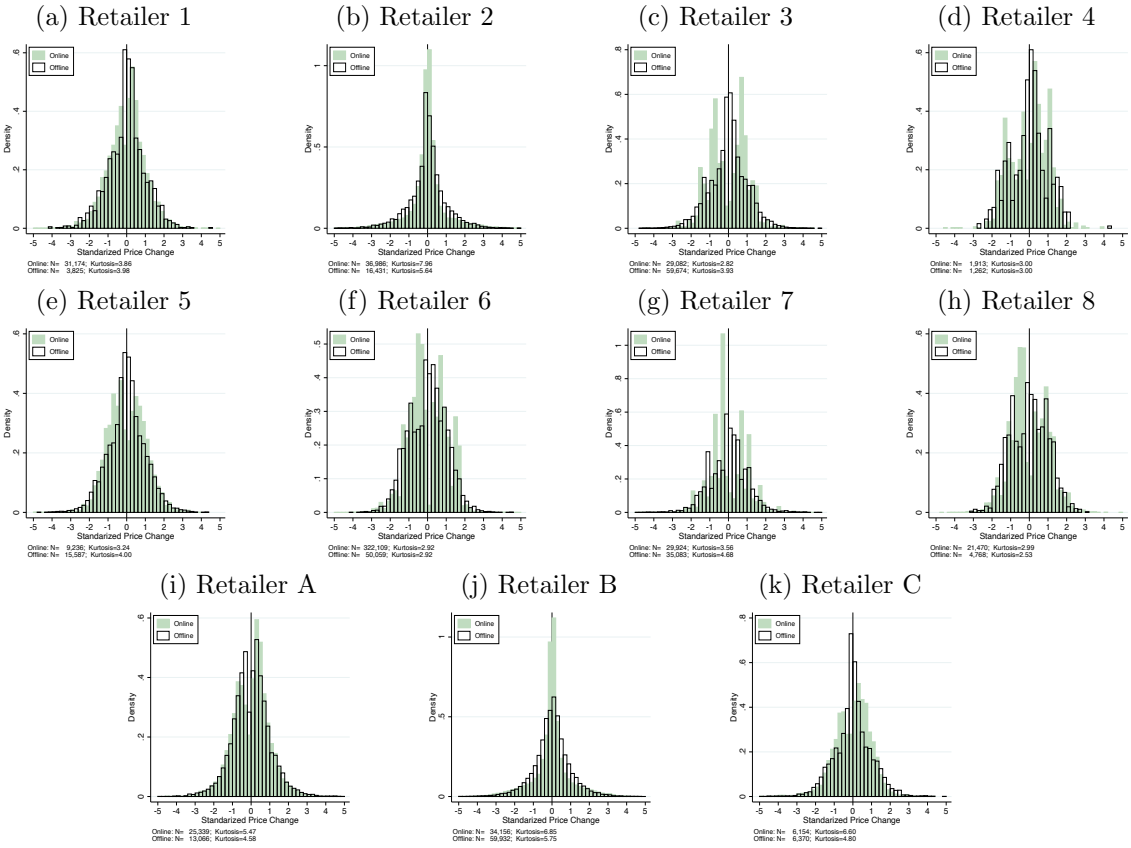
(d) Recrea' & Transport (e) Personal Care



Note: Each scatter represents one price category in a given retailer. The size of price changes from the online channel is highlighted in the vertical axis, while the horizontal axis comes from the offline price survey. The OLS slope and the 45 degree line are depicted as solid and dashed lines, respectively. Online prices gathered through web scraping techniques, while offline prices come from CPI microdata. The average size of non-zero price changes is computed using the day of the week that maximizes the Spearman between the frequency of adjustments of online and offline prices. Statistics computed on a fortnightly basis for non-food goods. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

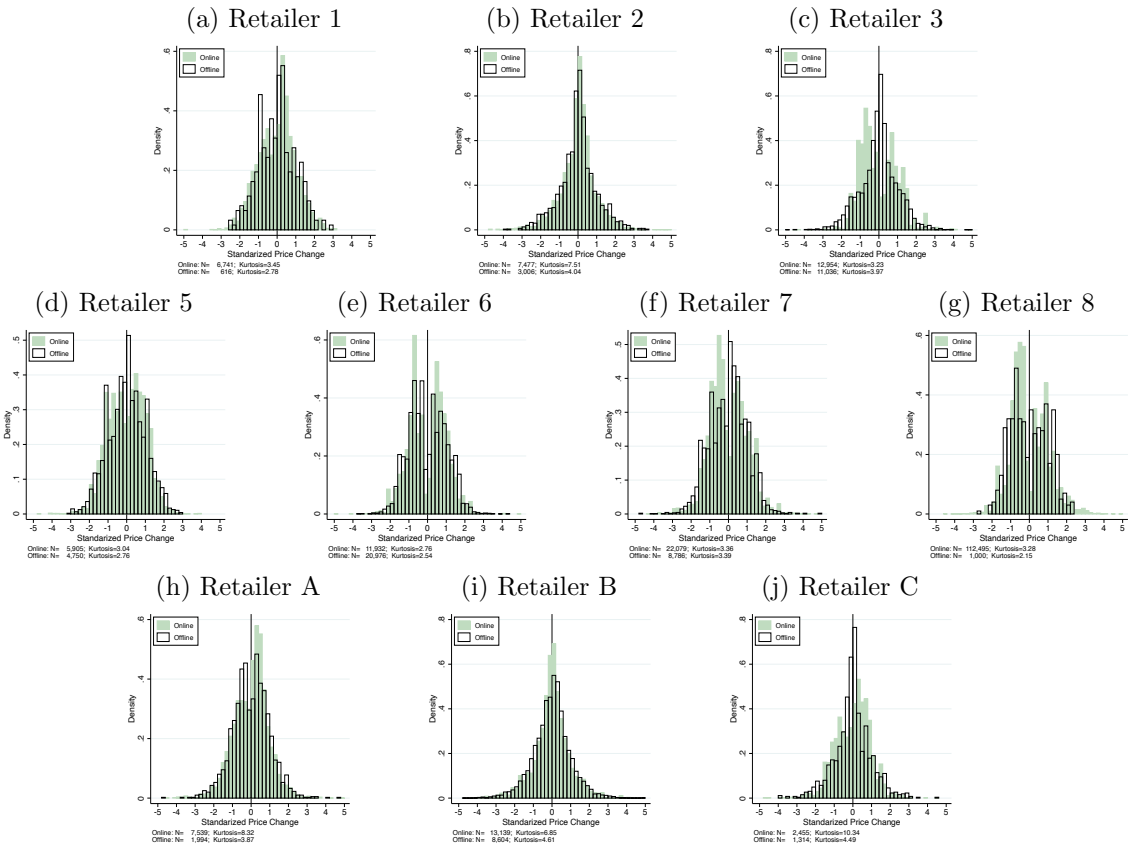
A.4 Kurtosis of Price Changes

Figure 21: Distribution of Standardized Non-Zero Price Changes in 2016-2019



Note: These distributions illustrate standardized price changes, as defined in Equation 4 and summarized in Table 18. Retailers 1 to 8 report the distribution of non-food categories, whereas Retailers A to C summarize the distribution of food categories. Solid colored bars come from price changes observed on websites, whereas those with black borders illustrate price adjustments observed at brick and mortar stores. The area in each histogram adds up to one. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 22: Distribution of Standardized Non-Zero Price Changes in 2020



Note: These distributions illustrate standardized price changes, as defined in Equation 4 and summarized in Table 18. Retailers 1 to 8 report the distribution of non-food categories (Retailer 4 is omitted due to small sample issues), whereas Retailers A to C summarize the distribution of food categories. Solid colored bars come from price changes observed on websites, whereas those with black borders illustrate price adjustments observed at brick and mortar stores. The area in each histogram adds up to one. For more on the methodology, see Section 3. Source: Author's own calculations based on data from INEGI and Banco de México.

A.5 Average Price Level

Table 26: Average Price Level by Retailer Between 2016 and 2019

	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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
Retailer 1	4.30	4.20	0.14	38	21	6	11	0.89	0.00	0.78	0.00	0.00
Retailer 2	4.33	4.34	0.89	38	20	2	16	0.82	0.00	0.78	0.00	0.01
Retailer 3	5.95	5.40	0.00	55	44	3	8	0.95	0.00	0.89	0.00	0.02
Retailer 4	7.02	6.46	0.00	23	17	2	4	0.80	0.00	0.77	0.00	0.02
Retailer 5	6.40	6.28	0.15	48	33	5	10	0.90	0.00	0.86	0.00	0.01
Retailer 6	6.97	6.81	0.13	49	30	2	17	0.90	0.00	0.80	0.00	0.00
Retailer 7	6.78	7.07	0.01	39	13	0	26	0.86	0.00	1.07	0.00	0.44
Retailer 8	7.86	7.59	0.01	35	19	6	10	0.89	0.00	0.81	0.00	0.01
Pooled	6.17	5.99	0.00	325	197	26	102	0.92	0.00	0.90	0.00	0.00
B. Food												
Retailer A	3.67	3.53	0.00	89	60	6	23	0.84	0.00	0.78	0.00	0.00
Retailer B	3.62	3.36	0.00	73	57	1	15	0.85	0.00	0.79	0.00	0.00
Retailer C	4.83	4.54	0.00	54	40	1	13	0.68	0.00	0.60	0.00	0.00
Pooled	3.94	3.72	0.00	216	157	8	51	0.90	0.00	0.82	0.00	0.00

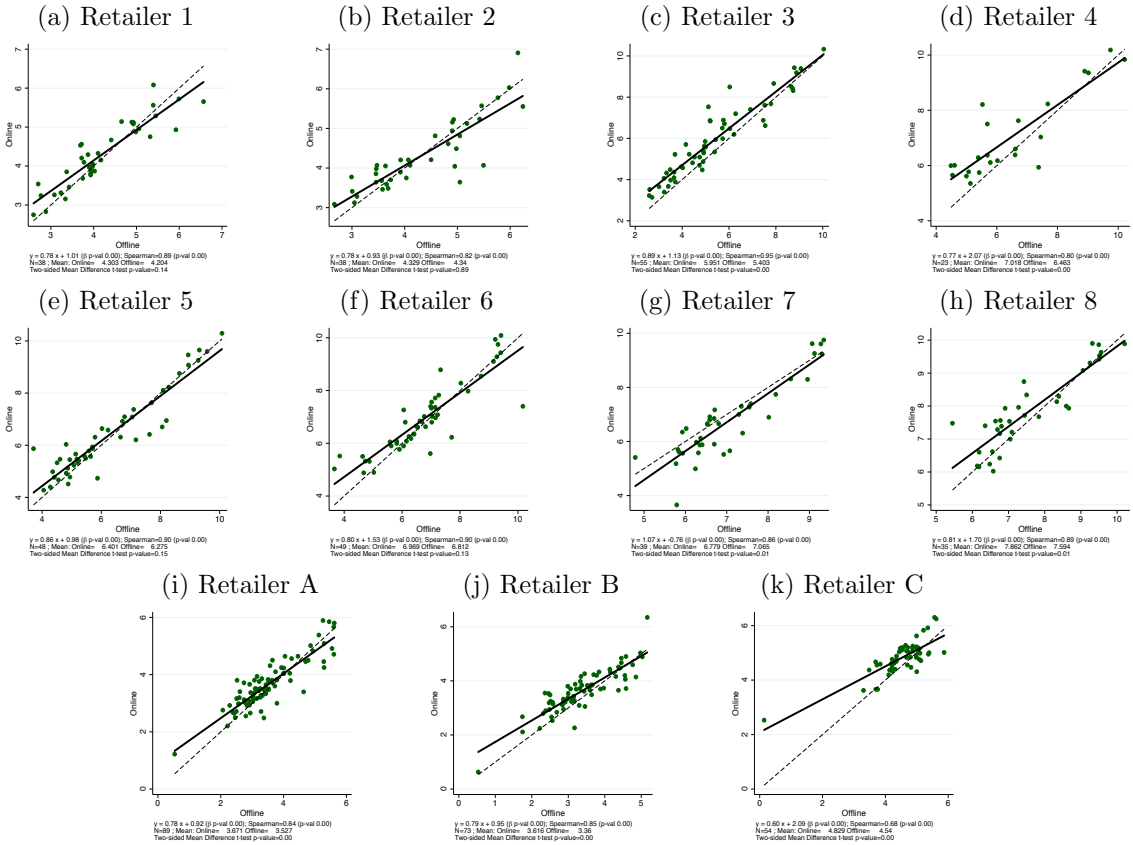
Note: Using data between 2016 and 2019 only. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions 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 z-test of proportion 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. Source: Author's own calculations based on data from INEGI and Banco de México.

Table 27: Average Price Level by COICOP Division Between 2016 and 2019

	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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
Apparel	6.24	6.06	0.01	61	38	3	20	0.78	0.00	0.84	0.00	0.02
Furnishings	6.70	6.45	0.00	124	80	10	34	0.96	0.00	0.90	0.00	0.00
Health	5.28	5.27	0.97	36	14	7	15	0.79	0.00	0.79	0.00	0.04
Recreation and Transport	6.94	6.96	0.89	39	18	3	18	0.92	0.00	0.95	0.00	0.47
Personal Care and Others	5.12	4.86	0.00	65	47	3	15	0.89	0.00	0.86	0.00	0.02
Pooled	6.17	5.99	0.00	325	197	26	102	0.92	0.00	0.90	0.00	0.00

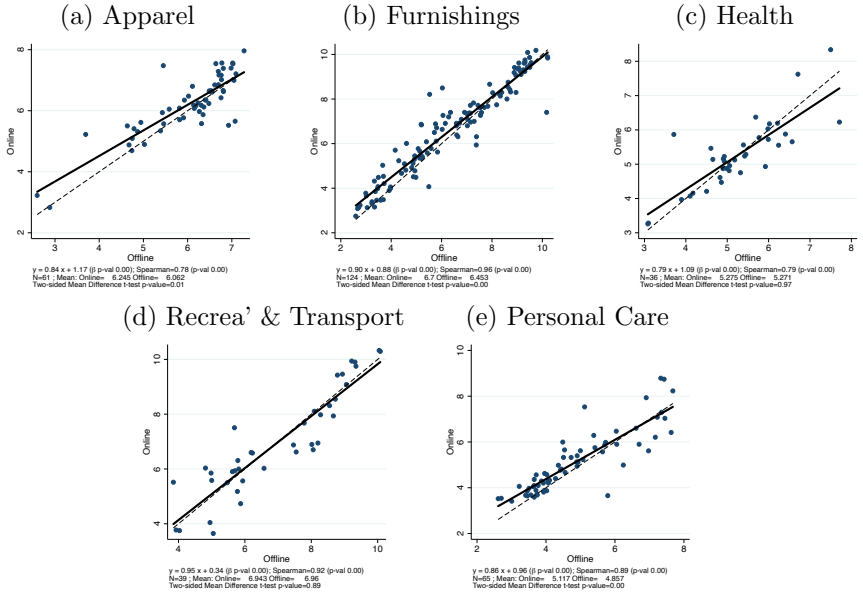
Note: Using data between 2016 and 2019 only. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions 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 z-test of proportion 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. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 23: Average Price Level by Retailer in 2016-2019



Note: See Subsection 5.1 for details. Retailers 1 to 8 report the distribution of non-food categories, whereas Retailers A to C summarize the distribution of food categories. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 24: Average Price Level by COICOP Division in 2016-2019



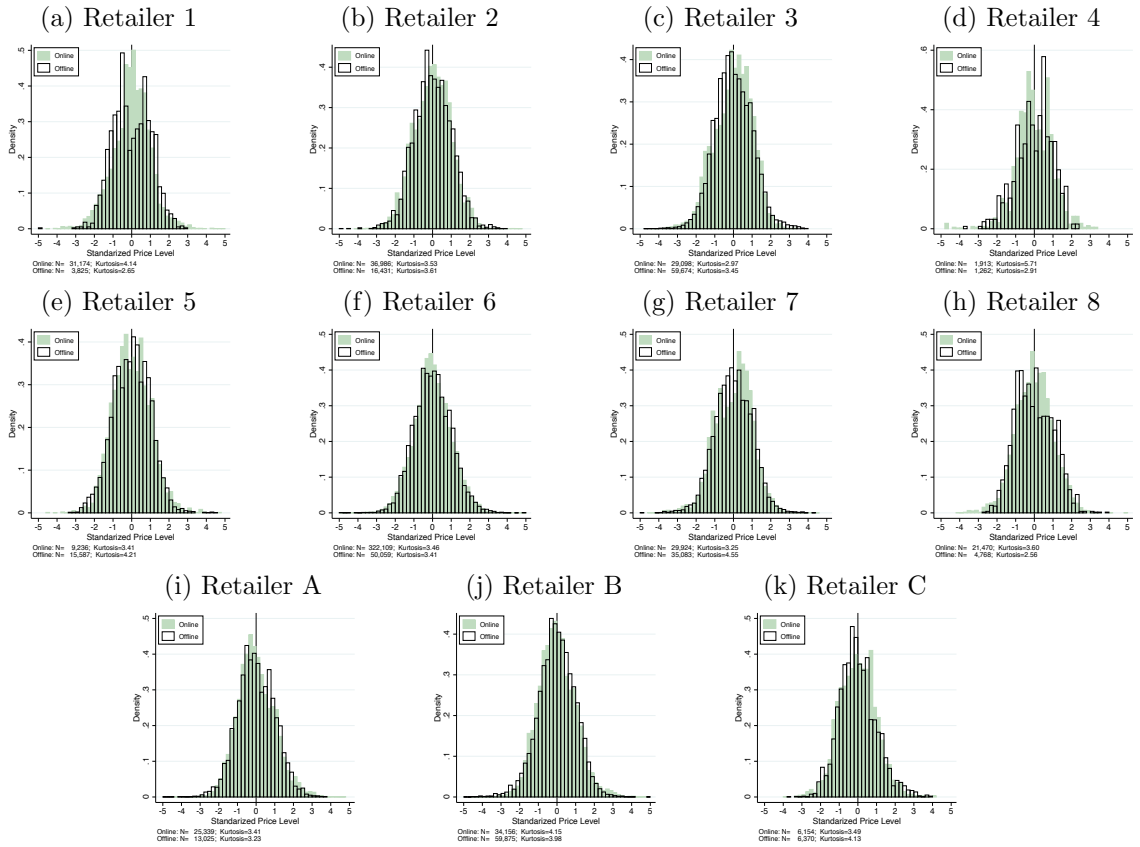
Note: See Subsection 5.1 for details. Source: Author's own calculations based on data from INEGI and Banco de México.

Table 28: Average Price Level by Retailer in 2020

	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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
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	6.14	5.72	0.00	44	35	1	8	0.92	0.00	0.84	0.00	0.01
Retailer 4	6.35	6.29	0.52	49	30	5	14	0.87	0.00	0.95	0.00	0.39
Retailer 5	7.04	6.97	0.44	38	20	1	17	0.90	0.00	0.87	0.00	0.04
Retailer 6	6.93	7.08	0.12	42	14	4	24	0.85	0.00	0.95	0.00	0.49
Retailer 7	7.47	7.36	0.28	35	16	6	13	0.85	0.00	0.84	0.00	0.04
Pooled	6.21	6.09	0.00	266	151	24	91	0.93	0.00	0.90	0.00	0.00
B. Food												
Retailer A	3.83	3.72	0.05	74	37	16	20	0.87	0.00	0.74	0.00	0.00
Retailer B	3.62	3.43	0.00	60	43	5	12	0.76	0.00	0.57	0.00	0.00
Retailer C	5.01	4.80	0.00	42	25	8	9	0.68	0.00	0.67	0.00	0.00
Pooled	4.04	3.88	0.00	176	105	29	41	0.88	0.00	0.79	0.00	0.00

Note: Using data between 2016 and 2019 only. 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 z-test of proportion 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. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 25: Distribution of Standardized Non-Food Categories Price Level in 2016-2019



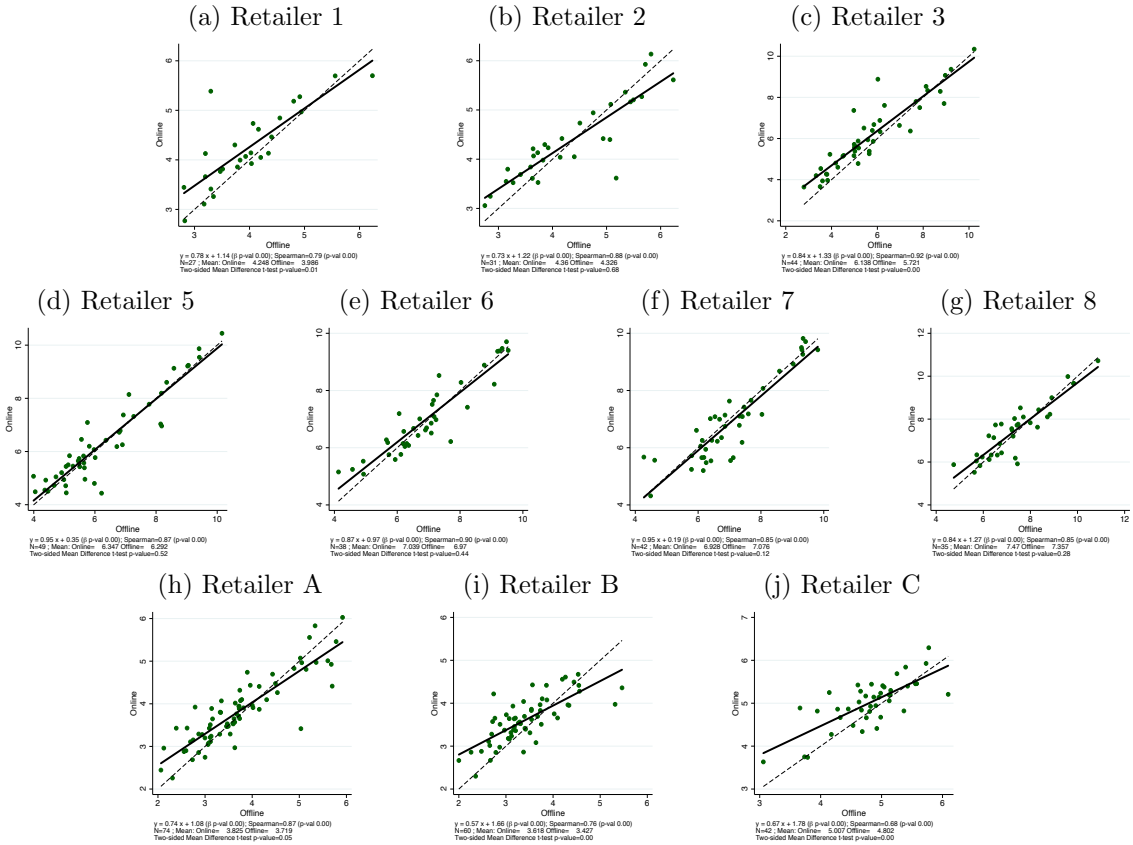
Note: These distributions illustrate the dispersion of standardized price levels across sales channels. Retailers 1 to 8 report the distribution of non-food categories, whereas Retailers A to C summarize the distribution of food categories. Solid colored bars come from price changes observed on websites, whereas those with black borders illustrate price adjustments observed at brick and mortar stores. The area in each histogram adds up to one. Source: Author's own calculations based on data from INEGI and Banco de México.

Table 29: Average Price Level by COICOP Division in 2020

	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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
Apparel	6.23	6.12	0.16	58	28	5	25	0.78	0.00	0.76	0.00	0.00
Furnishings	6.74	6.56	0.00	100	58	10	32	0.96	0.00	0.92	0.00	0.00
Health	5.21	5.29	0.61	25	11	3	11	0.74	0.00	0.48	0.00	0.00
Recreation and Transport	7.10	7.24	0.28	33	16	3	14	0.89	0.00	0.96	0.00	0.57
Personal Care and Others	5.03	4.78	0.00	50	38	3	9	0.94	0.00	0.89	0.00	0.05
Pooled	6.21	6.09	0.00	266	151	24	91	0.93	0.00	0.90	0.00	0.00

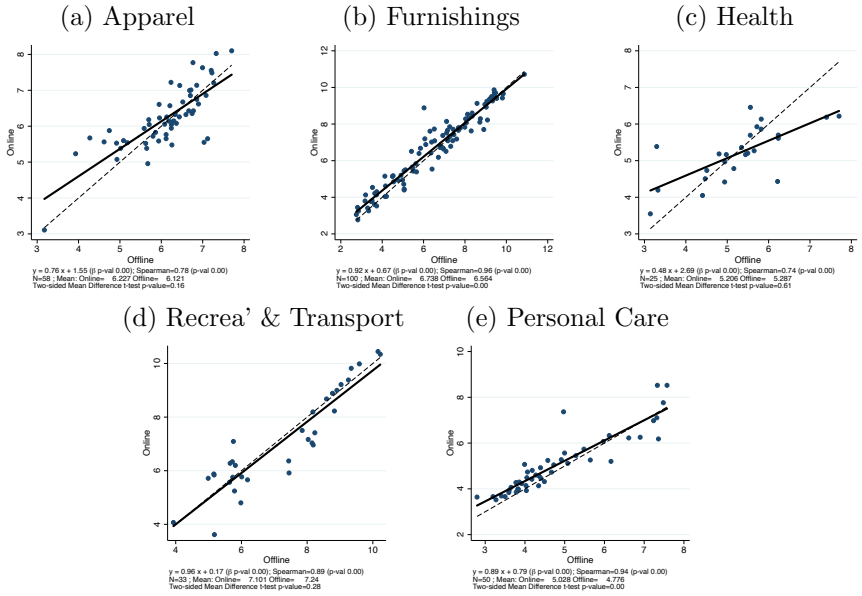
Note: Using data between 2016 and 2019 only. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions 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 z-test of proportion 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. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 26: Average Price Level by Retailer in 2020



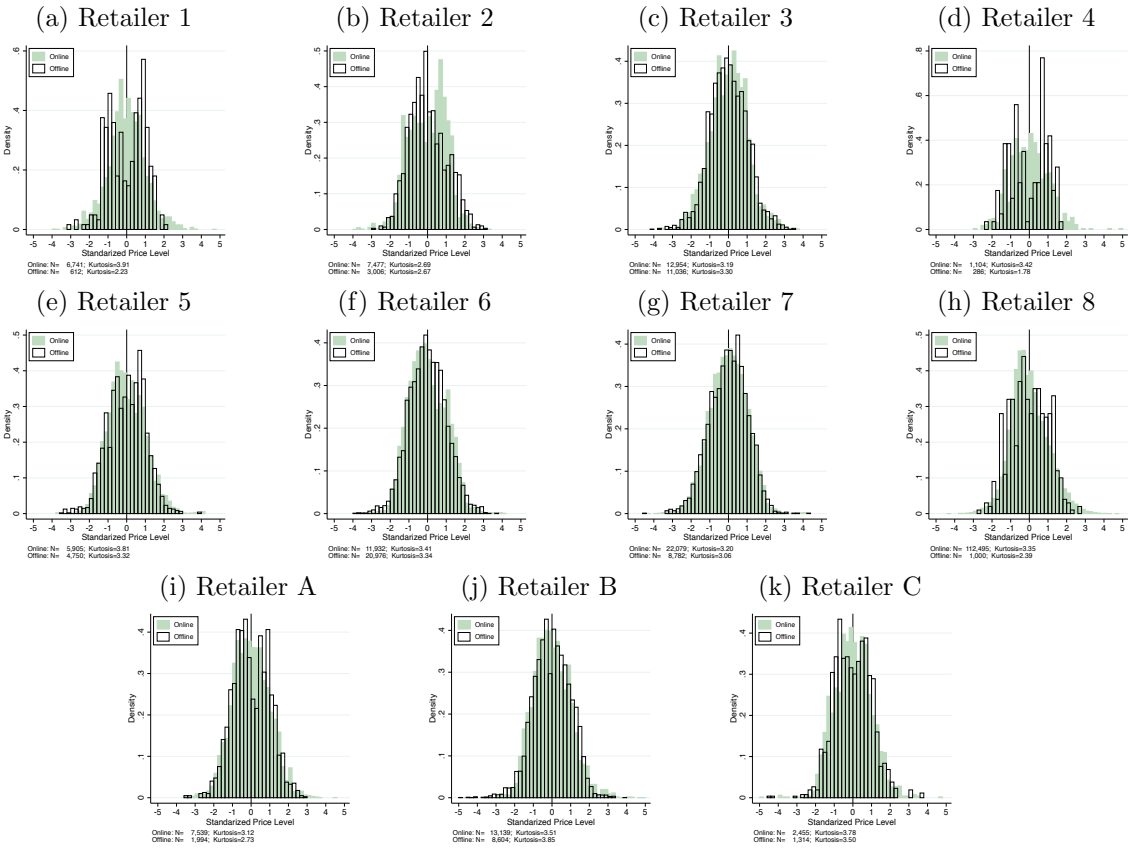
Note: See Subsection 5.1 for details. Retailers 1 to 8 report the distribution of non-food categories (Retailer 4 is omitted due to small sample issues), whereas Retailers A to C summarize the distribution of food categories. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 27: Average Price Level by COICOP Division in 2020



Note: See Subsection 5.1 for details. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 28: Distribution of Standardized Price Level of Non-Food Categories in 2020



Note: These distributions illustrate the dispersion of standardized price levels across sales channels. Retailers 1 to 8 report the distribution of non-food categories, whereas Retailers A to C summarize the distribution of food categories. Solid colored bars come from price changes observed on websites, whereas those with black borders illustrate price adjustments observed at brick and mortar stores. The area in each histogram adds up to one. Source: Author's own calculations based on data from INEGI and Banco de México.

A.6 Share of Missing Products

Table 30: Share of Missing Products by Retailer Between 2016 and 2019

	Share of Missing Products				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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
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
Pooled	15.69	8.67	0.00	325	190	63	72	0.17	0.00	0.24	0.08	0.00
B. Food												
Retailer A	4.06	5.42	0.01	89	17	36	36	0.21	0.05	0.17	0.00	0.00
Retailer B	14.31	4.27	0.00	73	67	6	0	0.28	0.02	0.73	0.00	0.25
Retailer C	2.43	6.13	0.00	54	4	17	33	-0.10	0.47	-0.05	0.29	0.00
Pooled	7.12	5.21	0.00	216	88	59	69	-0.05	0.44	-0.03	0.74	0.00

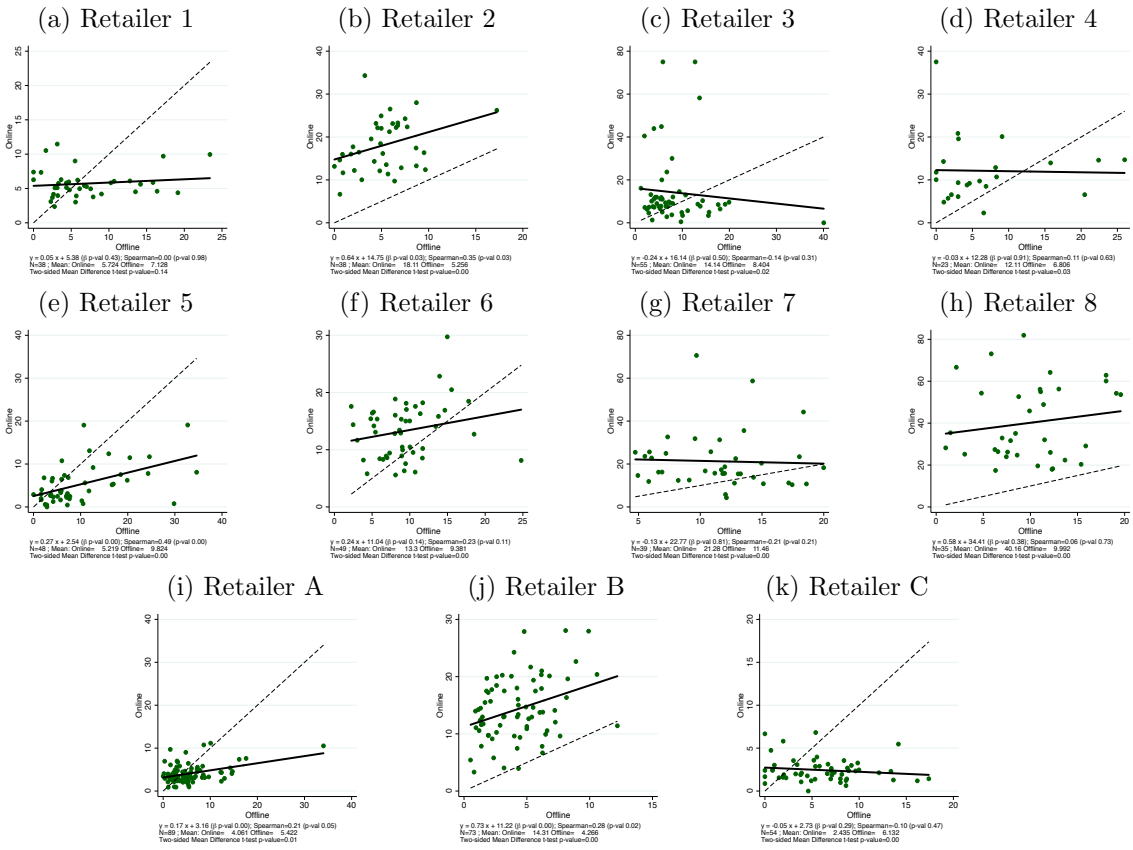
Note: Using data between 2016 and 2019 only. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions 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 z-test of proportion 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. Source: Author's own calculations based on data from INEGI and Banco de México.

Table 31: Share of Missing Products by COICOP Division Between 2016 and 2019

	Share of Missing Products				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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
Apparel	28.07	10.12	0.00	61	48	10	3	0.06	0.62	-0.08	0.90	0.09
Furnishings	13.23	8.42	0.00	124	67	26	31	0.12	0.17	0.11	0.50	0.00
Health	12.40	7.14	0.03	36	21	7	8	-0.27	0.11	-0.08	0.78	0.00
Recreation and Transport	12.43	10.45	0.23	39	18	7	14	0.15	0.36	0.06	0.78	0.00
Personal Care and Others	12.55	7.55	0.00	65	36	13	16	0.22	0.07	0.51	0.04	0.06
Pooled	15.69	8.67	0.00	325	190	63	72	0.17	0.00	0.24	0.08	0.00

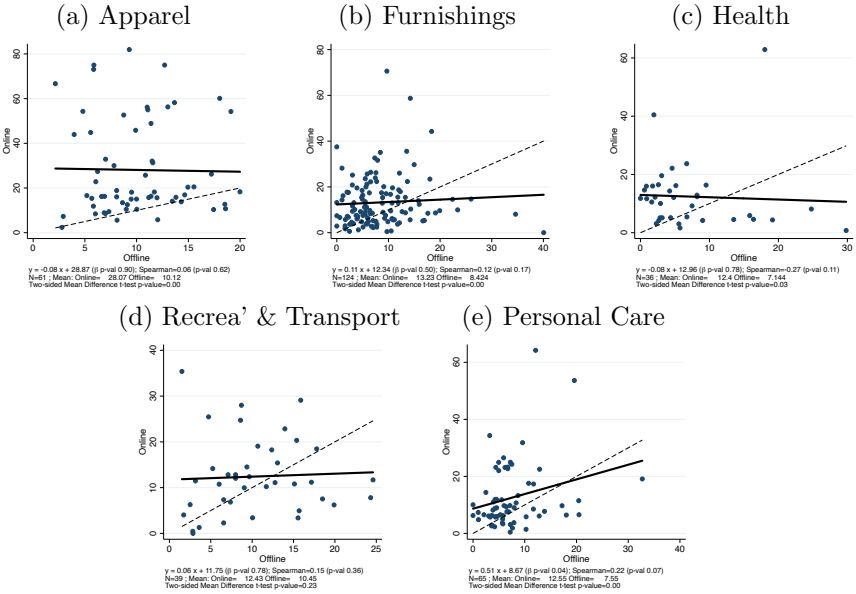
Note: Using data between 2016 and 2019 only. Averages are calculated across unweighted product categories. The third column reports the p-value from a two-sided t-test of mean differences. Spearman and linear fit are computed using the categories within each retailer. Beta coefficients come from regressions 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 z-test of proportion 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. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 29: Share of Missing Products by Retailer in 2016-2019



Note: See Subsection 5.2 for details. Retailers 1 to 8 report the distribution of non-food categories, whereas Retailers A to C summarize the distribution of food categories. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 30: Share of Missing Products by COICOP Division in 2016-2019



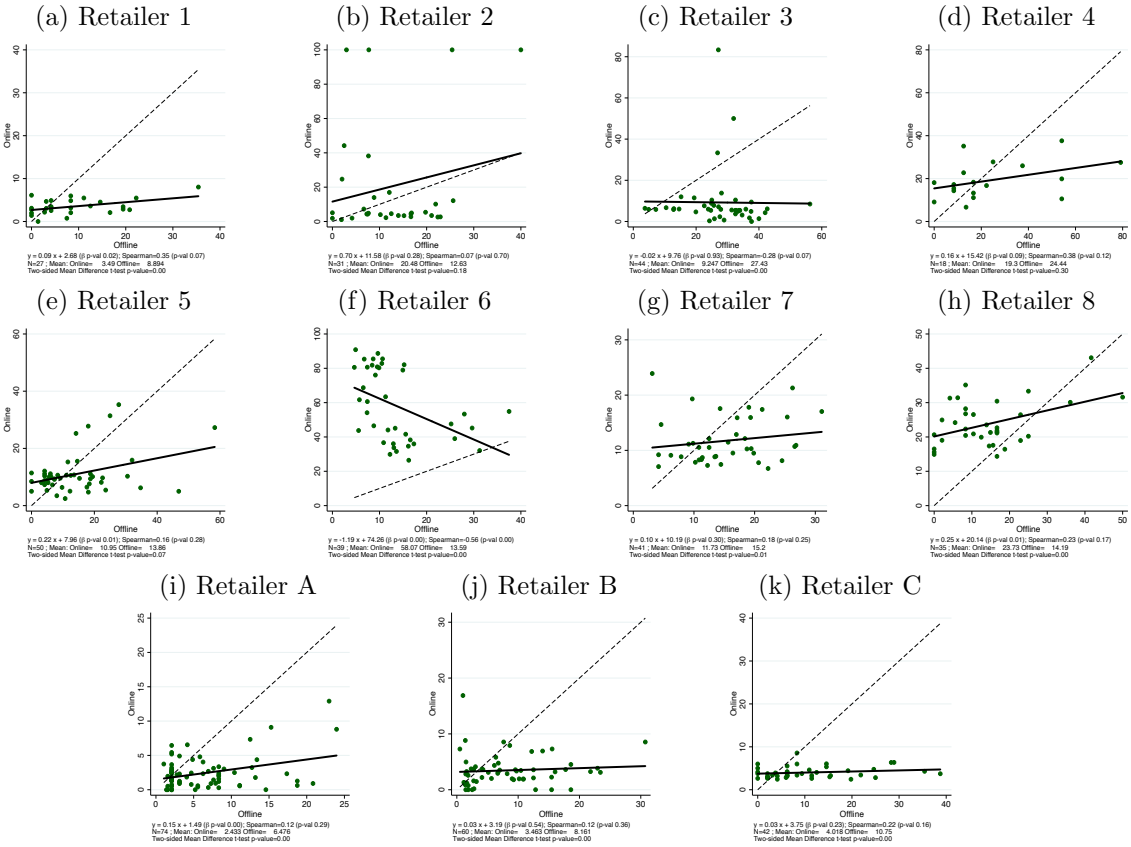
Note: See Subsection 5.2 for details. Source: Author's own calculations based on data from INEGI and Banco de México.

Table 32: Share of Missing Products by Retailer in 2020

	Share of Missing Products				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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
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
Pooled	19.67	16.22	0.02	285	90	88	107	0.02	0.74	-0.04	0.71	0.00
B. Food												
Retailer A	2.43	6.48	0.00	74	0	41	33	0.12	0.29	0.15	0.00	0.00
Retailer B	3.46	8.16	0.00	60	3	27	30	0.12	0.36	0.03	0.54	0.00
Retailer C	4.02	10.75	0.00	42	0	22	20	0.22	0.16	0.03	0.23	0.00
Pooled	3.16	8.07	0.00	176	3	90	83	0.20	0.01	0.07	0.00	0.00

Note: Using data from 2020 only. 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 z-test of proportion 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. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 31: Share of Missing Products by Retailer in 2020



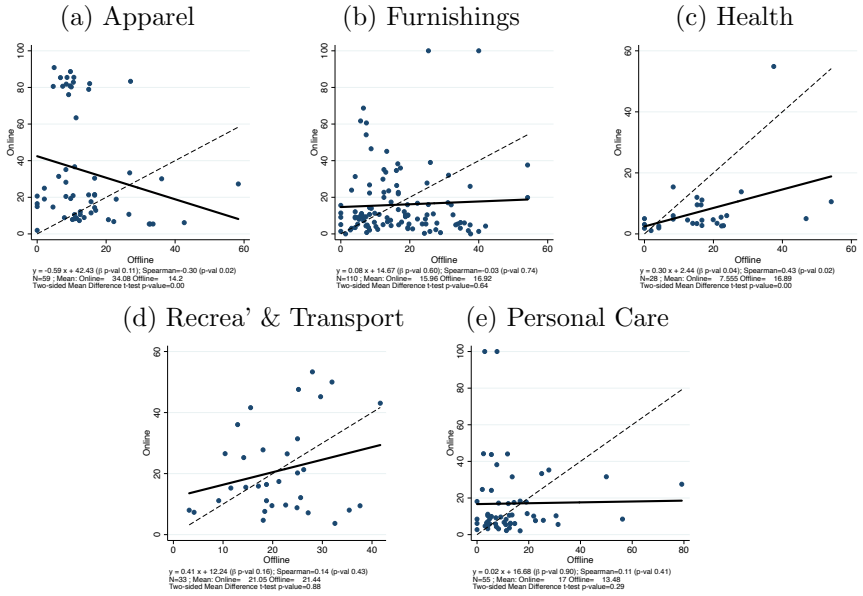
Note: See Subsection 5.2 for details. Retailers 1 to 8 report the distribution of non-food categories, whereas Retailers A to C summarize the distribution of food categories. Source: Author's own calculations based on data from INEGI and Banco de México.

Table 33: Share of Missing Products by COICOP Division in 2020

	Share of Missing Products				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
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
A. Non-Food												
Apparel	34.08	14.20	0.00	59	31	18	10	-0.30	0.02	-0.59	0.11	0.00
Furnishings	15.96	16.92	0.64	110	31	29	50	-0.03	0.74	0.08	0.60	0.00
Health	7.55	16.89	0.00	28	1	12	15	0.43	0.02	0.30	0.04	0.00
Recreation and Transport	21.05	21.44	0.88	33	9	12	12	0.14	0.43	0.41	0.16	0.05
Personal Care and Others	17.00	13.48	0.29	55	18	17	20	0.11	0.41	0.02	0.90	0.00
Pooled	19.67	16.22	0.02	285	90	88	107	0.02	0.74	-0.04	0.71	0.00

Note: Using data from 2020 only. 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 z-test of proportion 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. Source: Author's own calculations based on data from INEGI and Banco de México.

Figure 32: Share of Missing Products by COICOP Division in 2020



Note: See Subsection 5.2 for details. Source: Author's own calculations based on data from INEGI and Banco de México.