Competitive Dynamics of Online and Brick-and-Mortar Retail Prices

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I. Executive Summary

This paper analyzes the competitive interplay of prices amongst retail channels: offline (brick-and-mortar) and online (such as retailers' websites and online marketplaces). We find evidence of a close competitive relationship between the two channels, in which prices correspond tightly across channels. We find that prices are highly responsive to changes in the other channel; in other words, when offline prices increase (or decrease), online prices tend to respond by also increasing (or decreasing). This means that consumers online face similar pricing trends to consumers offline, and the competition between different retailers and across channels is vigorous.

We specifically find that online prices are more responsive to brick-and-mortar prices than the reverse, which is consistent with the technological capacity for online prices to adjust more rapidly than brick-and-mortar price tags. Both brick-and-mortar and online prices react similarly

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when they are the lower price, and tend to adjust upwards. But their responses are clearly different when they are the higher price: brick-and-mortar prices will tend to stay high, while online prices will be pulled down to lower levels. This is consistent with intense price competition both within and across retail channels.

For the set of products analyzed at the national aggregate level, we also find that both channels experience increases and decreases in dollar sales at the same time and to the same degree. This is consistent with the idea that both channels are subject to the same market forces.

Evidence in the literature demonstrates a close correspondence between prices online and in brick-and-mortar stores. This paper provides additional evidence in support of this finding, and expands on the current literature by providing evidence regarding price transmission and dynamics.

Of relevance for competition and regulation, our findings suggest that competition among retailers and across retail channels is intense, that they respond quickly to each other's prices and that, as a consequence, regulation affecting online commerce is expected to affect prices in brick-and-mortar stores, and vice versa. The increasing popularity of omnichannel shopping, whereby consumers mix and match online and offline components of their shopping journey, also may encourage convergence between online and offline prices.[4]

II. Literature Review

Academic literature provides various perspectives on whether online and brick-and-mortar prices are similar. Several papers from the early 2000s conclude that consumers face lower prices online than brick-and-mortar due to lower consumer search costs and other informational effects facilitated in an online shopping environment.[5]

[4] See, for example, Wagener, Simpson, and Kearns, (2022) Retail Today, available at https://www.deloittedigital.com/content/dam/deloittedigital/us/documents/offerings/offerings-20220125-insightiq-ccia-retail-today.pdf.

[5] See, for example, Brynjolfsson, Erik and Smith, Michael D., (2000), Frictionless Commerce? A Comparison of Internet and Conventional Retailers, Management Science, 46, issue 4, p. 563-585; Clay, Karen B. and Krishnan, Ramayya and Wolff, Eric D., (May 2001), Prices and Price Dispersion on the Web: Evidence from the Online Book Industry, NBER Working Paper No. w8271, Available at SSRN: https://ssrn.com/abstract=268880; Morton,

More recently, researchers find that prices are frequently identical at the online and brick-and-mortar stores of multi-channel retailers. For example, a 2016 paper by Alberto Cavallo makes use of hand-collected price data and finds that in the U.S., prices for the same goods at the same retailer are identical online and offline 69% of the time.[6] In this paper, we also present research based on a set of hand-collected price data and find that prices are identical an even greater percentage of the time (95%). The difference between our findings and Cavallo's is likely due to the difference in the set of goods we study and likely increasing convergence over time, as Cavallo's paper uses data from years before our data sets.

Academic literature also provides varying conclusions regarding the behavior of price movements online and offline. Cavallo's research, cited above, suggests price changes do not typically occur simultaneously in online and brick-and-mortar locations of the same retailer, but does find that prices change with similar frequency and magnitude in both channels.[7] In contrast, other research suggests that online prices change more frequently, but that price changes in brick-and-mortar stores are greater in magnitude.[8] Our research finds that, within the same retailer, medium-term price changes offline and online are typically contemporaneous and identical in magnitude, with frequent but short-term deviations in online prices.

III. Data Sources

For this research work we used two data sources: nation-wide aggregate price and volume data from NPD and hand-collected price observations from individual retail locations from Premise.

F.S., Zettelmeyer, F. & Silva-Risso, J, (2003), Consumer Information and Discrimination: Does the Internet Affect the Pricing of New Cars to Women and Minorities?. Quantitative Marketing and Economics 1, 65–92. https://doi.org/10.1023/A:1023529910567; Jeffrey R. Brown and Austan Goolsbee, (2002), "Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry," Journal of Political Economy, University of Chicago Press, vol. 110(3), pages 481-507; Sengupta, Anirban and Wiggins, Steven N., (November 2006), Airline Pricing, Price Dispersion and Ticket Characteristics on and Off the Internet. NET Institute Working Paper No. 06-07, Available at SSRN: https://ssrn.com/abstract=938609; Lieber and Syverson (2010) "Online vs. Offline Competition"

[6] Cavallo, Alberto, and Roberto Rigobon. (2016), The Billion Prices Project: Using Online Prices for Measurement and Research. Journal of Economic Perspectives, 30 (2): 151-78.

[7] *Ibid.*

[8] Gorodnichenko, Yuriy, and Oleksandr Talavera, (2017), Price Setting in Online Markets: Basic Facts, International Comparisons, and Cross-Border Integration. American Economic Review, 107 (1): 249-82.

Together, these two data sources allow us to study various aspects of cross-channel and intra-channel price dynamics for a variety of goods. Below, we describe each data source and describe the advantages and limitations of each.

NPD

Comprehensive aggregate national weekly price-scanner data for juvenile bed/bath products, covering 2018-2019

Advantages:

- Time series of consistent set of products
- Comprehensive coverage of all dollar and unit volume at partner retailers

Limitations:

- Cannot observe price unless units are sold
- Data masks regional variation, retailer-specific variation, and promotional pricing

Point-of-sale data, also referred to as "scanner data," is a commonly-used type of data in economic studies of retail prices and competition. Scanner data captures all sales that occur at partner retailers. NPD partners with a range of retailers including mass merchants, specialty retailers, and department stores; the exact list of partner retailers is not released publicly. The NPD data covers hundreds of thousands of retail locations. Scanner data allows the analysis of sales volume, which is not possible with pricing data collected purely by third party observers.

For this analysis, we purchased a license for NPD data for one product subcategory for two years. We selected juvenile (i.e. baby and child) bed/bath products,[9] for 2018-2019.[10] We licensed the most granular data available: weekly data, aggregated for all retailers and locations. For each product in each week, the data shows the total dollar sales and total unit volume, thus each week we observe the weighted average price of units sold. Retailer- or location-specific data was not available.

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[9] As of today, NPD offers separate brick-and-mortar and online pricing data for four product categories: Juvenile Products (i.e. baby and child products), Beauty, Office Supplies, and Video Games. For the purposes of this project, we selected the Juvenile Products category, as it likely has the most widespread customer base of these four choices. Within the Juvenile Products category we further needed to select a single product Subcategory; we selected the "Bed/Bath" subcategory as it contained the largest number of SKUs and the widest variety of products.

[10] We selected the most recent two years of data pre-pandemic. Early 2020 saw major (though largely temporary) disruptions to many aspects of the retail process: supply-side issues like global supply chain disruptions, shipping delays, brick-and-mortar retail location closures; and demand-side changes such as lost income and changes in the types of goods consumers wish to buy. Given only two years of data, we would not be able to reliably separate "normal" competitive effects from reactions to these many sources of disruption.

NPD's Juvenile Products Bed/Bath data contains eight separate product subcategories, summarized in **Figure 1** below. NPD's data contains all products sold by its partner retailers falling within each category. Therefore, our data contains the entire choice set available to customers at these retailers.[11]

FIGURE 1: SUMMARY OF PRODUCT SUBCATEGORIES IN NPD JUVENILE PRODUCTS DATA

Subcategory	Total Sales	Number of Products	25th Percentile Price	Average Price	75th Percentile Price
Bath Accessories	$83,125,331	123	$8.67	$14.18	$17.00
Bath Toys	$134,306,987	520	$5.51	$9.93	$12.91
Bath Tubs	$83,163,576	83	$17.59	$30.24	$36.39
Bedding	$334,208,022	3945	$13.25	$33.90	$36.00
Changing Pads	$67,272,281	373	$11.89	$18.67	$21.00
Diapering Systems	$126,510,512	96	$14.60	$25.94	$29.37
Potty Training	$139,883,905	220	$10.67	$16.82	$21.00
Sound Machines	$34,926,051	29	$14.24	$29.88	$40.40

Source: NPD

PREMISE PRICE TRACKER

Detailed hand-collected brick-and-mortar and online pricing covering 10/25/21 – 12/2/21.

Premise

Advantages:

- Repeated paired online-offline observations for a consistent set of grocery products and locations

Limitations:

- Short date range of availability
- Limited number of products and geographical coverage

[11] Some subcategories – such as Bath Tubs and Sound Machines – consist of products that are all roughly substitutes for each other. Other subcategories contain a wider variety of products that are complementary and not necessarily directly comparable (for example, Bath Accessories contains storage units for bath toys as well as drain plugs, among other products).

Premise is a crowd-sourced data collection platform, through which individual users hand-collect and enter prices through Premise's software. Data was collected for the following five staple grocery products:

- **Barilla Spaghetti** (1 lb)
- **Cheerios** (one box, 8.9 oz)
- **Gold Medal All-Purpose Flour** (2 lbs)
- **Jif Creamy Peanut Butter** (16 oz)
- **Land O' Lakes Salted Butter** (1 lb, 4 sticks / 8 half sticks)

Prices were collected from a consistent set of 18 retail locations in the Los Angeles metropolitan area, belonging to five retailers: Albertsons, Food 4 Less, Target, Vons, and Walmart. Each of the retail locations is indicated on the map in **Figure 2** below.

Data was collected between October 25, 2021, and December 2, 2021.[12] Prices for the five products were gathered in-person at each of the 18 brick-and-mortar retail locations. Prices for the five products were also gathered from the websites of each of the retailers (not inclusive of delivery fees).[13]

Together, these price observations comprise a month-long set of paired online-offline data observations perfectly controlling for retailer and geography. In total, the data has observations for 3,477 unique combinations of retail location, product, and date, of which 2,605 have price observations for both online and brick-and-mortar channels.

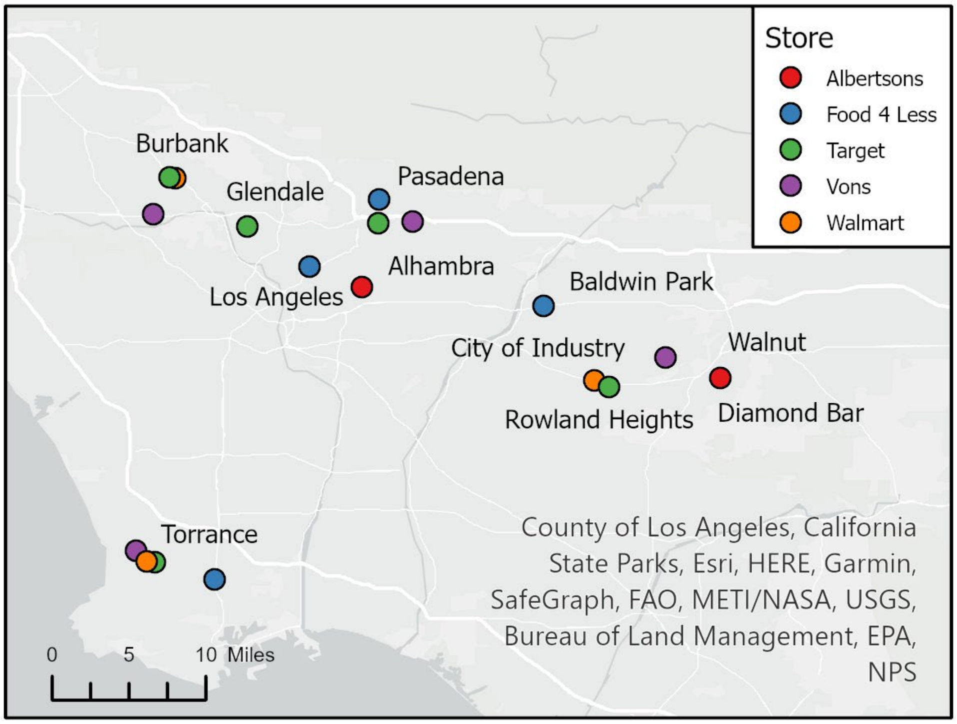
We note that because the hand-collected data covers a narrow scope of products, retailers, and geographical locations, the conclusions drawn from this data are not necessarily generalizable to all retail commerce. Further research using additional products, retailers, and cities would be

[12] The Premise data was collected based on an app through which contributors could gather prices in response to daily posted requests. For redundancy and quality control, multiple daily requests were posted per retail location, product, date, and channel. Contributors were required to submit a photograph (for brick-and-mortar) or screenshot (for online) as supporting evidence for their price observations. Based on these photos and screenshots, invalid prices were removed from the data (for example, if the submitter entered the price for the wrong product or wrong package size). Occasionally, valid price submissions were made for a given retail location, product, date, and channel (whether because no data contributor fulfilled the request on the app, or because the prices submitted were invalid).

[13] Price contributors collected online prices while physically located in the same neighborhood as the corresponding brick-and-mortar retail location. Neighborhoods, rather than zip codes, were used to identify geographical market areas corresponding to each of the 18 physical retail locations. Each retail location fell into one of 11 neighborhoods: Alhambra, Baldwin Park, Burbank, City of Industry, Diamond Bar, Glendale, Los Angeles, Pasadena, Rowland Heights, Torrance, and Walnut.

needed to test whether our specific conclusions hold generally. However, we also note that the research in our paper makes use of two datasets covering two different sets of products and geographies, both providing consistent evidence that online and offline retail channels are subject to the same market forces; therefore, our research is strongly indicative of competition between these two channels.

FIGURE 2: MAP OF RETAIL LOCATIONS FROM WHICH PREMISE COLLECTED PRICE DATA



Source: Premise

IV. Online and Brick-and-Mortar Price Levels Are Consistent with Both Channels Being Driven by Common Competitive Forces

From both data sources, we find strong evidence that online and offline prices correspond closely to one another. We first explore the hand-collected paired grocery price data from Premise, which provide a micro-level view into pricing trends, explicitly controlling for retailer and geography. We then supplement our findings with national aggregate data from NPD, which involves a longer expanded time series, a national geographical scope, and a selection of thousands of products.

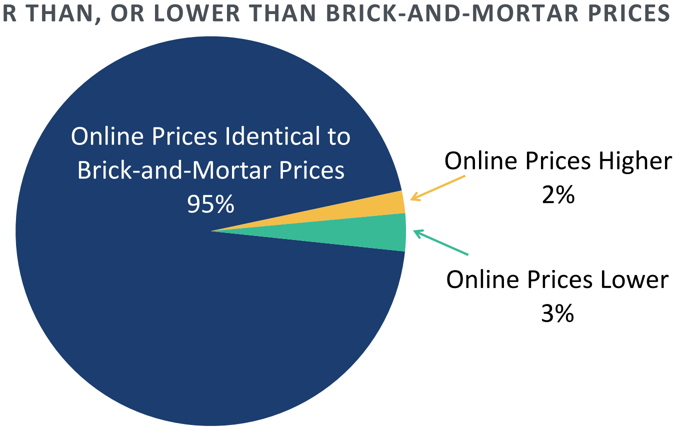
A. Evidence from Hand-Collected Paired Price Data

Online and brick-and-mortar prices are identical the overwhelming majority of the time, after controlling for product, retailer, and location. Deviations are the exception rather than the rule and tend to be brief, typically lasting no longer than a day before returning to the prior level. We find no evidence that retailers have the ability to set completely different price levels in different channels; on the contrary, online and offline prices appear to be tightly constrained by one another.

1. Summary of Price Differences

First, we summarize the comparison of brick-and-mortar versus online prices by counting the frequency with which prices in both channels are the same, or whether one channel prices higher or lower than the other. **Figure 3** below illustrates the breakdown of price observations, based on all products, retailers, and locations, for all dates between October 25, 2021, and December 2, 2021. The graph shows that for 95% of paired price observations, online and brick-and-mortar prices are identical. For the remaining 5% of observations where online and offline prices differ, online prices are higher roughly half of the time. We find no evidence that online prices routinely over-price or under-price the brick-and-mortar channel. Instead, in the rare cases that prices deviate, online prices are very slightly more likely to be lower than higher.

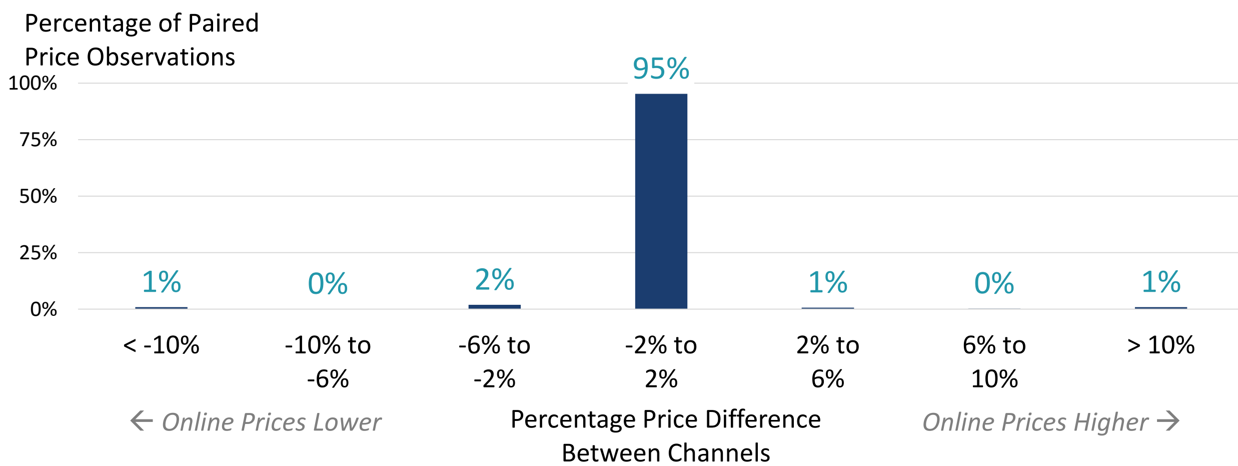
FIGURE 3: PERCENTAGE OF PAIRED PRICE OBSERVATIONS FOR WHICH ONLINE PRICES ARE IDENTICAL TO, HIGHER THAN, OR LOWER THAN BRICK-AND-MORTAR PRICES



Source: Premise

Figure 4 below provides an alternate way of viewing the same data, showing the distribution of the percentage difference between online and brick-and-mortar prices for the same retailer, location, and date. The height of the bar indicates the proportion of paired price observations falling within a given range. As the chart shows, the overwhelming majority (95%) of paired online and offline prices are within +/- 2% of each other. This is consistent with price competition between channels.

FIGURE 4: DISTRIBUTION OF THE PERCENTAGE DIFFERENCES BETWEEN ONLINE AND BRICK-AND-MORTAR PRICES FOR THE SAME PRODUCT, RETAILER, LOCATION, AND DATE



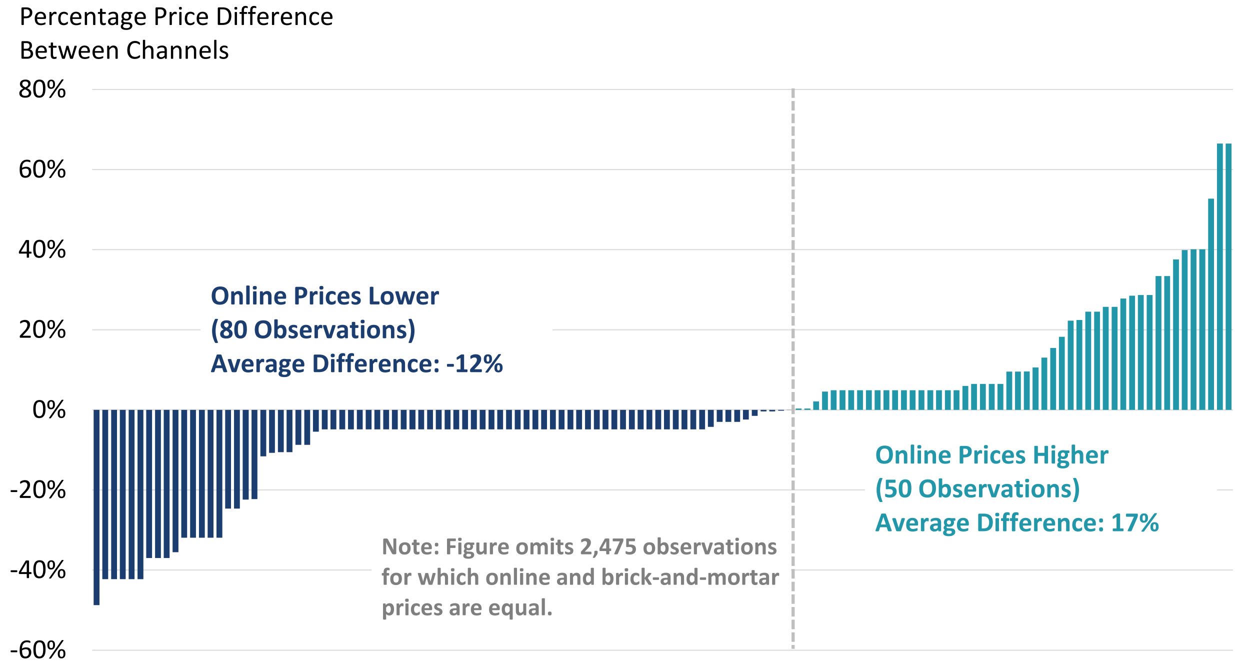
Source: Premise

Percentage price difference between channels is calculated as ([Online Price] – [Brick-and-Mortar Price]) / (Average of Online and Brick-and-Mortar Prices)

We next focus on the 5% of paired price observations for which online and brick-and-mortar prices differ. While these represent a minority of price observations, this allows us to more clearly zoom in on the magnitude of price differences when they are present.

Figure 5 below shows the data for 130 paired price observations for which online and brick-and-mortar prices differ. Each bar in the figure corresponds to a single retail location, product, and date. The height of the bar indicates the percentage difference between online and brick-and-mortar prices, and the bars are sorted from smallest to largest. The dark blue (negative) bars correspond to the 80 observations for which online prices are lower, showing an average difference of 12% between the channels. The teal (positive) bars correspond to the 50 observations for which online prices are higher, showing an average difference of 17% between the channels.

FIGURE 5: PERCENTAGE PRICE DIFFERENCE BETWEEN CHANNELS, ISOLATING RETAIL LOCATION, PRODUCTS, AND DATES FOR WHICH ONLINE AND BRICK-AND-MORTAR PRICES DIFFER



Source: Premise
Percentage price difference between channels is calculated as ([Online Price] – [Brick-and-Mortar Price]) / (Average of Online and Brick-and-Mortar Prices)

The chart above shows that for the rare instances in which prices differ between channels, we find that online prices are slightly more likely to be lower than higher. We further find that the average price discrepancy between channels is larger when online prices are higher as compared to when they are lower.

2. Specific Examples

In this subsection, we present specific examples of online and brick-and-mortar prices. Each specific example below focuses on a specific retailer (say, "Retailer X")[14] in a specific location

[14] "Retailer X" refers to one of the 5 retailers from which data was collected: Albertsons, Food 4 Less, Target, Vons, or Walmart.

(say, "Neighborhood Y")[15] for one specific product (say, "Product Z").[16] The identities of the specific retailers, neighborhoods, and products are obfuscated in accordance with our data license.

In each diagram, blue squares represent brick-and-mortar prices for Product Z, collected at Retailer X's location in Neighborhood Y. Teal diamonds represent prices collected from Retailer X's website for Product Z, as seen by a shopper located in Neighborhood Y.[17] Note that some days may have two teal diamonds if two different price contributors each observed different prices for Product Z on Retailer X's website that day.[18]

Because we are not able to share our full raw dataset publicly, these specific examples were selected to showcase the common patterns we observe in the data.

Figure 6 below shows prices for Retailer A, in Neighborhood B, for Product C. A few patterns are evident:

- Online and brick-and-mortar prices are **typically identical** (i.e., the teal diamonds typically fall on top of the blue squares).
- Product C goes on sale (for approximately 50% off) between November 4th and November 16th, and the sale begins and ends on the **same day in both channels** for this specific retailer.
    - In other words, Retailer A began the sale on November 4th at its location in Neighborhood B; on the exact same day, shoppers on Retailer A's website visiting from Neighborhood B also saw the discounted price.
    - Similarly, Retailer A ended the sale on November 16th at its location in Neighborhood B, and shoppers to Retailer A's website visiting from Neighborhood B also saw the regular price return that day.

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[15] "Neighborhood Y" refers to one of the 11 neighborhoods from which data was collected: Alhambra, Baldwin Park, Burbank, City of Industry, Diamond Bar, Glendale, Los Angeles, Pasadena, Rowland Heights, Torrance, or Walnut.

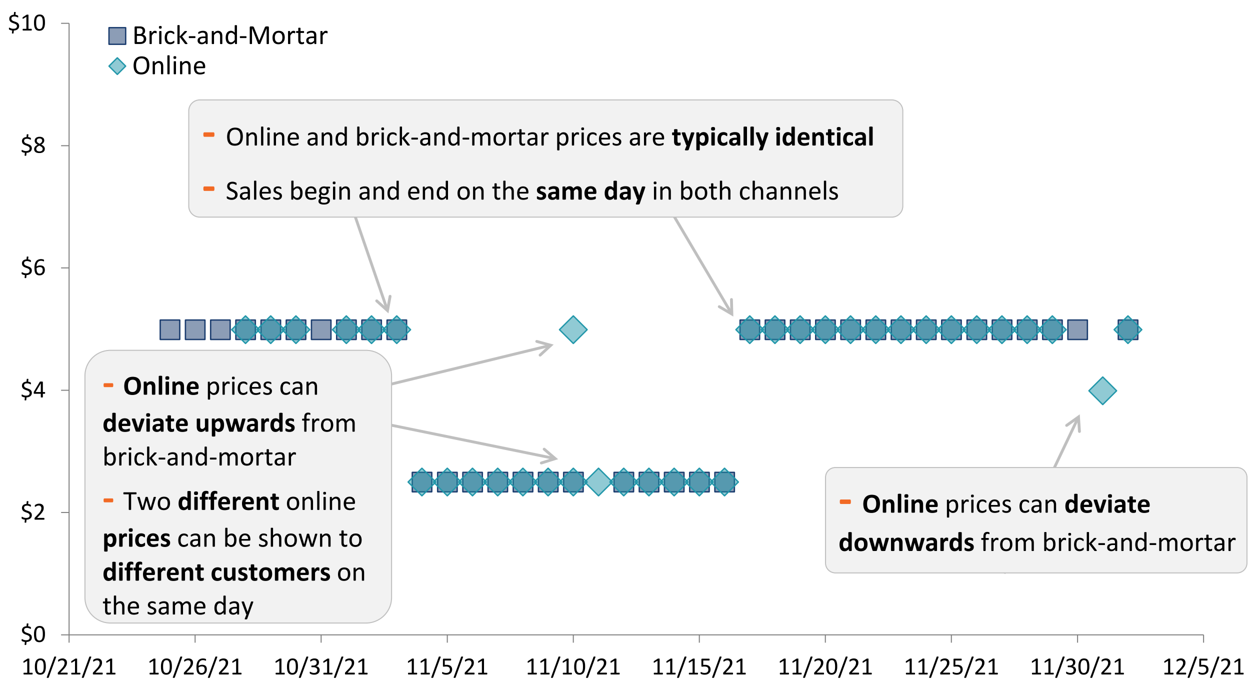
[16] "Product Z" refers to one of the 5 products for which data was collected: Barilla Spaghetti (1 lb), Cheerios (one box, 8.9 oz), Gold Medal All-Purpose Flour (2 lbs), Jif Creamy Peanut Butter (16 oz), or Land O' Lakes Salted Butter (1 lb, 4 sticks / 8 half sticks).

[17] Occasional gaps in the data series (i.e. a blue square or teal diamond missing for a given day) occur when no pricing was available for a given retail location, product, date, and channel. In some instances, no submitter fulfilled the request on the app; in other instances, a price observation may have been submitted but was invalid (i.e., collected for the wrong product or package size).

[18] This is consistent with "A/B testing" which we will discuss in more detail below. For a discussion of A/B testing, *see, e.g.*, Gallo, Amy. "A Refresher on A/B Testing." Harvard Business Review (June 28, 2017). *Available at* https://hbr.org/2017/06/a-refresher-on-ab-testing.

- Two **different online prices** were observed on the same day for shoppers on Retailer A's website. As we discuss in more detail at the end of this section, this is consistent with "A/B testing."
  - In the graph below, on November 10th, one visitor to Retailer A's website saw the discounted price of $2.50 for Product C. On the same day, another visitor to Retailer A's website saw only the regular price of $4.99, with no discount.
- Online prices **rarely deviate** away from the brick-and-mortar price. In this example, the deviation can be in the upward or downward direction.
  - On November 10th, Retailer A's online price for Product C (as shown to at least one shopper) deviated upwards from the price available in-store in Neighborhood B.
  - On December 1st, a visitor to Retailer A's website saw a discounted price of $3.99 for Product C. Although no corresponding brick-and-mortar price was collected on December 1st, this is below the regular price of $4.99 observed in the Neighborhood B retail location on the day before and day after.

FIGURE 6: EXAMPLE OF ONLINE AND BRICK-AND-MORTAR PRICES FOR RETAILER A, IN NEIGHBORHOOD B, FOR PRODUCT C



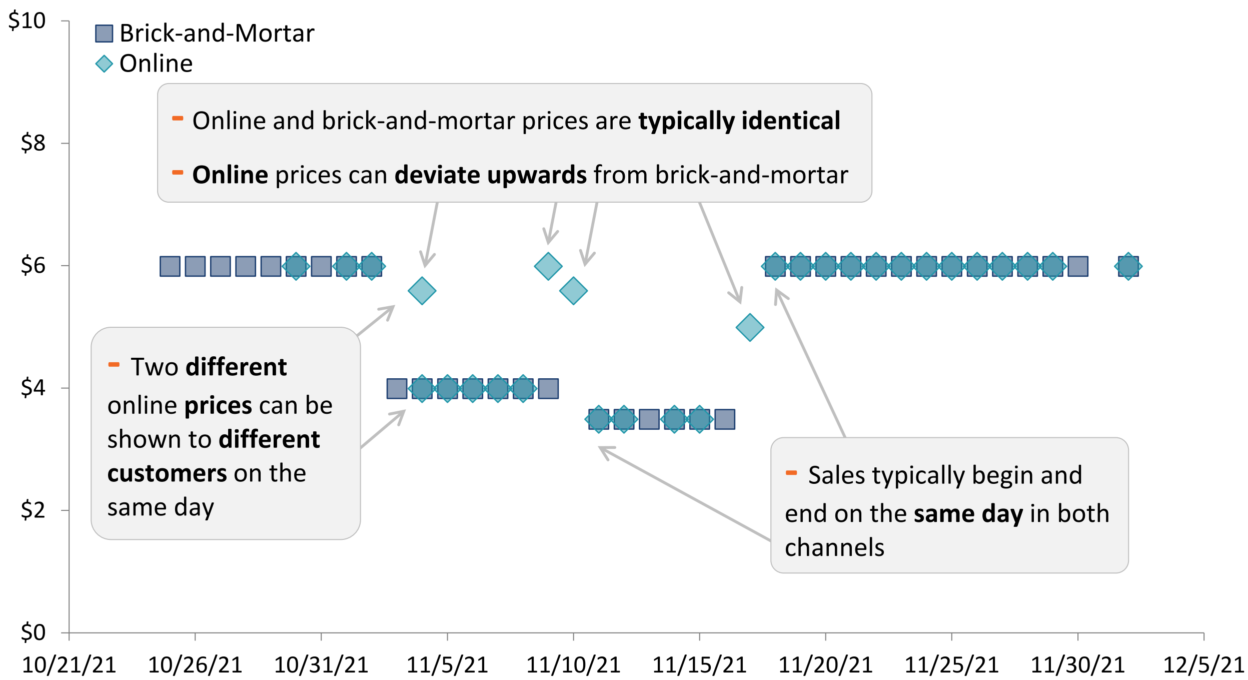
Source: Premise

Note: Our data license agreement prevents us from identifying the specific product, retailer, and location.

Figure 7 below shows prices for Retailer D, in Neighborhood E, for Product F. Similar patterns are evident:

- Online and brick-and-mortar prices are **typically identical.**
- Sales typically – but not universally – begin and end on the **same day in both channels** for this retailer.
  - In this example, there are two sale periods: prices are discounted from November 3rd to November 9th, and further discounted from November 11th to November 16th. Prices return to pre-sale levels beginning on November 18th.
- Two **different online prices** can be shown to different customers on the same day.
- Online prices **rarely deviate** away from brick-and-mortar prices. In this example, online prices deviate upwards but not downwards.

FIGURE 7: EXAMPLE OF ONLINE AND BRICK-AND-MORTAR PRICES FOR RETAILER D, IN NEIGHBORHOOD E, FOR PRODUCT F



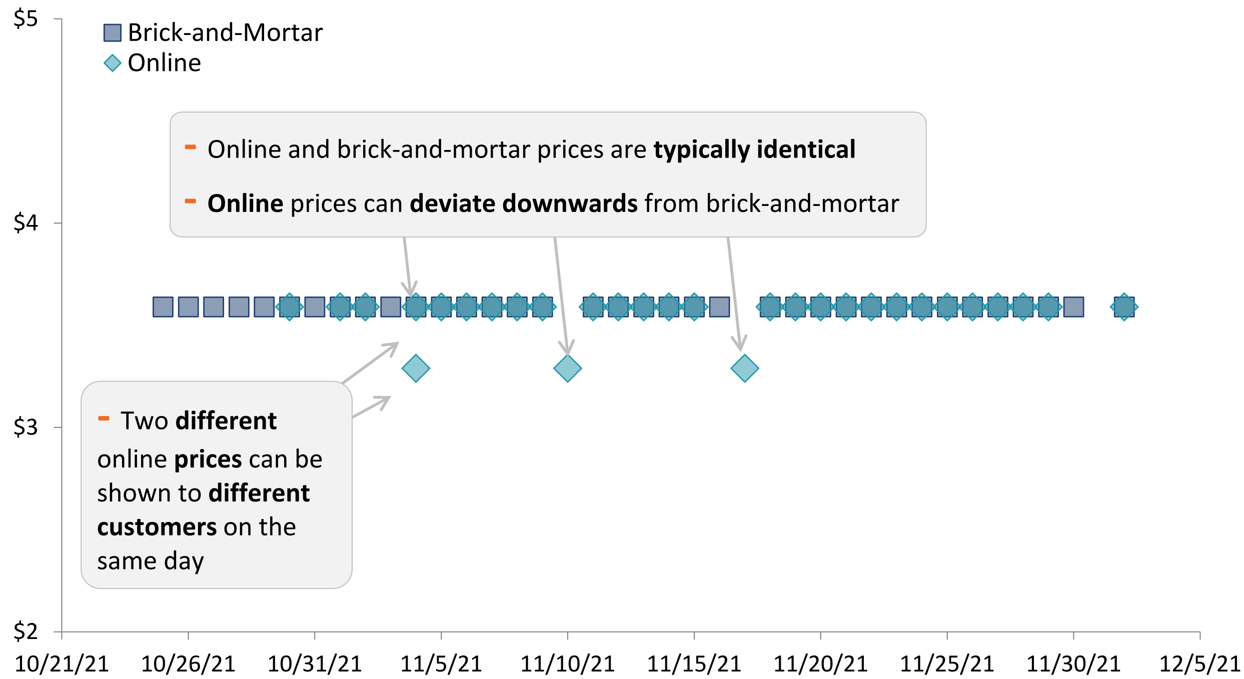
Source: Premise

Note: Our data license agreement prevents us from identifying the specific product, retailer, and location.

Finally, **Figure 8** below provides prices for Retailer G, in Neighborhood H, for Product I. In this example, we observe:

- Online and brick-and-mortar prices are **typically identical.**
- Two **different online prices** can be shown to different customers on the same day.
- Online prices **rarely deviate** away from brick-and-mortar prices. In this example, online prices deviate downwards but not upwards.

FIGURE 8: EXAMPLE OF ONLINE AND BRICK-AND-MORTAR PRICES FOR RETAILER G, IN NEIGHBORHOOD H, FOR PRODUCT I



Source: Premise
Note: Our data license agreement prevents us from identifying the specific product, retailer, and location.

In summary, the specific examples above illustrate the following common patterns in the Premise data:

- **Online and brick-and-mortar prices are typically identical** for the same product, retailer, and location, and date.
- **Promotional sales and discounts typically begin and end on the same day in both channels for a given retail location.** We find no evidence of persistent or widespread differences in the timing of price changes online and offline. This evidence suggests that a given retailer decides what price to use for a particular product and geographical location, and simultaneously implements this price across channels.

- **Online prices rarely deviate away from brick-and-mortar prices**, **and can deviate both upwards and downwards**. This is consistent with the fact that changing prices in a brick-and-mortar store involves a relatively more costly physical effort, whereas online prices can be updated more quickly and easily.
- **Different customers shopping at the same retailer online can see different prices on the same day**. This is consistent with the practice of "A/B testing" whereby a retailer's online channel performs an experiment to test the effect of a price change and help achieve the profit-maximizing price.[19] A subset of customers is shown an alternate price, and quantities purchased can then be compared against the customers who are shown the original price. This pattern of price movement is consistent with very short-term information gathering which helps retailers rapidly respond to changes in demand. The price quickly shifts back to its baseline level, consistent with the online channel being competitively constrained by brick-and-mortar prices.

3. Patterns in Price Variations by Retail Location and Product

As another way of looking at this data, we separately examine each of the 18 retail locations (i.e., each dot on the map in Figure 2). For each of the five products, we examine prices at each brick-and-mortar retail location, as compared to the corresponding online prices. We test whether online and offline prices are always identical on all days covered by our data, or whether there is ever a difference between online and offline prices. In the instances in which we see a difference, we characterize which channel's prices deviate away from the typical price level[20] prevailing for that product at that retail location.

Our results are shown in **Figure 9** below, which can be read as follows:

- The dark blue bars indicate retail locations for which online and brick-and-mortar prices are always identical between October 25, 2021, and December 2, 2021.
- The teal bars indicate retail locations for which online prices deviate from the typical prevailing price level, both in the upwards and downwards directions. Figure 6 above

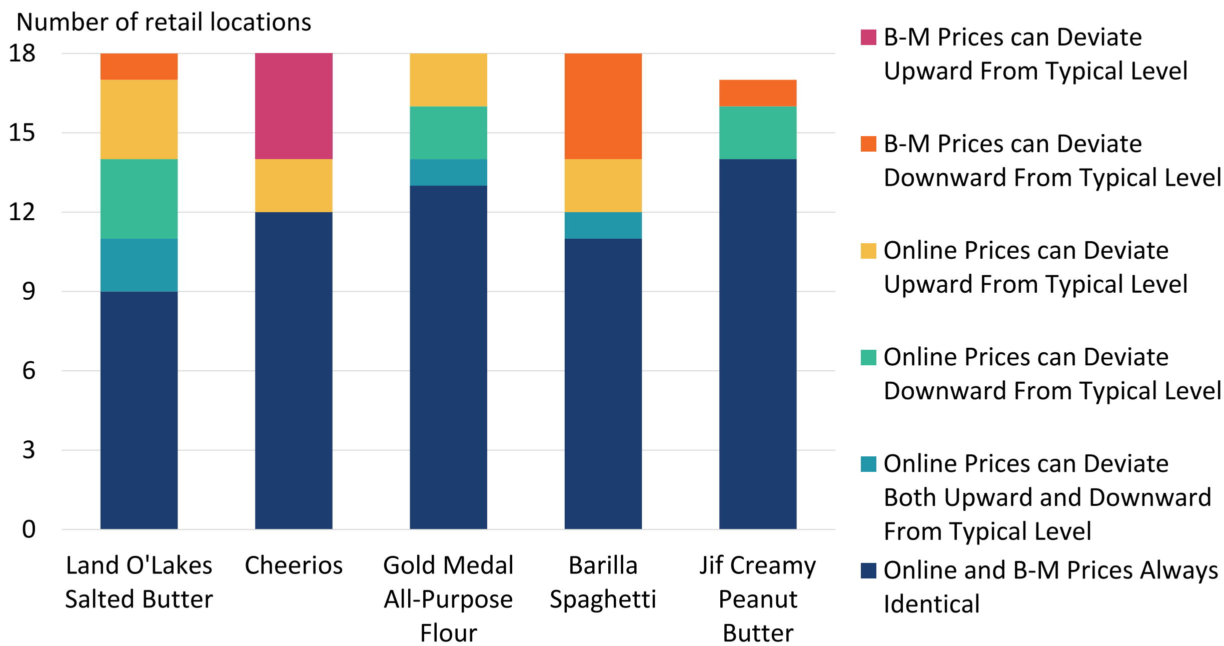
[19] For a discussion of A/B testing, *see, e.g.*, Gallo, Amy. "A Refresher on A/B Testing." Harvard Business Review (June 28, 2017). *Available at* https://hbr.org/2017/06/a-refresher-on-ab-testing.

[20] We define the "typical price level" as the mode price during a rolling five-day period centered on the day in question.

provides an example of this pricing pattern: we see the online price deviate once upwards and once downwards.

- The green bars indicate retail locations where online prices can deviate from the typical price level, but only in the downwards direction. Figure 8 above shows an example of this pricing pattern: we observe the online price deviating downwards three times but never upwards.
- The yellow bars indicate cases where online prices can deviate from the typical price level, but only in the upwards direction.
- The orange bars indicate cases where brick-and-mortar prices can deviate from the typical price level, in the downwards direction.
- Finally, the red bars indicate cases where brick-and-mortar prices can deviate from the typical price level, in the upwards direction.

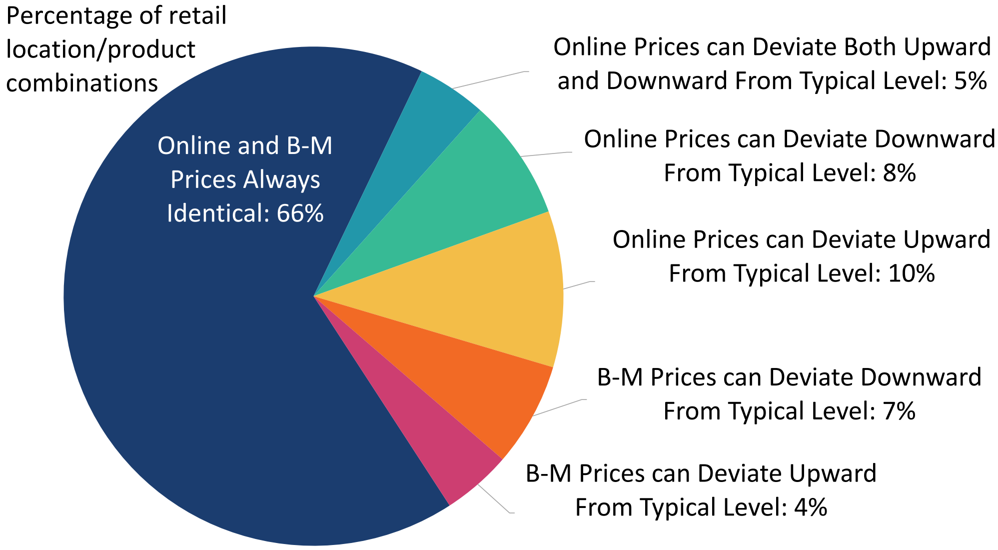
FIGURE 9: FOR EACH PRODUCT, NUMBER OF RETAIL LOCATIONS FOR WHICH ONLINE AND OFFLINE PRICES ARE ALWAYS IDENTICAL, OR EXHIBIT DIFFERENCES, FOR THE PERIOD 10/25/21 – 12/2/21



Source: Premise
Note that Jif Creamy Peanut Butter is has no corresponding online price observations for one retail location.

Figure 10 below presents the same data as Figure 9, combined together for all products.

FIGURE 10: PERCENTAGE OF PRODUCTS AND RETAIL LOCATIONS FOR WHICH ONLINE AND OFFLINE PRICES ARE ALWAYS IDENTICAL, OR EXHIBIT DIFFERENCES, FOR THE PERIOD 10/25/21 – 12/2/21



Source: Premise

Figure 9 and Figure 10 show that for all products, the majority of retail locations *always* see the same price online and offline during the period of observation. That is, during the period of study, consumers visiting the retail location in-person would see the same prices for the five products as customers shopping on that retailer's website.

The remainder of retail locations have at least one day during the period of study for which prices online and offline can differ. For these, we observe no consistent pattern suggesting one channel's ability to deviate permanently from the other: both channels can deviate from the typical price level, sometimes upwards, sometimes downwards. These deviations are not persistent, and prices tend to come together again quickly.

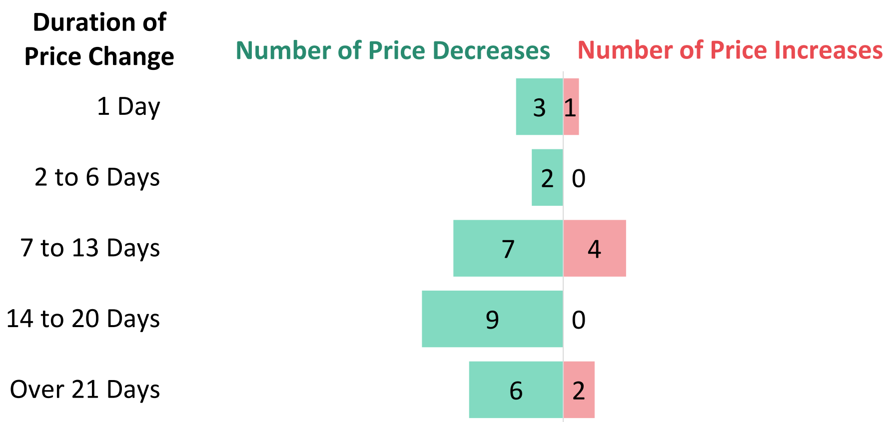
Finally, to contextualize these findings, recall from Figure 4 above that even when prices between the online and offline channels differ, the magnitude of the difference is small.

4. Price Movements

In our final analysis of the hand-collected pricing data, we summarize the price movements we observe in both channels, demonstrating that although prices between both channels remain tightly inter-locked, the overall pricing pattern is far from static.

Figure 11 below summarizes the number and duration of brick-and-mortar price changes. Overall, we observe 34 price change events in the brick-and-mortar data, between October 25 and December 2, 2021. The majority of these (79%) are price decreases. Very few price changes last less than a week (only 6 total), due to the costly nature of posting new prices in brick-and-mortar stores. Most price changes last one or two weeks. We also see some examples of longer-term changes: 6 price decreases, and 2 price increases, lasting over 21 days.

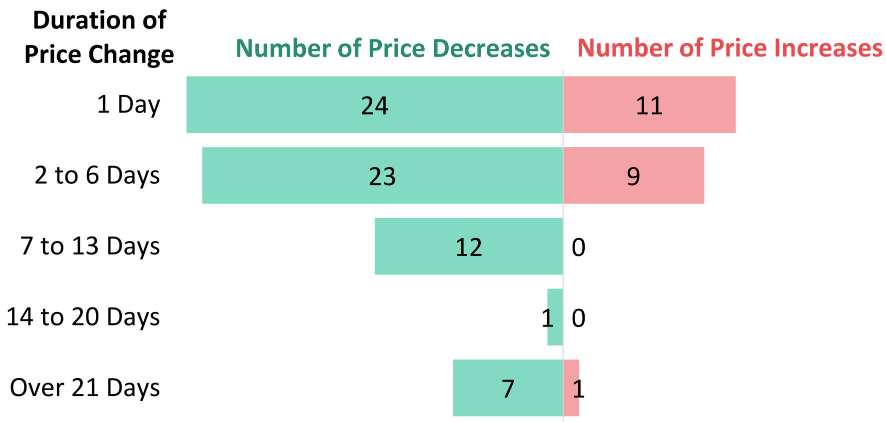
FIGURE 11: NUMBER AND DURATION OF BRICK-AND-MORTAR PRICE CHANGES



Source: Premise

Figure 12 below presents a similar analysis of online price changes. We observe more price changes online (88 total); however, prices still end up the same as the brick-and-mortar price 95% of the time (per Figure 3 above). Online price changes frequently last only a single day, consistent with the low cost of adjusting the prices that customers see online. The majority of price changes are decreases (76%). We see do see some effectively permanent changes in online prices: 7 price decreases and 1 price increase, which largely align with the same price changes occurring in the brick-and-mortar channel.

FIGURE 12: NUMBER AND DURATION OF ONLINE PRICE CHANGES



Source: Premise

The patterns above are consistent with the relative costs associated with adjusting prices in each channel. Because online retailers can adjust prices without incurring significant labor or material costs, it may be worth adjusting prices only briefly, if this maximizes revenue. This is consistent with the short-term information-gathering price research, or A/B testing, that we discussed above. A price increase would lead to a higher revenue per item but lower volume sold, and a price decrease would lead to a lower revenue per item but higher volume sold; both of these scenarios could lead to higher total revenues depending on consumer demand. If the price change turns out not to have increased revenue, the online retailer can simply move prices back to the previous level. However, because brick-and-mortar retailers have higher labor and material costs associated with posting new prices, a brief price change may not be worth the cost of adjusting prices (and adjusting them back in the event that the price adjustment was detrimental to revenue). Moreover, it is not possible to establish a randomized experimental treatment and control group in a brick-and-mortar setting, as all customers see prices posted on the shelf.

Moreover, brick-and-mortar retailers benefit more than online retailers from the “loss-leader” effect whereby lower prices on one product (such as the staple groceries studied in this sample) attract customers to the store, where customers purchase additional goods while under one roof. For example, a customer could come into the store because of a sale on spaghetti, and then also buy spaghetti sauce while they are there, and other groceries as well. In this hypothetical example, the spaghetti would be the “loss leader.” The grocery store can benefit from loss leaders because many goods are sold under one roof, and it is costly for customers to compare prices across brick-and-mortar retailers and visit multiple retail locations.

The “loss leader” effect can occur in online retail but may be less pronounced because it is easy for the consumer to shop at multiple stores online. For example, a customer visiting Retailer A’s website because of a sale on spaghetti might also find it convenient to purchase other items (such as spaghetti sauce) on Retailer A’s website. However, the shopper may also quickly research sauce prices across different stores online and choose to purchase sauce more cheaply from Retailer B’s website. Thus the “loss leader” effect may be less pronounced online.

For medium-term price changes lasting over one week, the vast majority (95%) of online price movements occur in the downwards direction. In other words, we see no evidence that online retailers have the ability to raise and sustain higher prices in the longer term.

All of the foregoing analyses show that within the Premise data, pricing patterns are consistent with retailers engaging in active pricing research online and finding they are competitively constrained. Even when retailers experiment with raising prices online, the price does not remain higher than brick-and-mortar prices for long, which is consistent with competitive pressure bringing it back to a baseline level. The pricing patterns are generally strong evidence of intense price competition in retail, especially within the consumer packaged goods (“CPG”) market that the Premise data draws from.

B. Evidence from National Aggregate Data

The NPD data provides additional evidence of persistent similarity in prices between the online and brick-and-mortar channels.

Because of the national aggregate nature of the NPD data, we expect to find some degree of difference between prices online and offline as recorded in that data. The NPD data shows the weighted average price of units that are actually sold. Because the NPD data aggregates together all sales at all partner retailers, we are unable to distinguish price variation by channel from any other reasons prices might differ (e.g., regional variation across different geographical locations, different pricing by different retailers, location-specific promotional pricing).

A simplified example may help illustrate why the aggregate sales data may introduce apparent noise into the price series that we observe. Suppose that widgets are sold at two retailers: Retailer A, which prices them at $5 both online and offline; and Retailer B, which prices them at $3 both online and offline. If we were able to observe the list prices directly for both retailers, we would conclude there is $0 difference between online and offline prices. However, depending on how many units are sold by each retailer in each channel, the national aggregate data may show a different picture. For example, **Figure 13** below depicts a hypothetical example that would make it appear that widget prices are higher online than they are offline.

FIGURE 13: HYPOTHETICAL EXAMPLE OF NOISE INTRODUCED INTO NATIONAL AGGREGATE PRICING DATA

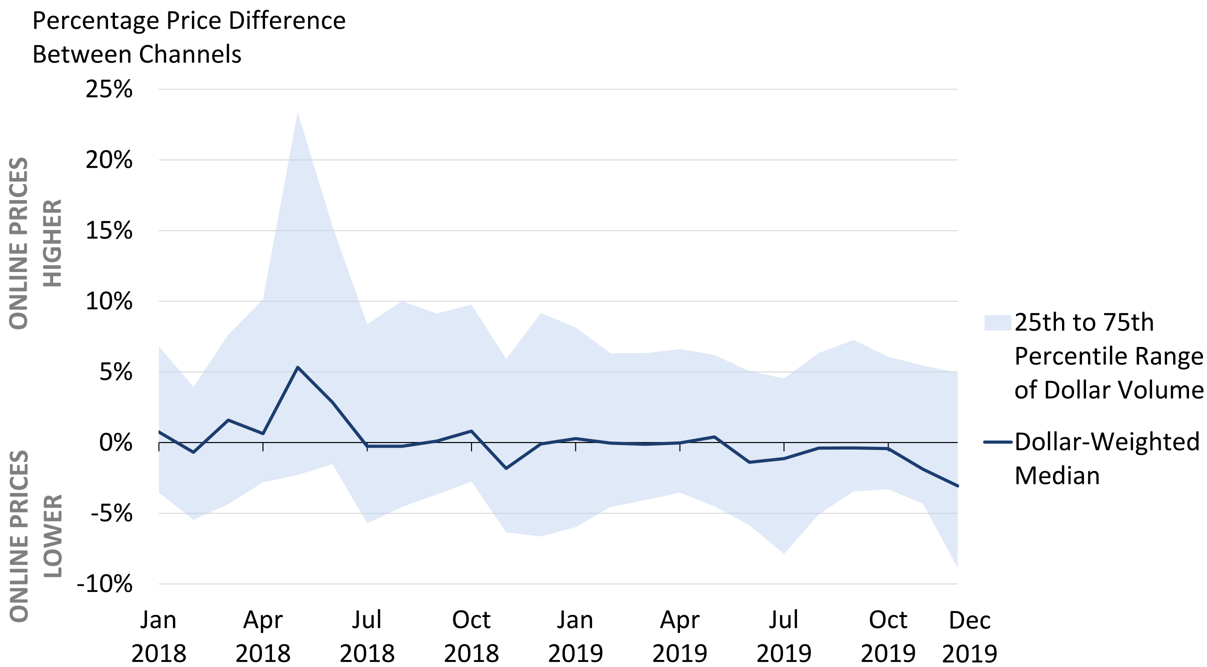
Retailer A			
Price (online and offline)	$5.00	[1]	
Units sold online	1	[2]	
Units sold offline	1	[3]	
Retailer B			
Price (online and offline)	$3.00	[4]	
Units sold online	1	[5]	
Units sold offline	10	[6]	
Nationwide Aggregate Data			
Total units sold online	2	[7]	= [2] + [5]
Total revenue online	$8	[8]	= ([1] x [2]) + ([4] x [5])
Observed weighted average price online	**$4.00**	[9]	= [8] / [7]
Total units sold offline	11	[10]	= [3] + [6]
Total revenue offline	$35	[11]	= ([1] x [3]) + ([4] x [6])
Observed weighted average price offline	**$3.18**	[12]	= [11] / [10]

Despite this limitation of the data, we still see a close correspondence between prices online and brick-and-mortar in the NPD data. **Figure 14** below summarizes the distribution of the percentage difference between online and offline prices within each month.[21] The dark blue line depicts the dollar-weighted median difference (i.e., half of dollar volume has price differences above the blue line and half of dollar volume has price differences below the blue line). The light blue shaded region indicates the 25th to 75th percentile range of dollar volume (i.e. in total, half of all dollar volume is represented within the light blue shaded area). Thus the

[21] Specifically, we calculate this as ([Online Price] – [Brick-and-Mortar Price])/(Average of Online and Brick-and-Mortar Prices).

data indicate very tight price correspondence between channels for most of the dataset, with small percentage differences between online and brick-and-mortar prices. The large spike in May 2018 is likely due to the Toys R Us bankruptcy and subsequent liquidation.[22] A high volume of products sold cheaply at liquidating brick-and-mortar locations could cause the national aggregate weighted-average price data for brick-and-mortar products to appear lower than online products (similar to the hypothetical example illustrated in Figure 13).

FIGURE 14: ONLINE AND BRICK-AND-MORTAR PRICES ARE TYPICALLY SIMILAR, BASED ON AGGREGATE NATIONWIDE DATA FOR MANY PRODUCTS



Source: NPD

[22] In March 2018, Toys R Us announced it would close all U.S. locations of Toys R Us and Babies R Us stores. The closures were not immediate; for example, the retailer continued to accept gift cards and other rewards through April 2018. *See, e.g.*, Bhattarai, Abha, "Toys R Us to close all 800 of its U.S. stores," *The Washington Post*, March 14, 2018, *available at* https://www.washingtonpost.com/news/business/wp/2018/03/14/toys-r-us-to-close-all-800-of-its-u-s-stores/; Bhattarai, Abha, "They opened a registry at Babies R Us. Now, these parents-to-be are in liquidation limbo," *The Washington Post*, March 21, 2018, *available at* https://www.washingtonpost.com/business/economy/they-opened-a-registry-at-babies-r-us-now-these-parents-to-be-are-in-liquidation-limbo/2018/03/21/0c44e8c4-2c78-11e8-b0b0-f706877db618_story.html.

V. Cross-Channel Pricing Dynamics Are Consistent With a Dynamically Competitive Market

In this section, we apply a selection of time-series methodologies to study price dynamics over time in the national aggregate data. The Technical Appendix included at the end of the paper provides details for the methods applied in this section.

In our time series analyses, we study the evolution of prices over time by using past price levels to explain the current price levels. For each channel, we simultaneously study both the "own-channel" dynamics (using past online prices to explain current online prices, and past brick-and-mortar prices to explain current brick-and-mortar prices), and the "cross-channel" dynamics (using past online prices to explain current brick-and-mortar prices, and vice versa). This allows us to examine how online prices react to an increase in brick-and-mortar prices and vice versa.

We find that when explaining the variation in brick-and-mortar prices, past values of brick-and-mortar prices have *virtually identical* explanatory power as past values of online prices. The same is true for explaining online prices. This is consistent with a very responsive and competitive market between the two channels.

We further find that online prices move towards brick-and-mortar prices, whether the latter are higher or lower than the former. The data suggests that online sales channels are subject to constant competitive pressures and generally respond to competition by matching the lowest price on offer within or across channels.

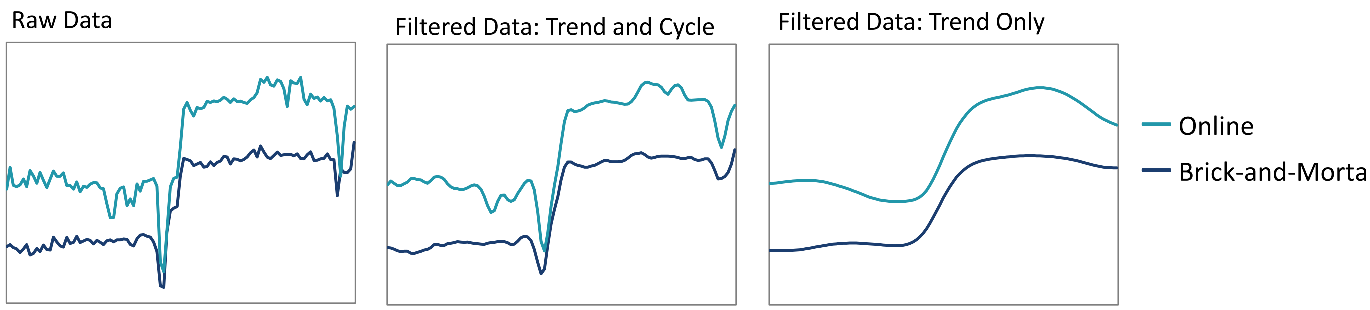
A. Time Series Filters

To compensate for the noisy nature of the aggregate national data, we apply a time series filter that smooths the data to remove some of the noisiest week-to-week movements.[23] In each of our results, we apply two degrees of smoothing: a lesser degree of filtering which keeps "trend and cycle" movements, and a stronger degree of filtering which keeps "trend" movements only.

[23] Specifically, we apply the Hodrick-Prescott filter; the Technical Appendix provides details.

Figure 15 below illustrates how the filter affects the data. Three graphs are shown: the left-hand side graph has raw data for Product X (which we cannot identify in accordance with our licensing agreements). The middle graph shows the filtered data after applying the "Trend and Cycle" figure. The right-hand-side graph shows the filtered data after applying the "Trend Only" filter, which produces a smooth data series.

FIGURE 15: EXAMPLE OF FILTERED PRICE DATA FOR A SINGLE PRODUCT



Source: NPD. Note that we omit the product name and the specific price levels, in accordance with our data license agreement.

Detailed specifications of these analyses, including the mathematical definition of the smoothing filter, are presented in the Technical Appendix.

B. Own-Channel and Cross-Channel Explanatory Strength

In our first analysis, we measure to what extent price movements in one channel can be attributed to price movements in the other channel. In other words, we are asking: when prices online vary over time, is this likely due to market forces specific to the online channel, or to market forces that affect both the online and offline channels? Similarly, when brick-and-mortar prices vary from one week to the next, is this likely due to market forces specific to the brick-and-mortar channel, or is it based on market

To explain the variation in brick-and-mortar prices, past values of brick-and-mortar prices have virtually identical explanatory power as past values of online prices. The same is true for explaining online prices.

This is consistent with a very responsive and competitive market between the two channels.

forces affecting both channels? We find that the answer is "both," which is consistent with a very responsive and competitive market that includes both channels.[24]

In technical terms, this analysis measures the explanatory power of own-channel and cross-channel effects to explain observed price variation.[25] We conduct this analysis for each variation of the filter, and for three time windows (one week prior, 4 weeks prior, and 12 weeks prior).

We find that cross-channel and own-channel prices each explain roughly half of the variation in prices, for both brick-and-mortar and online prices. This holds true even when looking at the trend-and-cycle filter (which allows for more high-frequency noise). Both series are highly responsive to each other, and they are almost equally responsive to cross-channel price movements as they are to own-channel movements. Specifically, when a brick-and-mortar price goes up this week, there is about a 53% chance that it is moving in response to a price increase last week from brick-and-mortar, and 47% chance that it was due to a price increase for online last week. This is highly consistent with a very responsive and competitive market that includes both channels.

The pattern is consistent with strong competition both within and across channels. Prices not only respond to variation in prices within the same channel, but also in variation in the other channel. We observe that prices are only slightly more responsive to their own price variation than to price variation coming from the other channel.

C. Analysis of Asymmetric Responses

Our second time series analysis quantifies the size and direction of price responses to movements in the same and other channel. In this analysis, we explore the magnitude of own-channel and cross-channel price responses, depending on whether this channel's prices are higher or lower than the other channel's prices. In other words, we look to analyze potential asymmetric responses. Again, the results are consistent with a very competitive setting across channels.

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[24] Moreover, the increasing popularity of omnichannel retail options could have blurred the line between online and offline channels, putting pressure on prices to converge across sales channels.

[25] Specifically, we are performing a variance decomposition analysis for a set of regression equations; the Technical Appendix provides our model specification and results.

While we do find statistically significant evidence of asymmetry of responses between channels depending which channel's prices are higher or lower, the dollar magnitude of the asymmetry present in the effect size is small. For practical purposes, the behavior of both channels is effectively identical.

Again, we conduct this analysis for each variation of the filter, and for three time windows (one week prior, 4 weeks prior, and 12 weeks prior).

Our "explanatory power" analysis above finds that current prices are about as likely to vary due to past own channel price variation as cross channel price variation. This means that, at any moment in time, price for one channel already reflects price movements from both channels about equally. Therefore, if we want to guess what brick-and-mortar prices will be this week, all we need to do is look at what brick-and-mortar prices were last week, because last week's prices already summarize *both* channels' prices.[26]

At intervals of two to three months, we find an increased responsiveness to the other channel's prices, for both online and brick-and-mortar. This result holds for both the trend-only filter (which captures low-frequency patterns) and the trend-and-cycle filter (which captures both low-frequency patterns and high-frequency patterns).

Online prices move towards brick-and-mortar prices, whether the latter are higher or lower than the former.

We find the following patterns in brick-and-mortar prices:

- When brick-and-mortar prices are higher than online prices, brick-and-mortar prices do ***not*** tend to adjust to meet the lower online prices.
- However, when brick-and-mortar prices are lower than online prices, brick-and-mortar prices ***do*** tend to adjust upward to meet higher online prices.

We find the following patterns in online prices:

- When online prices are higher than brick-and-mortar prices, online prices tend to be pulled down towards the lower brick-and-mortar prices.

[26] While this is always true for both types of filters and at the various time windows, the effect is are stronger at shorter time windows and for the cycle-and-trend filter.

- When online prices are lower than brick-and-mortar prices, online prices tend to be pulled up towards the higher brick-and-mortar prices. This effect is stronger than the reaction when online prices are higher.

In summary, both brick-and-mortar and online prices react similarly when they are the lower price, and tend to adjust upwards. But their responses are clearly different when they are the higher price: brick-and-mortar prices will tend to stay high, while online prices will be pulled down to lower levels.

As a general statement, the story that emerges is that online prices move towards brick-and-mortar prices, whether the latter are higher or lower than the former. But while brick-and-mortar prices increase towards online prices when online prices are higher, they will not decrease if online prices are lower. This pattern suggests that online channels are subject to constant competitive pressures and generally respond to competition by matching the lowest price on offer within or across channels. All of our findings are highly consistent with evidence of competition between online and offline channels.

The data suggests that online channels are subject to constant competitive pressures and generally respond to competition by matching the lowest price on offer within or across channels.

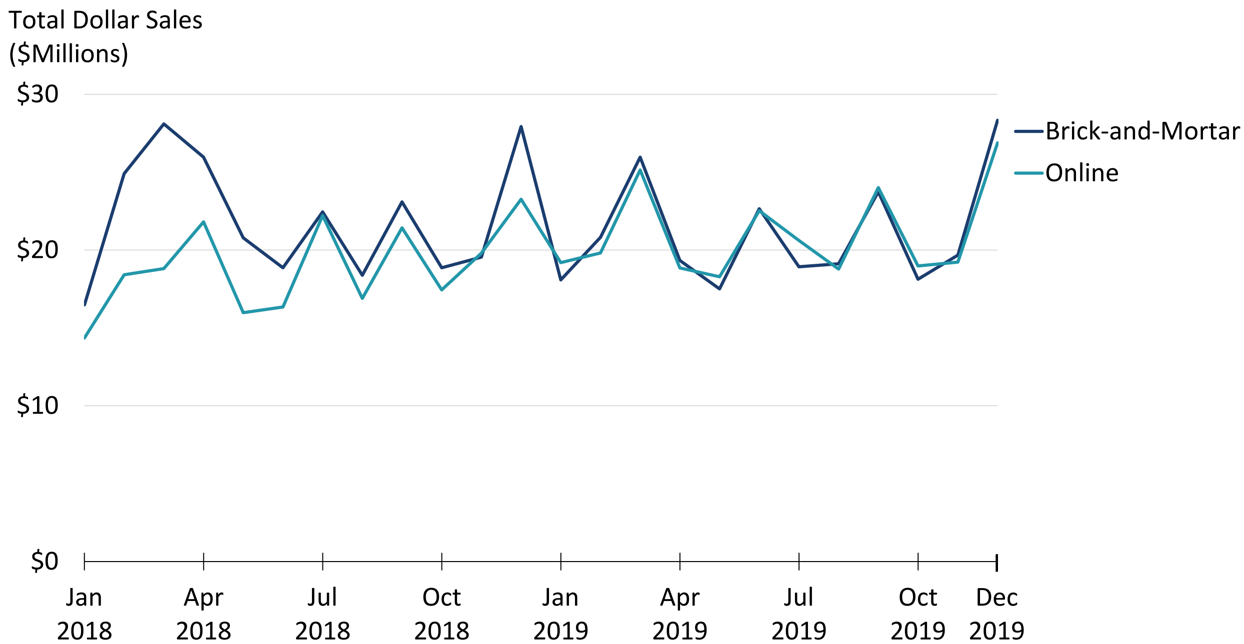
VI. Dollar Volume of Brick-and-Mortar Versus Online Sales are Consistent with Both Channels Being Subject to the Same Market Forces

The NPD data allows us to observe the proportion of sales occurring online versus brick-and-mortar. We see that in each week, roughly the same dollar volume is transacted online as in brick-and-mortar stores, for the subset of products available in the data. Moreover, this is true both during periods of high dollar sales and periods of low dollar sales. This suggests that the two channels are subject to the same market forces.

We note that because our national aggregate data is limited to a certain set of products, our findings regarding the proportional market share of e-commerce are not representative of all retail for all products. For example, St. Louis Fed data shows overall e-commerce represented approximately 10% of all retail activity during the same time period of 2018-2019.[27]

Figure 16 plots the total dollar sales in each channel. Some seasonal trends are evident, with both channels seeing a spike in sales approximately every three months (April, July, September, and December of 2018, and March, June, September, and December of 2019).[28] The synchronization of changes in sales trends between channels is consistent with both channels being subject to the same market conditions. In other words, the same drivers of supply and demand that drive changes in dollar sales appear to affect both online and offline sales similarly.

FIGURE 16: DOLLAR SALES BY CHANNEL, SHOWING PERIODS OF HIGHER AND LOWER SALES



Source: NPD
Source: NPD

[27] https://fred.stlouisfed.org/series/ECOMPCTSA.

[28] As a robustness check (not pictured), we also performed this analysis within each product category. The spikes in sales occur in the majority of product categories. A notable exception was the Bath Toys product category which saw pronounced spikes only in December of 2018 and 2019, coinciding with holiday shopping.

VII. Conclusion

In this paper, we demonstrate evidence of a dynamic competitive relationship between online and brick-and-mortar channels for retail goods. We find that online prices competitively constrain brick-and-mortar prices, and vice versa. This has implications in policy and regulatory settings, as many regulations targeting one retail channel will likely affect pricing in the other retail channel as well due to intense competition between online and offline retail.

We find that online prices are subject to frequent changes that appear to be related to short-term information gathering and price research. Nonetheless, we find online prices closely adhering to brick-and-mortar prices in the longer term. Thus, we find no evidence that one channel has the ability to systematically raise and sustain higher prices in comparison to the other channel.

Our analyses show several patterns consistent with intense competition between online and offline retail, with both channels appearing to respond to the same market forces. This suggests that in the context of antitrust, analyses involving dynamic competition and substitutability for retail goods should incorporate information from both online and brick-and-mortar retail sales.

VIII. Technical Appendix

This appendix provides technical details for the methods applied in this paper. In this appendix, we denote online prices as “OLP” and brick-and-mortar prices as “BMP”.

A. Time Series Filters

We apply the Hodrick-Prescott (“HP”) filter to the log online price and log brick-and-mortar price series for each product.[29] This filter is a one parameter filter which smooths a time series. In the limit, if the parameter (traditionally denoted λ) is 0, there is no smoothing; if it is infinite, the result is the best linear time trend through the data. Intermediate values of λ produce more versions of the data with greater or lesser degrees of smoothing.

[29] For each product, we require at least 52 weekly price observations which are based on at least 2 unit sales. This leaves us with 396 Products.

The parameter λ is the “penalty” parameter on the local volatility of the filtered data. Increasing the penalty results in a smoother time series. A straight line has no local volatility; hence, the filter approaches a linear time trend as the penalty parameter increases.

The Hodrick-Prescott filter solves the following problem:

$$\boldsymbol{HP}(\boldsymbol{x}) = \underset{z}{\operatorname{argmin}} \left\{ \sum_{t=1}^{T} (\boldsymbol{x}_t - \boldsymbol{z}_t)^2 + \boldsymbol{\lambda} \sum_{t=2}^{T-1} \left((\boldsymbol{z}_{t+1} - \boldsymbol{z}_t) - (\boldsymbol{z}_t - \boldsymbol{z}_{t-1}) \right)^2 \right\} \tag{1}$$

We will denote the filtered brick-and-mortar price series as $\widetilde{BMP}$ and the filtered online price series as $\widetilde{OLP}$.

We repeat each of our analyses for two versions of the filter:

- The “Trend and Cycle” version of the filter (corresponding to λ = 1) is less aggressive, capturing both most short- and long-term movements while filtering out the very noisiest price fluctuations.
- The “Trend Only” version (corresponding to λ = 400) is more heavily filtered and captures broader long-term movements.

We further conduct three variations of each analysis, focusing on different windows of time, allowing us to explore the speed with which prices react and the persistency of shocks to prices (both within-channel and cross-channel):

- The “1 week prior” version of each analysis explores the relationship between this week’s prices versus prices from last week.
- The “4 weeks prior” version explores the relationship between this week’s prices versus prices last month (i.e. four weeks ago).
- The “12 weeks prior” version explores the relationship between this week’s prices versus prices from three months ago (i.e. twelve weeks).

B. Explanatory Power Analysis

Our analysis of explanatory power is based on a variance decomposition of the model:

$$\widetilde{BMP}_t = \alpha^{BM} + \beta_1^{BM} \widetilde{BMP}_{t-s} + \beta_2^{BM} \widetilde{OLP}_{t-s} + \varepsilon_t^{BM} \tag{2}$$

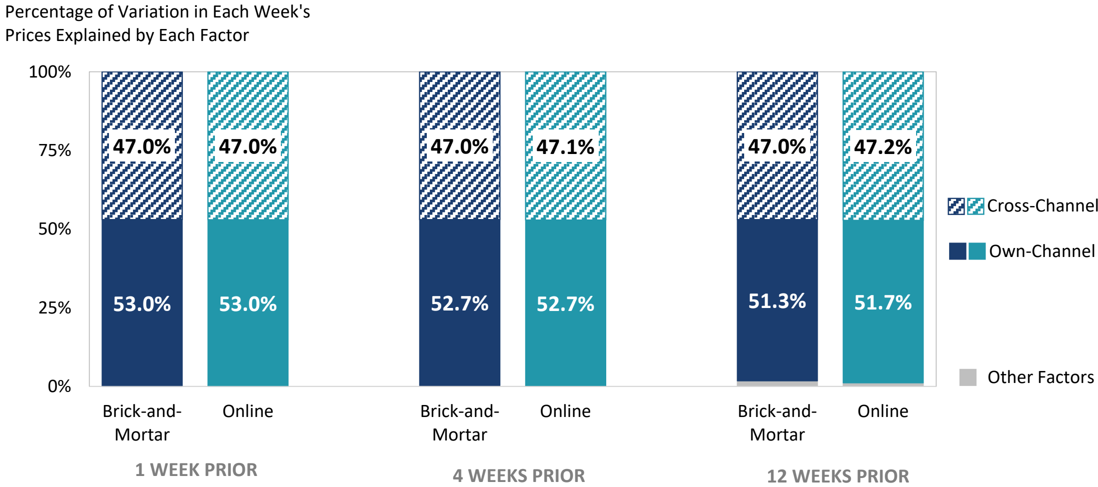
$$\widetilde{OLP}_t = \alpha^{OL} + \beta_1^{OL}\widetilde{OLP}_{t-s} + \beta_2^{OL}\widetilde{BMP}_{t-s} + \varepsilon_t^{OL} \tag{3}$$

The variance decomposition asks how much of the variation in *y* is explained by each *x*. We find that results are remarkably stable across filtering parameters and lags. Each series is explained about 52%/47% by their own lags versus the lags of the other price series.

Figure 17 below presents results for the trend-only filter (i.e., for $\lambda = 400$), and **Figure 18** presents results for the trend-and-cycle filter (i.e., for $\lambda = 1$). Each figure has three sets of bars, corresponding to three models using different time window (1 week prior, 4 weeks prior, or 12 weeks prior). For each time window, the results can be read as follows:

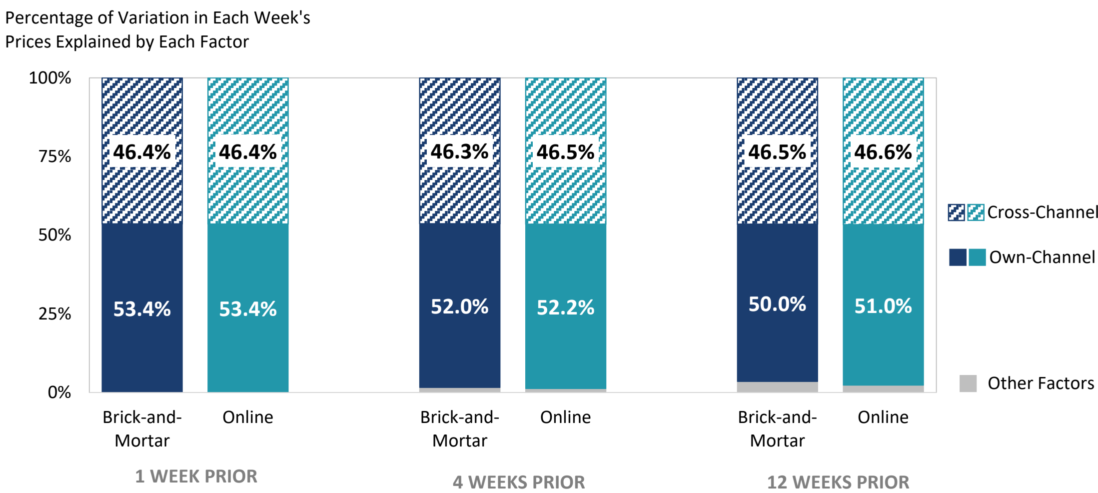
- The solid bars represent the explanatory value of own-price-channel effects:
  - The solid dark blue bars plot the own-channel explanatory power for brick-and-mortar ($\widehat{\beta_1^{BM}}$ from Equation 2).
  - The solid teal bars plot the own-channel explanatory power for online ($\widehat{\beta_1^{OL}}$ from Equation 3).
- The striped bars represent the explanatory value of cross-price-channel effects:
  - The striped dark blue bars plot the cross-channel explanatory power for brick-and-mortar ($\widehat{\beta_2^{BM}}$ from Equation 2).
  - The striped teal bars plot the cross-channel explanatory power for online ($\widehat{\beta_2^{OL}}$ from Equation 3).
- The very small light grey bars, labeled “other factors,” represents the small amount of price variation that is not captured by past price values of either own or cross channels ($\widehat{\alpha^{BM}}$ and $\widehat{\alpha^{OL}}$ from Equations 2 and 3, respectively).

FIGURE 17: EXPLANATORY POWER OF PREVIOUS WEEKS' VARIATION IN OWN-CHANNEL AND CROSS-CHANNEL PRICES TO EXPLAIN PRICE VARIATION (TREND-ONLY FILTER)



Source: NPD.

FIGURE 18: EXPLANATORY POWER OF PREVIOUS WEEKS' VARIATION IN OWN-CHANNEL AND CROSS-CHANNEL PRICES TO EXPLAIN PRICE VARIATION (TREND AND CYCLE FILTER)



Source: NPD.

As the graphs show, roughly half of the variation of each channel's prices are explained by their own lags versus the lags of the other channel's prices.

We observe that prices are slightly more responsive to their own price variation than to price variation coming from the other channel, but that such difference slightly decreases as past prices reflect a time further away from current prices (1 week, 4 weeks, or 12 weeks). In addition, about 100% of the price variation is explained by both own and cross prices, but as we move from 1 week to 12 weeks in the past, the influence of own price variation is slightly reduced, with an increase in importance of other factors. Results are very similar between both filters, with a reduced contribution of cross past prices to current prices for the trend-and-cycle version.

C. Asymmetric Response Analysis

Our second analysis is to regress the (filtered) price series on its own lag and the lag of the other price series while allowing parameters to change depending on which price series was greater:

$$\begin{aligned}\widetilde{BMP}_t = \alpha^{BM} + \beta_1^{BM}\widetilde{BMP}_{t-s} + \beta_2^{BM}\widetilde{OLP}_{t-s} + \\ 1\left(\widetilde{BMP}_{t-s} < \widetilde{OLP}_{t-s}\right)\cdot\left(\delta^{BM} + \gamma_1^{BM}\widetilde{BMP}_{t-s} + \gamma_2^{BM}\widetilde{OLP}_{t-s}\right) + \varepsilon_t^{BM}\end{aligned} \tag{4}$$

$$\begin{aligned}\widetilde{OLP}_t = \alpha^{OL} + \beta_1^{OL}\widetilde{OLP}_{t-s} + \beta_2^{OL}\widetilde{BMP}_{t-s} + \\ 1\left(\widetilde{OLP}_{t-s} < \widetilde{BMP}_{t-s}\right)\cdot\left(\delta^{OL} + \gamma_1^{OL}\widetilde{OLP}_{t-s} + \gamma_2^{OL}\widetilde{BMP}_{t-s}\right) + \varepsilon_t^{OL}\end{aligned} \tag{5}$$

This asks the question, which series is a better predictor of today's price, and how does that change when the own price is the lower of the two? **Figure 19** and **Figure 20** plot the coefficients of this model for $\lambda = 400$ and $\lambda = 1$, respectively. The figures can be read as follows:

- Each row of graphs represents a time window (1-week, 4-week, and 12- week effects).
- Own-channel effects are plotted with solid-filled bars, on the left-hand side of the graph.
  - The dark blue bars labeled "B-M, When Higher" plot $\widehat{\beta_1^{BM}}$ from Equation 4.
  - The dark blue bars labeled "B-M, When Lower" plot $\widehat{\beta_1^{BM}} + \widehat{\gamma_1^{BM}}$ from Equation 4.
  - The teal bars labeled "Online, When Higher" plot $\widehat{\beta_1^{OL}}$ from Equation 5.
  - The teal bars labeled "Online, When Lower" plot $\widehat{\beta_1^{OL}} + \widehat{\gamma_1^{OL}}$ from Equation 5.
- Cross-channel effects are plotted with striped bars, on the right-hand side of the graph.
  - The striped dark blue bars labeled "B-M, When Higher" plot $\widehat{\beta_2^{BM}}$ from Equation 4.
  - The striped dark blue bars labeled "B-M, When Lower" plot $\widehat{\beta_2^{BM}} + \widehat{\gamma_2^{BM}}$ from Equation 4.
  - The striped teal bars labeled "Online, When Higher" plot $\widehat{\beta_2^{OL}}$ from Equation 5.

– The striped teal bars labeled “Online, When Lower” plot $\widehat{\beta_2^{OL}} + \widehat{\gamma_2^{OL}}$ from Equation 5.

Figure 19 below illustrates that when prices for either channel are lower, they are responsive to the other channel. The strength of the cross-channel effect is highest for the 12-week timeframe (i.e. the bottom-right set of striped bars in Figure 19 are larger than the top or middle sets). The cross-channel coefficients show the following:

- When brick-and-mortar prices are higher, they are effectively unresponsive to online prices. This is shown by the “B-M, When Higher” bar in the bottom-right group of bars, which is near zero. This bar plots $\widehat{\beta_2^{BM}}$ from Equation 4.
- When brick-and-mortar prices are lower, they are responsive to online prices. This is shown by the “B-M, When Lower” bar in the bottom-right group, which is equal to 0.140. This bar plots $\widehat{\beta_1^{BM}} + \widehat{\gamma_1^{BM}}$from Equation 4.
- When online prices are higher, they are responsive to brick-and-mortar prices. This is shown by the “Online, When Higher” bar in the bottom-right group, which is equal to 0.068. This bar plots $\widehat{\beta_2^{OL}}$ from Equation 5.
- When online prices are lower, they are even more responsive to brick-and-mortar prices. This is shown by the “Online, When Lower” bar in the bottom-right group, which is equal to 0.160. This bar plots $\widehat{\beta_2^{OL}} + \widehat{\gamma_2^{OL}}$ from Equation 5.

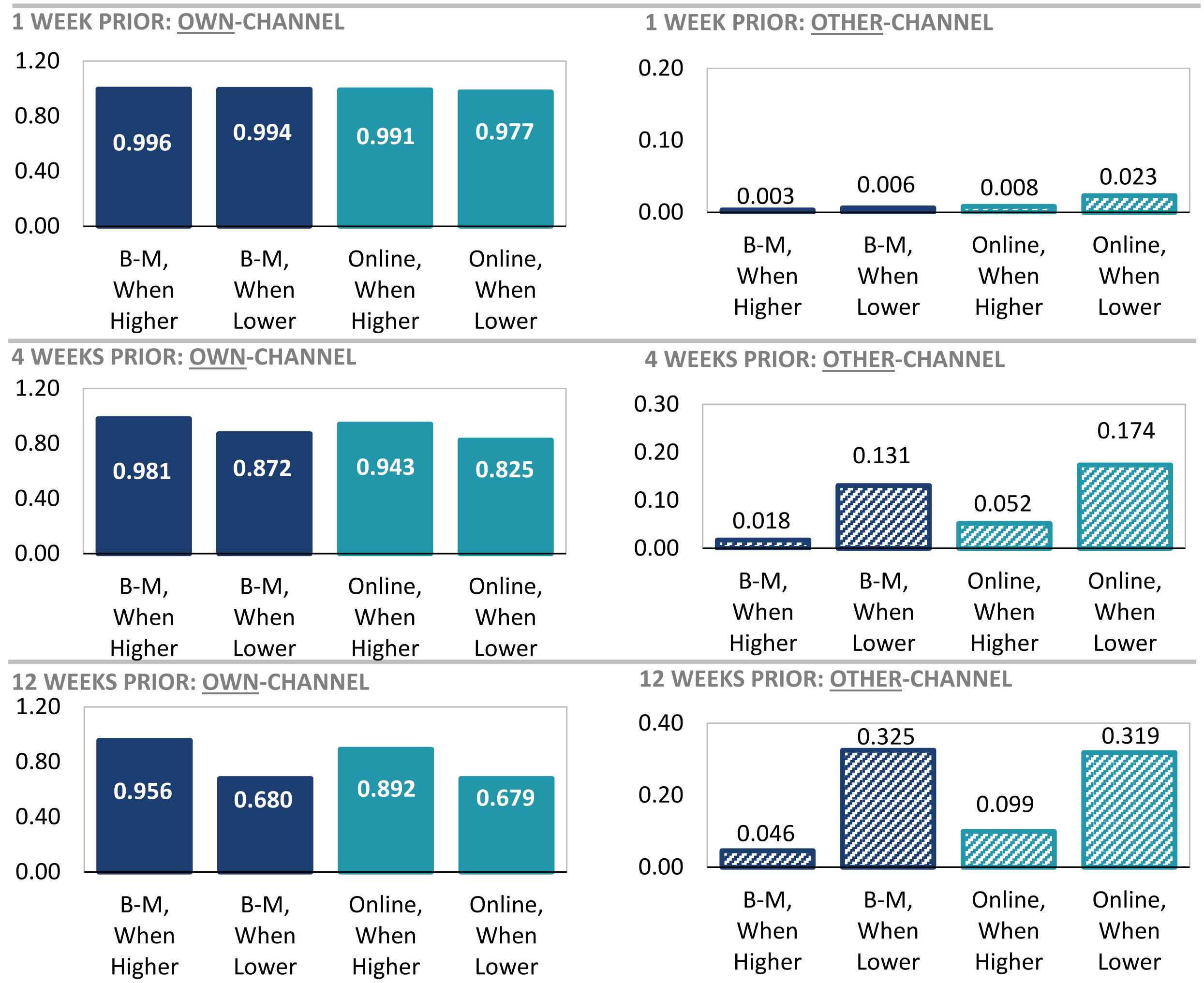
FIGURE 19: ASYMMETRIC CROSS-CHANNEL AND OWN-CHANNEL PRICE RESPONSES: PERCENTAGE-POINT CHANGE IN PRICE, PER EACH PERCENTAGE-POINT CHANGE IN PAST PRICES (TREND-ONLY FILTER)

Source: NPD

Figure 20 below presents results for the trend-and-cycle filter. For the 4-week and 12-week timeframes, the story is the largely same as we saw in Figure 19 for the trend-only cycle, with more pronounced results.

- The only qualitative difference in results is that brick-and-mortar prices do show some slight responsiveness to online prices when brick-and-mortar is higher under the 12-week lag timeframe. The "B-M, When Higher" bar in the bottom-right is above zero, equaling 0.046. This bar plots $\widehat{\beta_1^{BM}} + \widehat{\gamma_1^{BM}}$ from Equation 4.

FIGURE 20: ASYMMETRIC CROSS-CHANNEL AND OWN-CHANNEL PRICE RESPONSES: PERCENTAGE-POINT CHANGE IN PRICE, PER EACH PERCENTAGE-POINT CHANGE IN PAST PRICES (TREND AND CYCLE FILTER)



Source: NPD.

As we note in the main text, while we do find statistically significant evidence of asymmetry of responses between channels depending which channel's prices are higher or lower, the dollar magnitude of the asymmetry present in the effect size is small.[30] For practical purposes, the behavior of both channels is effectively identical.

[30] Additionally, we acknowledge that there are statistical issues with this specification, since the HP filter works by averaging leads and lags of the data. The value of the filtered data at time *t* is thus a blend of past and future values. Nevertheless, while the standard errors of the regression are not correctly measured (and while the R2 will almost certainly be very high), that is not our primary interest. We interpret the results in the spirit of finding the "best linear predictor" of *y* given *x*.