

More Amazon Effects: Online Competition and Pricing Behaviors

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Abstract

I study how online competition, with its algorithmic pricing technologies and the transparency of the Internet, can change the pricing behavior of large retailers and affect aggregate inflation dynamics. In particular, I show that online competition has raised both the frequency of price changes and the degree of uniform pricing across locations in the U.S. over the past 10 years. These changes make retail prices more sensitive to aggregate “nationwide” shocks, increasing the pass-through of both gas prices and nominal exchange rate fluctuations.

JEL Classifications: E30, E60

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I Introduction

Online retailers such as Amazon are a growing force in consumer retail markets. Their share of sales continues to grow, particularly in the U.S., prompting economists to wonder about their impact on inflation. Much of the attention among central bankers and the press has focused on whether the competition between online and traditional retailers is reducing retail markups and putting downward pressure on prices.¹ This “Amazon Effect” could help explain the relatively low levels of inflation experienced by the US in recent years, but the lack of firm-level costs and price information makes it empirically hard to distinguish from other forces. Furthermore, while potentially sizable, there is a limit to how much markups can fall. Will the Amazon Effects disappear when that limit is reached, or are there longer-lasting effects of online competition on inflation dynamics?

In this paper I focus instead on the way online competition is affecting pricing behaviors, such as the frequency of price changes and the degree of price dispersion across locations. Changes in the way these pricing decisions are made can have a much more persistent effect on inflation dynamics than a one-time reduction in markups. In particular, I focus on two pricing behaviors that tend to characterize online retailers such as Amazon: a high degree of price flexibility and the prevalence of uniform pricing across locations. When combined, these factors can increase the sensitivity of prices to “nationwide” aggregate shocks, such as changes in average gas prices, nominal exchange rates, or import tariffs.

To document these new trends in U.S. retail pricing behaviors, I use several micro-price databases available at the Billion Prices Project (BPP) at Harvard University and MIT.² An advantage of these data is that they are collected from large brick-and-mortar retailers that also sell online (“multi-channel retailers”), at the intersection of both markets. These firms still concentrate the majority of retail transactions and are sampled accordingly

¹See Yellen (2017). For recent articles in the press, see Berman (2017), Torry and Stevens (2017), and Cohen and Tankersley (2018). Some arguments resemble those on the “Walmart effect” a decade ago, as in Whitehouse (2006). Academic papers at the time, such as Hausman and Leibtag (2007), focused on the “outlet substitution bias” that occurs when the Bureau of Labor Statistics (BLS) methodology implicitly assumes that quality explains most of the price difference among retailers.

²See Cavallo and Rigobon (2016) and <http://www.thebillionpricesproject.com> for more information.

by the Bureau of Labor Statistics (BLS) for Consumer Price Index (CPI) calculations.³ For this paper, I enhance the BPP data by scraping a random subset of Walmart’s products and automatically searching their product descriptions on the Amazon website to build a proxy for online competition at the level of individual goods. I also simultaneously collect prices in more than one hundred zip-codes to compare the extent of uniform pricing by Amazon and other large U.S. retailers.

I first show that the aggregate frequency of price changes in multi-channel retailers has been increasing for the past 10 years. The resulting implied duration for regular prices, excluding sales and temporary discounts, has fallen from 6.7 months in 2008–2010 to approximately 3.65 months in 2014–2017, a level similar to what Gorodnichenko and Talavera (2017) found for online-only retailers in the past. The impact is particularly strong in sectors where online retailers tend to have high market shares, such as electronics and household goods. To find more direct evidence of the link between these changes and online competition, I use a sample of individual products sold on the Walmart website from 2016 to 2018 to show that those goods that can be easily found on Amazon tend to have implied durations that are 20% shorter than the rest. These results are consistent with intense online competition, characterized by the use of algorithmic or “dynamic” pricing strategies and the constant monitoring of competitors’ prices.

I then focus on the prices of identical goods across locations. Most retailers that sell online tend to have a single-price or “uniform pricing” strategy, regardless of buyer’s location. Uniform pricing has been documented separately for online and offline retailers by papers such as Cavallo et al. (2014) and DellaVigna and Gentzkow (2017). Going a step further, I make a direct comparison by collecting prices in multiple zip codes for Amazon and three large traditional U.S. retailers: Walmart, Safeway, and Best Buy. I find that the degree of uniform prices in these firms is only slightly lower than Amazon’s, and nearly all of the geographical price dispersion is concentrated in the Food and Beverages category. I then use Walmart’s grocery products to show that goods found on Amazon are more likely to have a higher share of identical prices and a lower average price difference across locations. These results are consistent with recent evidence by Ater and Rigbi (2018), sug-

³See Bureau (2018). The BLS website states that “As of 2017, about 8 percent of quotes in the CPI sample (excluding the rent sample) are from online stores.” See BLS (2018).

gesting that online transparency imposes a constraint on brick-and-mortar retailers' ability to price discriminate across locations.

Next, I discuss potential implications for pass-through and inflation. Retailers that adjust their prices more frequently *and* uniformly across locations can be expected to react faster to nationwide shocks. Consistent with this hypothesis, I use Walmart microdata for 2016–2018 to find that online competition increases the short-run pass-through into prices stemming from gas prices and exchange rate fluctuations. Using a longer time series of sector-specific price indices and a matched-product, cross-country dataset, I further show that the degree of price-sensitivity to exchange rates has been increasing over time, approaching levels previously only seen for tradable goods “at-the-dock”. Overall, these results suggest that retail prices have become less insulated from this type of aggregate shock than in the past.

My paper is part of a growing literature that studies how the Internet is affecting prices and inflation. The most closely related papers are Gorodnichenko and Talavera (2017) and Gorodnichenko et al. (2018a), which find evidence that prices in online marketplaces such as Google Shopping are far more flexible and exhibit more exchange-rate pass-through than prices found in CPI data. I build on their findings to show how online competition is affecting traditional multi-channel retailers and their pricing across locations and over time. Goolsbee and Klenow (2018) use online data to argue that the CPI may be overestimating inflation by ignoring product-level quantities and higher levels of product turnover, which can be interpreted as an additional “Amazon Effect,” with implications for inflation measurements. My paper also contributes to the “uniform pricing” literature, by highlighting the connection between online and offline markets and the potential role played by transparency and fairness. It is also related to several papers in the price-stickiness literature. Specifically, the implied duration I find for the earliest years in my sample is similar to the levels reported by Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008) using historical data. I also contribute to the large literature on exchange-rate pass-through, summarized by Burstein and Gopinath (2014), by showing that retail pass-through increases with online competition.

The paper proceeds as follows. Section II describes the data, while section III presents evidence of an increase in price change frequency and its connection to online competition. Section IV provides similar evidence for uniform pricing within retailers, followed by Section V, which documents changes in gas price and exchange rate pass-through. Finally, Section VI

offers some conclusions.

II Data

I use several databases available at the BPP. In all cases, the micro data were collected using web-scraping methods from the websites of large multi-channel retailers. Each database has special characteristics that are described below.

To measure the U.S. pricing behavior statistics shown in Section III, I rely on a database constructed by PriceStats, a private firm. PriceStats collected daily prices for products sold by large multi-channel retailers from 2008 to 2017. Retailer names are not revealed for confidentiality reasons. Every individual product is classified with the UN’s Classification of Individual Consumption According to Purpose (COICOP) categories, used by most countries for CPI calculations. Statistics are aggregated using official expenditure weights in each country, as needed.⁴ I use this micro data to construct measures of pricing behaviors with a method described in Section III. In addition, I use sector-level price indices constructed by PriceStats to measure exchange-rate pass-through in Section V. More details on the micro data and an earlier version of the online price indices can be found in Cavallo and Rigobon (2016).

To measure pass-through into *relative* prices across countries in Section V, I use another database built by PriceStats by matching thousands of individual goods matching 267 narrow product definitions (for example, “Illy Decaf Coffee Beans” and “Samsung 61–65 Inch LED TV”). Per-unit prices (in grams, milliliters, or units) for individual goods are first calculated and then averaged per “product” within countries. This database was previously used and described in Cavallo et al. (2018).

Two additional product-level databases were collected by the BPP at Harvard University between 2016 and 2018. They have not been used in previous papers, so I describe them in greater detail below.

⁴The BLS uses a different classification structure for its CPI. When needed, BLS Expenditure weights at the “Entry-Level Item” (ELI) level are matched to their equivalent COICOP 3-digit level aggregate statistics in this paper. See <http://www.ilo.org/public/english/bureau/stat/download/cpi/coicop.pdf> for a detailed description of COICOP categories and Bureau of Labor Statistics (2015) for details on the US ELI classification structure.

To study the effects of online competition, I build a database with detailed information on nearly 50,000 products sold by Walmart in March 2018. For every product, I create a dummy variable that identifies whether it can also be easily found on Amazon’s website. This variable is used as a proxy for online competition in several sections of this paper. To create it, I used an automated software to replicate the procedure that a Walmart customer would likely follow to compare prices across the two websites: copying each product’s description and pasting it into the search box in Amazon’s website. If Amazon displayed “No results found”, the dummy variable has a value of 0. If Amazon reported one or more matching results, the dummy variable has a value of 1. Only matching products sold by Amazon LLC were counted. For each product, I also calculate the price-change frequency, using daily prices from 2016 to 2018, by taking the number of non-zero price changes divided by the total number of price-change observations. Missing price gaps shorter than 90 days were filled with the last available posted (or regular) price, following standard procedures in the literature. The implied duration at the product level is estimated as $1/frequency$.

To measure uniform pricing, I scraped zip-code-level price data from four of the largest retailers in the United States: Amazon, Walmart, Best Buy, and Safeway. These companies allow customers to select their location or “preferred store” on their website. Using an automated software, I collected data for a total of 10,292 products, selected to cover most categories of goods sold by Amazon. For every product, I scraped the prices in up to 105 zip codes within just a few minutes, to minimize the possibility of picking up price differences over time. These zip codes were selected to cover all U.S. states and provide the largest possible variation in unemployment rates within states, as explained in the Appendix.

III Price Flexibility

Online retailers tend to change prices much more frequently than brick-and-mortar retailers, a behavior that is often reported by the business press.⁵ In the academic literature, Gorodnichenko et al. (2018a) use data collected from 2010 to 2012 from the leading online-shopping/price-comparison website in the US to show that the frequency of online price changes was roughly twice as high as the one reported in comparable categories by Nakamura and

⁵See Mims (2017).

Steinsson (2008), with an implied duration for price changes of approximately 3.5 months compared to the 7.6 months in CPI data for similar categories of goods.⁶

The high frequency of online price changes may be caused in part by the use of automated algorithms to make pricing decisions. Already in 2012 the *Wall Street Journal* reported that retailers were “deploying a new generation of algorithms ... changing the price of products from toilet paper to bicycles on an hour-by-hour and sometimes minute-by-minute basis.”⁷ A particular type of algorithmic pricing, called “dynamic pricing” in the marketing literature, is designed to optimize price changes over time, allowing online retailers to more effectively use the vast amount of information they collect in real time. So far, academic studies have found evidence of dynamic pricing in airlines, travel sites, and sellers participating in online marketplaces such as Ebay and Amazon Marketplace.⁸ However, for a large online retailer like Amazon, which sold an estimated 12 million individual products on its website in 2016, using some kind of algorithmic pricing may be the only effective way to make pricing decisions. At the same time, there is some evidence that many retailers currently use web-scraping to monitor their competitors’ prices.⁹ As pricing strategies become more interconnected, a few large retailers using algorithms could change the pricing behavior of the industry as a whole.

III.A Aggregate Frequency of Price Changes

To better understand the impact of online competition on more traditional retailers, I start by looking at how aggregate price stickiness has changed in the U.S. from 2008 to 2017, when the share of online sales grew from 3.6% to 9.5% of all retail sales, according to the Census Bureau.¹⁰

⁶These numbers are monthly equivalents of the implied durations reported in weeks in Table 4 of Gorodnichenko et al. (2018a) for regular prices with imputations for missing prices. In a related paper, Gorodnichenko and Talavera (2017) used prices collected from 2008 to 2013 from another large price-comparison website in the U.S. and found a similarly high frequency of price changes.

⁷See Angwin and Mattioli (2012).

⁸See Bilotkach et al. (2010) and Chen et al. (2016), and Ferreira et al. (2015).

⁹See Dastin (2017). This practice seems so widespread that Amazon even filed a patent for a “robot mitigation” method in 2016. See Kowalski and Lategan (2016).

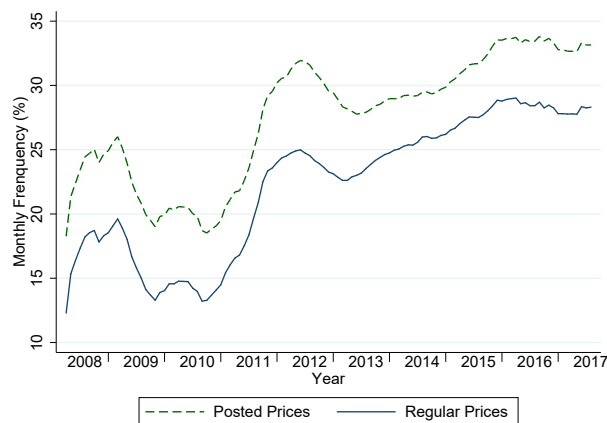
¹⁰See <http://fred.stlouisfed.org/series/ECOMPCTSA>. Estimates from market-research firms suggest that Amazon controlled over half of the U.S. online retail market in 2017.

Figure 1 plots the monthly frequency of price changes of large multi-channel retailers over time. This is computed as a weighted average of the number of non-zero price changes, divided by the total number of price-change observations, following standard methodologies in the literature. It is first calculated at the most disaggregated product classification level available (for example “Bread and Cereals” or “Milk, Cheese, and Eggs”) and then aggregated using weighted means with CPI expenditure weights published by the BLS.¹¹

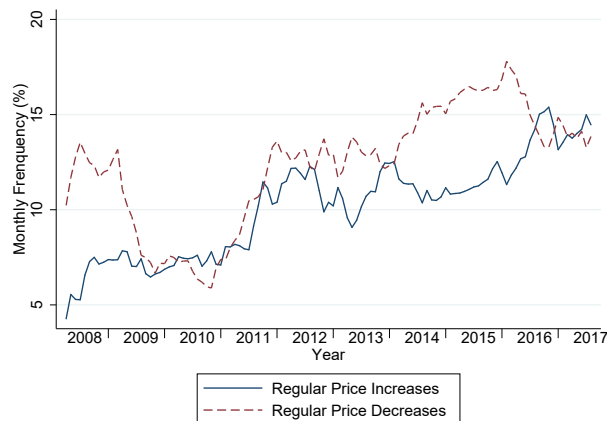
See Lunden (2018).

¹¹All the other statistics reported in this section are calculated in a similar way, with the exception of implied durations, which are directly computed at the aggregate level as $1/frequency$. The results in this section are similar when I use other aggregation methods such as medians and geometric means.

Figure 1: Monthly Frequency of Price Changes, 2008 to 2017



(a) Posted and Regular Price Changes



(b) Regular Price Increases and Decreases

Notes: “Regular Prices” exclude sale events and are computed using the one-month, v-shaped “Filter A” sale algorithm from Nakamura & Steinsson (2008). This chart shows the 12-month moving average of the monthly frequency. See the Appendix for results with alternative sale algorithms.

Panel A shows that the monthly frequency of *posted* prices increased from 21% in 2008–2010 to over 31% in 2014–2017. However, this frequency is greatly influenced by sales and other temporary price discounts, as noted by Nakamura and Steinsson (2008) and Klenow and Kryvtsov (2008). There is no consensus in the price-stickiness literature about the treatment of sales.

Papers such as Eichenbaum et al. (2011) and Kehoe and Midrigan (2008) argue that sale prices are less relevant for monetary policy, while Kryvtsov and Vincent (2016) find sales to be strongly cyclical in countries like the U.S. and the U.K. For the purposes of this paper, it is important to know whether the higher frequency over time simply reflects an increase in sale events. I therefore compute the frequency of “regular” prices, which exclude temporary sales, using standard methods in the literature.¹²

Excluding sales affects the level of the monthly frequency but not its behavior over time. The monthly frequency of *regular* prices nearly doubled from approximately 15% in the years 2008–2010 to almost 30% in 2014–2017. The increase in frequency is even greater if I exclude the recession years of 2008–2009. Consistent with Vavra (2013), Figure 1(a) shows a spike in the frequency of price changes in late 2008 and early 2009. Figure 1(b) indicates that this was entirely caused by the frequency of regular price *decreases*. By contrast, the frequency of regular price *increases* has been rising steadily since 2008.

In Table 1, I split the sample into three periods and show averages for various other statistics commonly used in the price-stickiness literature. From now on I focus on regular prices, but similar results with posted prices can be seen in the Appendix.

¹²Not all retailers have sale indicators, so I rely on one of the algorithms in Nakamura and Steinsson (2008) to remove both symmetric and asymmetric v-shaped sales that last a single month. Similar results can be obtained with alternative sale algorithms used in the literature, as shown in Appendix FigureA1.

Table 1: Behavior of Regular Prices in Large U.S. Retailers

	Period Averages		
	2008-2010	2011-2013	2014-2017
Frequency of Price Changes (%)	15.43	22.39	27.39
Implied Duration (months)	6.48	4.47	3.65
Frequency of Price Increases (%)	6.89	10.27	12.49
Frequency of Price Decreases (%)	8.94	12.12	14.96
Absolute Size of Price Changes (%)	17.45	16.24	15.02
Size of Price Increases (%)	18.3	17.09	15.42
Size of Price Decreases (%)	-16.79	-14.71	-14.02
Share of Price Changes under 1pc	6.59	5.23	8.01
Sales as Share of Price Changes (%)	4.02	3.98	3.29

The average implied duration of regular prices provides the first indication that these changes might be related to online retailers. The mean duration fell from about 6.5 months, a number close to what Nakamura and Steinsson (2008) find for historical CPI data, to just about 3.7 months, a number much closer to what Gorodnichenko et al. (2018a) find for online retailers with data from 2010–2012. Furthermore, as the frequency of price changes increases, their size is also getting small, but not by much. The absolute size of posted price changes fell only slightly, from 17.45% to 15.02%. This relative stability of the size of price changes is consistent with the results in Gorodnichenko et al. (2018a), which argue that “online sellers adjust their prices more often than offline retailers, but by roughly the same amounts.”

Table 2 shows the implied durations by sector, revealing bigger changes in product categories where online retailers tend to have larger market shares, such as “Recreation and Electronics” and “Furnishings and Household Goods.” By contrast, goods in “Food and Non-Alcoholic Beverages”—where online purchases only accounted for 0.4% of total retail sales in 2016—have a much more stable behavior over time.

Table 2: Implied Duration of Regular Price Changes by Sector

	Period Averages		
	2008-2010 (months)	2011-2013 (months)	2014-2017 (months)
Food and Non-Alcoholic Beverages	6.4	6.6	6.4
Clothing and Footwear	6.2	5.5	5.3
Furnishings and Household Goods	14.2	12.9	5.9
Health and Medical	12.1	13.6	8.5
Transportation Goods	3.6	2	1.8
Recreation and Electronics	13.1	10.1	5.5
Miscellaneous Goods	13.7	10.4	7.8
All Sectors	6.48	4.47	3.65

Notes: Implied durations are calculated as $1/\text{frequency}$. The table shows the average taking into account all months in every period. Regular price changes exclude monthly sales with the v-shaped “filter A” algorithm from Nakamura and Steinsson (2008). Similar results for posted prices and regular prices using other sale algorithms are shown in the Appendix.

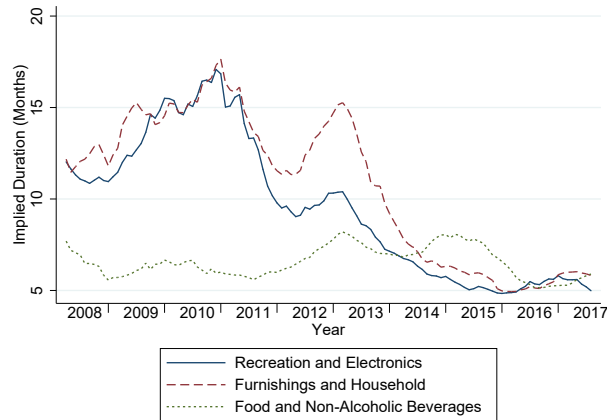
The timing of the fall in implied durations also seems to coincide with the timing of Amazon’s expansion in different sectors. This can be seen in Figure 2, which plots the implied duration every month for the three main categories discussed above. The implied duration of “Recreation and Electronics” started to fall in 2011, followed later by “Furnishings and Household Goods.”¹³ Interestingly, the implied duration for “Food and Beverages” appears to be falling since 2015, when Amazon started to expand more aggressively into groceries with its “Amazon Fresh” platform.¹⁴ According to the

¹³These results are not driven by changes in the composition of retailers sampled over time. Figure A5 in the Appendix shows that nearly all retailers sampled continuously in these categories exhibit an increase in the frequency of price changes over time.

¹⁴Amazon also acquired Whole Foods in 2017. Haddon and Nassauer (2016) report that

U.S. Census Bureau, online sales in food and beverages stores grew 27% in 2016, almost twice as fast as the 14% estimated for e-commerce as a whole.

Figure 2: Monthly Implied Duration of Regular Price Changes by Sector



III.B Online Competition and Implied Durations

While intriguing, these patterns do not provide direct evidence that the changes are related to online competition. To test this connection more formally, I built a database with a cross-section of Walmart’s products sold online from 2016 to 2018, their implied durations, and a dummy variable that identifies whether these products can be found on Amazon (used as a proxy for the degree of online competition). More details on how this database was constructed are provided in Section II. Table 3 shows the results of a regression of the daily implied duration and the “Found on Amazon” dummy. I include category fixed effects to capture the between-sector impact of omitted variables and provide separate results for different sectors.

The first column shows that products found on Amazon tend to have approximately 20% shorter implied durations, with goods “Found on Amazon” having an implied duration of posted prices that is 5.45 days shorter than the unconditional level of approximately 28 days.¹⁵

traditional grocers such as Walmart and Kroger have also aggressively expanded their online services in recent years.

¹⁵The unconditional implied duration is lower than the estimates in Table 2, because these daily prices include temporary sales within the month.

Table 3: Implied Duration for Walmart’s Products Found on Amazon

	All Sectors	Food & Beverages	Clothing & Footwear	Furnishings & Household	Health & Medical	Recreation & Electronics
Found on Amazon	-5.45 (0.46)	-3.63 (0.75)	-41.18 (4.78)	-1.55 (0.76)	-8.33 (6.38)	-5.71 (0.59)
Constant	27.95 (0.60)	30.97 (0.40)	94.98 (2.61)	22.42 (0.50)	59.25 (3.92)	23.43 (0.35)
Observations	49,867	15,766	2,719	11,152	973	16,541
Obs. on Amazon	17,498	4,554	831	4,858	420	6,040
R-squared	0.10	0.00	0.03	0.00	0.00	0.01

Notes: The dependent variable is the implied duration for posted prices, measured in days and using prices collected from 2016–2018. The variable “Found on Amazon” is a dummy that identifies whether the product was found by a scraping robot that searched for the first 100 characters of the product description on Amazon’s website. Fixed effects are computed using the product’s COICOP 3-digit category (for example, COICOP 1.1.1 corresponding to “Bread and Cereals”). Standard errors are in parentheses.

At the sector level, the largest impact —both in days and in percentage terms—is in “Clothing and Footwear,” a sector that has also experienced intense competition between Walmart and Amazon in recent years.¹⁶ The share of products found on Amazon for this category is relatively low, reflecting both the heterogeneous product descriptions in clothing and the fact that Walmart sells many “private-label” apparel brands in an attempt to distinguish itself from Amazon. The only sector without a statistically significant reduction in implied duration is “Health and Medical,” where Amazon does not yet have a major presence.¹⁷

One caveat with these results is that their validity rests upon the assumption that I am using a good proxy for online competition. While fixed effects control for omitted factors at the category level, the “Found on Amazon” dummy may be capturing the effects of some unobserved characteristic *within* categories that has nothing to do with the degree of online competition. One reason to be confident of the validity of this proxy is that the scraping software simply replicates what any customer would do if she wanted

¹⁶See Kapner (2017), Stevens (2018), and Boyle (2018).

¹⁷See Wingfield and Thomas (2017) and Langreth and Tracer (2018).

to compare prices: copy and paste the product description across websites. Another reason is that Amazon’s search algorithm probably works better for product descriptions that are searched more frequently on its website.¹⁸

The evidence in this section suggests that competition with online retailers has increased the frequency of price changes in U.S. retail markets. But if prices are adjusting more frequently to local shocks, this would have little impact on aggregate inflation dynamics. In particular, algorithms could be used to change prices based on local demand or supply conditions, individual store inventory levels, and even customers’ personal buying behaviors. To establish whether this is the case, in the next section I study how online competition is affecting pricing behaviors on a spatial —rather than temporal— dimension.

IV Uniform Pricing

A second characteristic shared by many online retailers —including Amazon— is that every product tends to have the same posted price regardless of buyers’ locations, a pricing strategy often referred to as “uniform pricing.”

Uniform pricing in *online* retailers has been documented in the academic literature before. In Cavallo et al. (2014), we note that, out of the ten largest U.S. retailers selling online, only Walgreens and Walmart used zip codes to localize prices at the time. When we scraped their websites, we found that over 85% of their products had identical prices across multiple locations. In Cavallo (2017), I collected data from 50 retailers in ten countries to find that nearly all had a single price online which matches the *offline* price at a randomly chosen location about 72% of the time. I also found that U.S. retailers do not adjust their prices based on the IP address, which identifies the location of a buyer’s computer.

In a world of pricing algorithms and “big data,” the lack of geographical price discrimination may seem puzzling. The technology to customize prices is widely available, and the U.S. Federal Trade Commission website states that customized prices are “generally lawful, particularly if they reflect the different costs of dealing with different buyers or are the result of a seller’s

¹⁸Amazon’s search algorithm was developed by one of its subsidiaries, called “A9.” On its website (Amazon.com (2018a)) A9 states, “We’ve been analyzing data, *observing past traffic patterns*, and indexing the text describing every product in our catalog long before the customer has even decided to search.” The emphasis in this quote was added by me.

attempts to meet a competitor’s offering.”¹⁹ So why are online retailers not doing more geographical price discrimination? The answer appears to be connected to the transparency of the Internet and the fear of antagonizing customers. Retailers that price discriminate across locations risk angering their customers, who may not consider this a fair practice. In a famous example, Amazon faced criticism in 2000 for apparently charging different prices for identical DVDs at the same time. The controversy ended when the firm issued a statement saying, “We’ve never tested and we never will test prices based on customer demographics.”²⁰ Most online retailers appear to follow a similar approach, which is why a CEA report on “Differential Pricing” published in 2015 concludes that this type of price discrimination is still being used in a “limited and experimental fashion.”²¹

In practice, uniform prices would matter little if online retailers could still price discriminate using different shipping costs. However, Amazon has long offered free shipping to all locations for orders above \$25; and for orders below that threshold, Amazon’s shipping costs depend on the selected shipping speed and the items’ weight but not on the buyers’ location.²² Furthermore, Amazon “Prime” members get free shipping for most purchases by paying an annual fee that is also the same regardless of the location of the member. Over the years, Walmart and many other retailers that compete with Amazon have adopted similar strategies. Retailers with uniform prices could also price discriminate using coupons, but personalized discounts are not collected by the BLS and therefore do not affect official inflation statistics. Moreover, DellaVigna and Gentzkow (2017) find evidence of uniform pricing even in unit-value prices that include coupons.

Some papers are also finding uniform pricing in *offline* retailers. For example, DellaVigna and Gentzkow (2017) use the U.S. Nielsen-Kilts scanner data for food, groceries, and mass-merchandise stores to conclude that “nearly-uniform pricing is the industry norm.” They further show that price variations within chains are far smaller than variations among stores in different chains, even for store locations with very different income levels or in

¹⁹It is also easy to find articles in the press describing how “big data” allows retailers to price discriminate based on demographic and even customers’ personal characteristics. See, for example Valentino-DeVries et al. (2012), Dwoskin (2014), and Useem (May 2017 Issue).

²⁰See CNN (2000) and Amazon.com (2000).

²¹CEA (2015).

²²See Amazon.com (2018b).

geographically segmented markets. The evidence for uniform prices in offline stores is more common when researchers are able to observe prices for identical goods sampled at higher frequencies, as in Daruich and Kozlowski (2017).

Is uniform pricing another “Amazon Effect?” The connection between online retailers and uniform pricing policies in offline retailers is not obvious. As DellaVigna and Gentzkow (2017) point out, a plausible explanation for uniform pricing in *offline* retailers is that it helps to reduce managerial decision-making costs, while fairness is “a less compelling explanation ... [because] few consumers visit multiple stores from a chain in geographically separated markets, so if chains did choose to price discriminate across these stores, few consumers would observe this directly.” Both of these conditions change with online competition, making fairness a more probable explanation. Decision-making costs fall with improvements in information technology, and as traditional retailers start to sell online, they inevitably reveal more information about their prices to consumers, researchers, and journalists. Consumers can now easily use computers and mobile phones to request price-matching across distribution channels and locations. Even if they are not able to arbitrage price differences, they can demand price-matching across locations, particularly within the same retailer.²³

The combination of online transparency and fairness concerns can be a powerful force for uniform pricing. Consistent with this idea, a recent paper by Ater and Rigbi (2018) provides evidence that the online disclosure of prices tends to reduce price dispersion in brick-and-mortar supermarkets. Transparency seems to play a role across countries as well. In Cavallo et al. (2014) we find that global retailers such as Apple, Ikea, Zara, and H&M tend to have uniform pricing policies within currency unions, where price differences across countries are trivial to detect.

IV.A Comparison between Amazon and Multi-Channel Retailers

To better understand the influence of online competition on uniform pricing in more traditional retailers, I simultaneously collected prices from Amazon and three large multi-channel retailers that sell online in the U.S. The data, described in more detail in Section II, include prices for over 10,000 identical

²³See Walmart (2018) for details on Walmart’s price matching policy and Cavallo (2017) for evidence of identical online and offline prices within retailers in the US and other countries.

goods sold in up to 105 different zip codes during a single week in March 2018. For the subset of Walmart prices, I also have the zip-code-level unemployment rate and the “Found on Amazon” dummy to compare how prices vary by local demand conditions and online competition.

Table 4 provides two measures of price dispersion commonly found in the literature. First, I calculate the share of identical prices for all bilateral comparisons between two stores in the same retail chain. For example, if a retailer sells in three locations and two of them have the same price, the share of identical prices is 0.33, because only 1 out of 3 bilateral comparisons is identical. Second, I compute the average price difference for the same sample, including those bilaterals where prices are identical (zero price difference between two locations).

Table 4: Evidence of Uniform Pricing in Large US Retailers

	Share of Identical		Average Price Difference	
	Other Retailers	Amazon	Other Retailers (%)	Amazon (%)
Panel A: All Sectors				
Mean	0.78	0.91	5.49	1.61
Standard Deviation	(0.30)	(0.19)	(9.44)	(4.44)
Number of Products	9469	823		
Average Zip Codes	22	80		
Panel B: Major Sectors				
Food & Beverages				
Mean	0.76	0.84	6.33	2.97
Standard Deviation	(0.31)	(0.24)	(9.84)	(5.26)
Number of Products	6588	344		
Average Zip Codes	15	65		
Recreation & Electronics				
Mean	0.99	0.99	0.006	0.003
Standard Deviation	(0.16)	(0.05)	(0.22)	(0.04)
Number of Products	1578	191		
Average Zip Codes	42	100		

Panel A shows that Amazon has a high degree of uniform pricing. Prices are identical 91% of the time, with an average price difference between stores of only 1.61%. These findings are more impressive when we consider that Amazon’s 823 products were sampled in an average of 80 zip codes, while the 9,469 products in multi-channel retailers were available only in an average of 22 zip codes.

Still, multi-channel retailers are not far behind: their share of identical prices is 78%, while the average price difference is 5.49%. These results resemble those in Cavallo (2017), where I find that prices collected using

mobile phones in different offline locations of nine U.S. retailers were also identical about 78% of the time, ranging from 66% in drugstores to 96% in electronics.

Panel B reveals that most price differences across locations occur in “Food and Beverages,” the sector with the lowest share of online sales. DellaVigna and Gentzkow (2017) also find a lower share of identical prices for groceries, at 53%, with a sample that contains many retailers that do not sell online. Interestingly, the share of identical prices for “Food and Beverages” in Amazon is also lower, at 84%, while the average price difference nearly doubles to 2.92%. By contrast, the prices for electronics have nearly perfect uniform pricing in all the retailers I sampled.

IV.B Online Competition and Uniform Pricing

To determine whether online competition affects uniform pricing, Table 5 follows a similar approach to the one used in the previous section. I focus on the subset of products sold by Walmart on its “Grocery” website (where there is at least some geographical price dispersion) and regress the share of identical prices and the average price difference on the “Found on Amazon” dummy variable, my proxy for online competition at the product level. I also include a variable that counts the number of zip codes where each product is found, as well as the average log difference in unemployment rates for all the bilateral combinations between those zip codes.

Table 5 shows that goods that can be easily found on Amazon are more likely to be priced identically by Walmart in multiple locations. The share of identical pricing for those products increases by 5.8 percentage points, from a level of 91% to almost 97%. A similar result is obtained for the average price difference, which falls by 1.9 percentage points for goods found on Amazon, from approximately 2.9% in the full sample.

Columns 2 and 4 show the effects of adding the number of zip codes sampled and the unemployment rate difference. I include the number of zip codes to help control for the possibility that the products “Found on Amazon” might belong to national brands sold in multiple locations. The coefficient has the right sign, but its magnitude is very small.

The results for the unemployment rate differences are more revealing. Column 2 shows that increasing the unemployment rate difference between two locations by 1% tends to reduce the share of identical prices by 0.6%. Assuming a linear relationship, we need a 10 percentage point difference

Table 5: Uniform Pricing for Walmart’s Grocery Products Found on Amazon

	Share of Identical		Average Price Difference	
Found on Amazon	0.058 (0.008)	0.055 (0.008)	-1.979 (0.306)	-1.891 (0.309)
Zip Codes Sampled		0.002 (0.000)		-0.044 (0.017)
UE Rate Difference		-0.006 (0.002)		0.386 (0.071)
Constant	0.914 (0.004)	0.921 (0.009)	2.939 (0.152)	1.794 (0.386)
Observations	3,982	3,949	3,778	3,746
Obs. on Amazon	934	929	908	903
R-squared	0.022	0.031	0.014	0.024

Notes: The dependent variables are measured using prices collected from multiple zip codes in March 2018. The variable “Found on Amazon” is a dummy that identifies whether the product was found by a scraping robot that searched for the first 100 characters of the product description on Amazon’s website. Fixed effects are computed using the product’s COICOP 3-digit category. Standard errors are in parentheses.

in unemployment between two locations to have the same effects as being “found on Amazon.” At the same time, column 4 suggests that unemployment differences have a greater impact on the size of price differences between locations. A 10% increase in the difference of unemployment would raise the average price difference by about 4%.

In sum, I find that traditional retailers that sell online tend to have a high degree of uniform pricing, which closely resembles Amazon’s behavior. In the cross section, the more a good competes with Amazon, the higher the degree of uniform pricing. While I am unable to see how uniform pricing has changed over time, this evidence suggests that as traditional retailers compete more with online retailers, their geographical price dispersion will continue to fall.

V Implications for Pass-through and Inflation

A higher frequency of price changes can increase their sensitivity to various types of shocks. Consistent with this hypothesis, Gorodnichenko and Talavera (2017) find evidence of a much higher exchange rate pass-through in online retailers. But as noted by DellaVigna and Gentzkow (2017), uniform pricing also tends to dampen the response to local economic conditions. So if online competition is making prices more flexible *and* uniform, we should expect to see an increase mainly in the price sensitivity to “nationwide” shocks. Examples of such shocks include changes in average gas prices or fluctuations in nominal exchange rates.²⁴

In this section, I look for evidence of this effect in multi-channel retailers. First, I confirm that online competition increases both exchange-rate and gas-price pass-through for Walmart’s products. Next, I document an increase in pass-through rates in more aggregate online data over time.

V.A Online Competition and Pass-through

I start by running a standard dynamic-lag pass-through regression with Walmart’s microdata. I use quarterly prices and consider separately the reaction of good-level prices to changes in both national-average gas prices and the nominal exchange rate, so that:

$$\Delta p_{ic,t} = \sum_{k=0}^1 \beta_k \Delta s_{ic,t-k} + \delta_{ic,t} \Delta X_{ic,t} + \epsilon_{ic,t} \quad (1)$$

where $\Delta p_{ic,t}$ is the change in the log price of good i in category c at time t , $\Delta s_{ic,t-k}$ is either the log change in gas prices or the nominal exchange rate, and k is the number of lags. $\Delta X_{ic,t}$ is a vector that includes fixed effects at the individual good level, fixed effects at the category level, and the first lag of the dependent variable to account for the persistence in inflation.

For gas prices, I follow Choi et al. (2018) and report the coefficient for the contemporaneous effect (a single quarter) in Table 6. For exchange rates, I follow Burstein and Gopinath (2014) and report pass-through as the the sum of the coefficients for two lags of the change in the nominal exchange

²⁴By “nationwide” I mean shocks common to all locations, though not necessarily common to all products.

rate, which is usually considered to be the “short-run pass-through” in the literature. To measure the exchange rate, I use the trade-weighted value of the U.S. dollar against the currencies of a broad group of trading partners, as published by Board of Governors of the Federal Reserve. I invert the index so that an increase is a depreciation of the U.S. dollar that is expected to have a positive pass-through coefficient on prices.

Table 6 shows that retail prices at the product level exhibit a great deal of pass-through from both gas prices and exchange rates, and in both cases, pass-through increases significantly when products compete online. The gas-price pass-through rate is 22% in a single quarter, and it rises from 19% to 28% for goods that can be easily found on Amazon. The short-run exchange-rate pass-through is 32% and rises from 26% to 44% for products that can be found on Amazon.

Table 6: Short-Run Pass-through into Walmart's Prices (2016-2018)

	Full Sample	Found on Amazon	
		No	Yes
Gas Prices (1 quarter)	0.22 (0.02)	0.19 (0.02)	0.28 (0.03)
Observations	191,690	122,800	68,890
R-squared	0.17	0.17	0.16
Exchange Rate (2 quarters)	0.32 (0.03)	0.26 (0.04)	0.44 (0.05)
Observations	191,690	122,800	68,890
R-squared	0.17	0.18	0.16

Notes: All data are quarterly. The dependent variable is the log change in individual product prices, and the independent variables include the first lag of the dependent variable and lags of either the log change in gas prices or the trade-weighted nominal exchange rate broad index published by the Board of Governors of the Federal Reserve (TWEXB). The index is inverted so that an increase is a depreciation of the U.S. dollar and the sign of the pass-through estimates is consistent with those reported in the literature. This table shows the results using a fixed-effects estimator at the individual product level and COICOP 3-digit category and reports the contemporaneous (1-quarter) pass-through for gas price changes and the sum of the contemporaneous and first lag (2 quarters) of the nominal exchange rate changes. Standard errors are in parentheses.

The estimated levels of pass-through are sensitive to the number of lags and other details in the regression, but the observed increase in pass-through when a product is found on Amazon holds under many different model specifications. In particular, in the Appendix I show similar results with different estimation techniques, including OLS, fixed effects, difference and system GMM, as well as a regression that includes both gas prices and exchange rates at the same time.

V.B Pass-through over Time

The previous results show that online competition increases the price sensitivity to shocks at Walmart, but does it affect other retailers, and is there evidence that pass-through is increasing over time?

To answer these questions, I now focus on exchange rate pass-through, for which I have better data and a variety of methodologies used in the literature. My main objective is to study how pass-through has changed over time, regardless of the specific method used to measure it.

In Table 7, Panel A, I start by running regression (1) using price indices computed with online data from a large number of multi-channel retailers in the U.S. from 2008 to 2017.²⁵ One advantage of these data is the large number of multi-channel retailers and sectors. The other is the long time series, which makes it possible to split the sample into two periods, from 2008 to 2012 and from 2013 to 2017. All available COICOP 3-digit sectors are included, with the exception of gas price indices.

²⁵I use sector-level price indices computed by PriceStats with a proprietary methodology that includes adjustments to correct for methodological differences that can cause long-term differences in inflation levels relative to the CPI. These adjustments remain constant and do not affect pass-through estimates over time.

Table 7: Price Sensitivity to Exchange Rates Over Time

	By Period		
	Full Sample	2008-2012	2013-2017
Panel A: Online US Price Indexes (All goods excluding fuel)			
Short-Run (2 quarters)	0.16 (0.05)	0.12 (0.07)	0.25 (0.06)
Long-Run (2 years)	0.31 (0.09)	0.04 (0.37)	0.44 (0.12)
Panel B: Matched Relative Prices (2 sectors, 7 countries)			
Food & Beverages	0.38 (0.01)	0.23 (0.05)	0.45 (0.02)
Electronics	0.83 (0.03)	0.79 (0.14)	0.91 (0.07)

Notes: Panel A shows pass-through coefficients from a dynamic lag regression using price indices computed with online data from a large number of multi-channel retailers. Panel B shows the long-run *relative* pass-through coefficients from equation (2), using a database with carefully-matched products across seven countries. Standard errors are in parentheses.

Consistent with the increase in the frequency of price changes observed in Section III, the short-run (two quarters) effect of exchange rates on online price indices has doubled over time, from 12% to 25%. The long-run (eight quarters) effect is higher at 31% and also increases over time, from an insignificant 0.04% in 2008–2012 to a statistically significant 44% in recent years.

A major limitation of the regressions in Panel A is that these price indices include non-tradables and goods that are domestically produced, which may not only dampen the level of the coefficients but could also affect their

behavior over time if the composition of imported and domestic products is not constant. Furthermore, without information about the country of origin, I am unable to control for shocks in foreign production costs that may correlate with the nominal exchange rate.

An alternative way of measuring the long-run sensitivity of retail prices to the nominal exchange rate is to estimate a relative price regression using matched-product prices across countries in levels, as in Gorodnichenko and Talavera (2017):

$$\ln \left(p_{i,t}^{us} / p_{i,t}^z \right) = \alpha^{us,z} + \beta \ln \left(e_t^{us,z} \right) + \epsilon_{i,t}^{us,z} \quad (2)$$

where $p_{i,t}^{us}$ denotes the price of good i at time t in the U.S., z is the notation for another country, and $e_t^{us,z}$ is the nominal exchange rate defined as the number of U.S. dollars per unit of z (so an increase in $e_t^{us,z}$ is a depreciation of the U.S. dollar). The coefficient β is the estimate of long-run exchange rate pass-through into relative prices. Under full pass-through, the β would be 1, and the law of one price would hold in relative terms.²⁶

At the retail level, using relative prices provides the advantage of implicitly controlling for production costs and other product-level shocks that affect prices in both countries and may be correlated with nominal exchange rates. This approach is rare in the literature because it requires access to micro data from identical products across countries. I use the same data described in Cavallo et al. (2018), which includes the prices of thousands of individual varieties matched into 267 narrowly defined “products.” The countries included, in addition to the the U.S., are Australia, Brazil, China, Japan, South Africa, and the United Kingdom. More details about the data can be found in Section II.

Table 7 Panel B shows the β coefficients for goods in the “Food and Beverages” and “Electronics” categories. The relative-price pass-through is higher for “Electronics,” at 83% versus only 38% for “Food and Beverages.” Just like with the price index results, both categories display a significant increase in the pass-through over time. The sensitivity in “Food and Beverages” doubles, from 23% in 2008-2012 to 45% in 2013-2017. Similarly, the pass-through for “Electronics” rises from 79% to 91% between the same periods.

²⁶The absolute version of the law of one price would further require that the $\alpha^{us,z}$ be zero.

Such high levels of exchange-rate pass-through are not commonly found at the retail level. Burstein and Gopinath (2014) estimate a long-run pass-through in tradable CPI prices of just 13% in the U.S. until 2011.²⁷ The 44% long-run pass-through in Panel A for 2013-2017 is closer to the level reported by Gopinath (2016) for U.S. import prices “at-the-dock.”²⁸ While differences in methods and data can affect pass-through estimates, the evidence suggests that online competition is making U.S. retail prices far more sensitive to exchange rates than in the past, gradually closing the gap between retail and border pricing behaviors.

VI Conclusions

Online competition can influence retail markets in many ways. An important and often overlooked mechanism is the way it changes retail pricing behaviors, which can have long-lasting effects on inflation dynamics. This paper studies pricing behaviors for large multi-channel retailers in the U.S. over the past 10 years and shows how online competition increases both the frequency and the extent of uniform prices across locations. When combined, these factors tend to make prices more sensitive to aggregate nationwide shocks, which I document by finding increasing levels of gas-price and nominal exchange-rate pass-through.

For policy-makers and anyone interested in inflation dynamics, these findings imply that retail prices are becoming less “insulated” from nationwide shocks. Fuel prices, exchange-rate fluctuations, or any other shock that may enter the pricing algorithms used by large retailers are more likely to have a larger impact on retail prices than in the past. In terms of cost shocks, a natural extension of my work would be to measure the retail pass-through from the recent increase in U.S. tariffs. Demand-side shocks, not addressed here, also provide a promising area for future research. Gorodnichenko et al. (2018b) find no evidence of a high-frequency price response to macroeconomic policy announcements that do not affect firm-level demand. More research on the specific metrics and mechanisms used by online firms in their pricing algorithms could give macroeconomists a better understanding of what

²⁷Using a different method, Gopinath (2016) reports a long-run CPI pass-through of 0.052 in the U.S., a similar number to the one I found for online prices in 2008-2012.

²⁸See Gopinath and Itskhoki (2010) for results showing how the frequency of price changes increases pass-through in import prices.

type of demand shocks are likely to have the greatest impact on aggregate inflation dynamics.²⁹

For monetary models and empirical work, my findings suggest that the focus needs to move beyond traditional nominal rigidities: labor costs, limited information, and even “decision costs” –related to inattention and the limited capacity to process data– will tend to disappear as more retailers use algorithms to make pricing decisions. One of the few remaining costs for price-setters may soon be “fairness concerns,” as in the work by Rotemberg (1982) and Kahneman et al. (1986). This topic has received relatively little attention in the economic literature as an additional reason for price stickiness.³⁰ The evidence in this paper suggests that fairness is currently more important to understand price differences between locations than for price changes over time. However, what people consider to be “fair” in terms of pricing can change across countries, sectors, and time periods. More work connecting pricing technologies, web transparency, and fairness will be needed to understand how pricing behaviors and inflation dynamics are likely to evolve in the future.

²⁹See den Boer (2015) for a review of the dynamic pricing literature in operations research and related fields. Ferreira et al. (2015) provide an example of the type of pricing algorithms that can be implemented by online retailers.

³⁰More recent papers on pricing and fairness include Rotemberg (2005), Rotemberg (2011), and Englmaier et al. (2012).

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A Appendix

A.A Zip-Codes selected for Uniform Pricing Data

Using BLS and Census data, I selected the zip-codes in each state with the highest and lowest unemployment rates for February 2018 (the last non-preliminary month of data available at the time the data was merged.) The unemployment data from BLS is available at the county level, so I merged it with a zipcode-county correspondence table from Census. A single county may have multiple zip codes, and a zip code may expand across many counties. To simplify, I only kept zip-codes that fall fully within a county and then selected the zip-code with the largest population in every county. Finally, I selected the zip-codes with the highest and lowest unemployment rate in each state. I added zipcode 02138 (my location) and 98101 (Amazon's Seattle headquarters).

A.B Tables

Table A1: Behavior of Posted and Regular Prices in Large US Retailers

	Period Averages		
	2008-2010	2011-2013	2014-2017
Panel A: Posted Prices			
Frequency of Price Changes (%)	21.28	28.02	31.72
Implied Duration (months)	4.70	3.57	3.15
Frequency of Price Increases	9.93	13.18	14.72
Frequency of Price Decreases	11.42	14.84	17.04
Absolute Size of Price Changes (%)	18.65	17.84	15.52
Size of Price Increases	21.45	19.29	16.69
Size of Price Decreases	-17.95	-15.3	-14.48
Share of Price Changes under 1pc	5.62	4.94	7.57
Kurtosis of Price Changes	4.13	5.17	5.3
Panel B: Regular Prices			
Frequency of Price Changes (%)	15.43	22.39	27.39
Implied Duration (months)	6.48	4.47	3.65
Frequency of Price Increases (%)	6.89	10.27	12.49
Frequency of Price Decreases (%)	8.94	12.12	14.96
Absolute Size of Price Changes (%)	17.45	16.24	15.02
Size of Price Increases (%)	18.3	17.09	15.42
Size of Price Decreases (%)	-16.79	-14.71	-14.02
Share of Price Changes under 1pc	6.59	5.23	8.01
Kurtosis of Price Changes	4.12	4.87	5.47
Sales as Share of Price Changes (%)	4.02	3.98	3.29

Table A2: Walmart Pass-through Using Alternative Estimators

	Full Sample	Found in Amazon	
		No	Yes
Panel A: Gas Prices (1 quarter)			
OLS	0.32 (0.02)	0.30 (0.02)	0.34 (0.03)
Fixed Effects	0.22 (0.02)	0.19 (0.02)	0.28 (0.03)
Difference GMM	0.14 (0.03)	0.06 (0.04)	0.35 (0.05)
System GMM	0.10 (0.02)	0.06 (0.03)	0.23 (0.04)
Panel B: Exchange Rates (2 quarters)			
OLS	0.47 (0.03)	0.44 (0.03)	0.52 (0.04)
Fixed Effects	0.32 (0.03)	0.26 (0.04)	0.44 (0.05)
Difference GMM	0.38 (0.03)	0.46 (0.05)	0.47 (0.05)
System GMM	0.69 (0.03)	0.66 (0.04)	0.69 (0.05)

Notes: Standard errors in parenthesis. Fixed effects at the individual product and COICOP 3-digit category levels.

A.C Figures

Figure A1: Monthly Frequency of Price Changes with Different Sales Filters

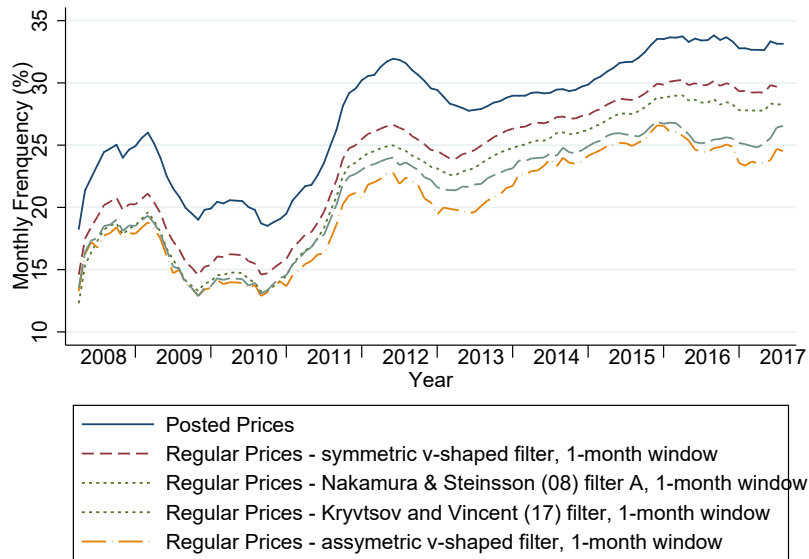


Figure A2: Monthly Frequency of Price Changes by COICOP Sector

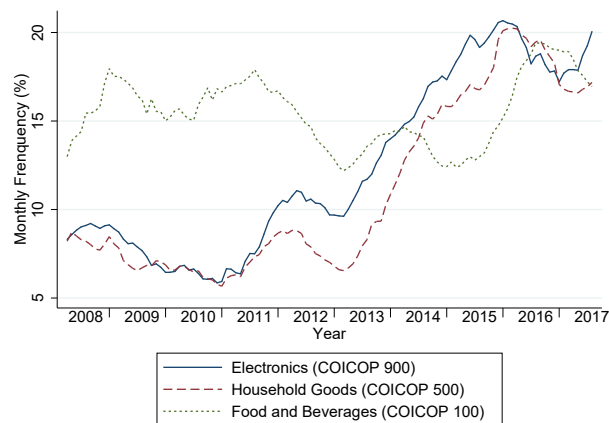


Figure A3: Implied Duration of Price Changes

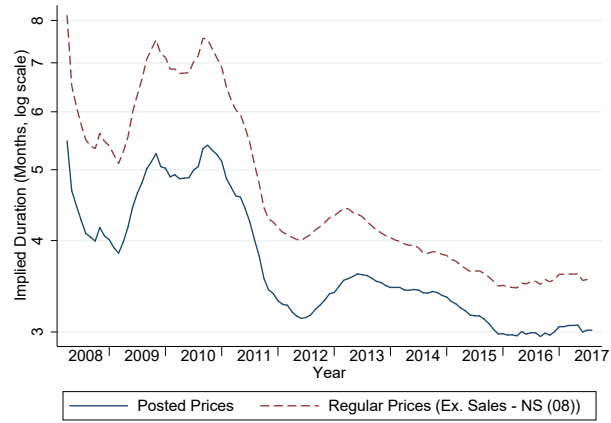


Figure A4: Mean Absolute Size of Price Changes

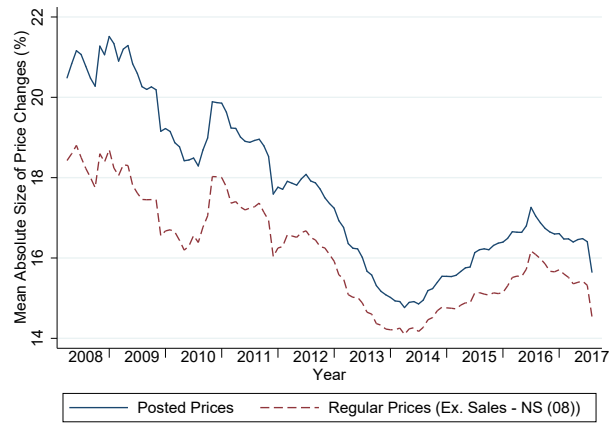


Figure A5: Average Monthly Frequency by Retailer and Sector

