More Amazon Effects: Online Competition and Pricing Behaviors

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Abstract

I study how online competition, with its shrinking margins, algorithmic pricing technologies, and the transparency of the web, can change the pricing behavior of large retailers in the U.S. and affect aggregate inflation dynamics. In particular, I show that in the past 10 years online competition has raised both the frequency of price changes and the degree of uniform pricing across locations. 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 US, prompting economists to wonder about their impact on inflation. Much of the attention among central bankers and the press has been 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 or 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, the nominal exchange rate, or import tariffs.

To document these new trends in US 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 in 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 by the Bureau of Labor Statistics (BLS) in the construction of the the Consumer Price

[1]See Yellen (2017). For recent articles in the press, see Berman (2017), Torry and Stevens (2017), and Cohen and Tankersley (2018). Some arguments are similar to 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 price differences between retailers are mostly driven by quality.

[2]See Cavallo and Rigobon (2016) and http://www.thebillionpricesproject.com.

Index (CPI).[3] For this paper, I enhanced the BPP data by scraping a random subset of Walmart's products, collecting their country of origin information to run exchange-rate pass-through regressions, and automatically searching product descriptions on the Amazon website to construct a proxy for online competition at the level of the individual good. I also collect prices simultaneously in more than one hundred zip-codes to compare the extent of uniform pricing in 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 last 10 years. The implied duration for regular price changes, which exclude sales and temporary discounts, has fallen from 6.7 months in 2008–2010 to approximately 3.65 in 2014–2017, a level similar to what Gorodnichenko and Talavera (2017) found for online-only retailers in the past. The reduction 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 of these changes to online competition, I use a regression of individual products sold on the Walmart website from 2016 to 2018 and 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 competitor's prices.

I then focus on the prices of identical goods across locations. Nearly all retailers that sell online tend to have a single-price or "uniform pricing" strategy regardless of the location of the buyer. Uniform pricing has been documented before separately for online and offline retailers by papers such as Cavallo et al. (2014) and DellaVigna and Gentzkow (2017). I go a step further and make a direct comparison by collecting prices in multiple zip codes for Amazon and three large traditional retailers in the U.S.: Walmart, Safeway, and Best Buy. I show that the degree of uniform prices in these firms is high and only slightly lower than in Amazon, 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 those goods found on Amazon are more likely to have a higher share of identical prices and lower average price difference across locations. These results are consistent with

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

recent evidence by Ater and Rigbi (2018) suggesting that the transparency of the web 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 compete online and 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 coming from gas prices and exchange rate fluctuations. Using a longer time series of sectoral price indices and a matched-product, cross-country dataset, I further show that the degree of sensitivity of prices to exchange rates has been increasing over time and is approaching levels previously only seen for tradable imported goods "at-the-dock". Overall, these results suggest that retail prices are less insulated from this type of aggregate shock than in the past.

My paper builds on 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 found 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 the measurement of inflation. My paper also contributes to the "uniform pricing" literature, by highlighting the connection between online and offline markets and the potential role transparency and fairness, and is related to several papers in the price-stickiness literature. In particular, 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 body of literature on exchange-rate pass-through, summarized by Burstein and Gopinath (2014), by showing that retail pass-through increases with online competition and over time.

The paper proceeds as follows. Section II describes the data. Section III presents evidence of an increase in the frequency of price changes and its connection to online competition. Section IV provides similar evidence for uniform pricing within retailers. Section V documents changes in gas price and exchange rate pass-through. Section VI provides 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 US pricing behavior statistics shown in Section III, I use 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. Each individual product is classified with the UN's Classification of Individual Consumption According to Purpose (COICOP), used by most countries for the construction of CPI. Statistics are aggregated using official expenditure weights in each country, as needed.[4] I use the 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 constructed by PriceStats by matching thousands of individual goods into 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 within countries at the "product" level. 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 in 2016–2018. They have not been used in previous papers, so I describe them in greater detail below.

[4]The 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 built a database with detailed information on nearly 50,000 products sold by Walmart during March 2018. For each good, I created a dummy variable that identifies whether the product can also be easily found on the Amazon website. This variable is used as a proxy for online competition in several sections of this paper. To build 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 from the Walmart website and pasting it into the search form in Amazon's website. If Amazon displays "No results found" or similar, the dummy variable has a value of 0. If Amazon reports one or more matching results, the dummy variable has a value of 1. Only matching products sold by Amazon LLC were counted. For all goods, I also calculated the price-change frequency using daily prices from 2016 to 2018 by taking the number of non-zero price changes divided by the number of observations where there can be a price change. The implied duration at the good level is estimated as $1/frequency$. For a subset of goods, I also scraped the "country of assembly" and "country of manufacturing" displayed on the Walmart website, and I use this information to measure exchange-rate pass-through for imported goods in Section V.A.

To measure uniform pricing, I scraped zip-code-level price data from four of the largest retailers in the US: Amazon, Walmart, Best Buy, and Safeway. All of these companies allow customers to select their location or "preferred store" on their website. Safeway does not show prices unless the customer first selects a zip code. I scraped the prices for a total of 10,292 products from these websites. For each product, I collected the prices in up to 105 zip codes within a few minutes, to minimize the possibility that I could pick up price differences over time. The products were selected to cover categories of goods that are sold on Amazon. The zip codes were selected to cover all US 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) used data collected

[5] See Mims (2017).

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 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 from the activity on their sites. So far, the academic evidence has found evidence of dynamic pricing in airlines, travel sites, and sellers participating in online marketplaces such as Ebay and the Amazon Marketplace.[8] But 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 evidence that many retailers currently use web scraping to monitor their competitor's 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 in more traditional retailers, I start by looking at how aggregate price stickiness has changed in the U.S. from 2008 to 2017, a period when the share of online sales grew

[6]These 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 US and found a similarly high frequency of price changes.

[7]See Angwin and Mattioli (2012).

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

[9]See Dastin (2017). The practice appears to be so extended that Amazon filed a patent for a "robot mitigation" method in 2016. See Kowalski and Lategan (2016).

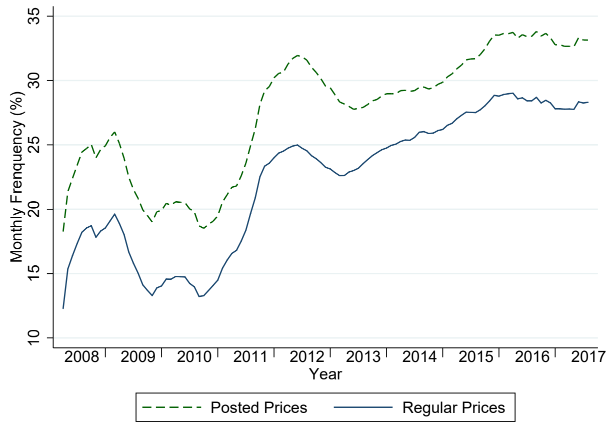
from 3.6% to 9.5% of all retail sales according to the Census Bureau.[10]

In Figure 1, I plot 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]

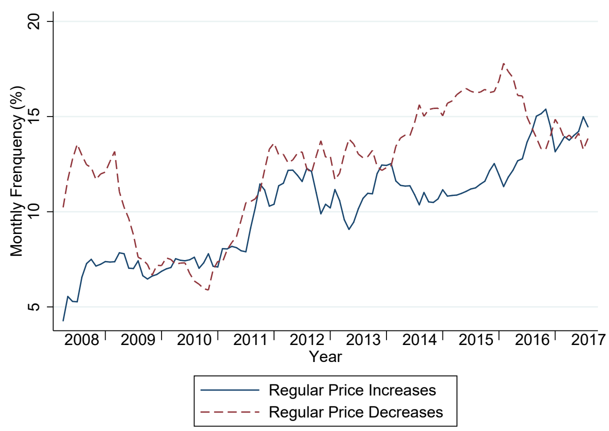
[10]See http://fred.stlouisfed.org/series/ECOMPCTSA. Estimates from market-research firms suggest that Amazon controlled over half of that U.S. online retailer market in 2017. See Lunden (2018).

[11]All 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). The 12-month moving averages of the monthly frequency series are shown in this graph. 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 affected 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) found sales to be strongly cyclical in countries like the US and the UK. For my purposes, it is important to know if the higher frequency over time is simply reflecting an increase in sale events. I therefore computed 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 doubled, rising 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. Using historical CPI data, Vavra (2013) found that the frequency of price changes tends to be higher during recessions, even after the exclusion of temporary sales. Consistent with that result, Figure 1(a) shows a spike in the frequency of both posted and regular price changes at the end of 2008 and the beginning of 2009. Figure 1(b) shows that this was entirely caused by the frequency of regular price decreases. By contrast, the frequency of regular price increases has been steadily rising 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.

[12] Not 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 FigureA1 of the Appendix.

Table 1: Behavior of Regular Prices in Large US 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) found for historical CPI data, to just about 3.7 months, a number much closer to what Gorodnichenko et al. (2018a) found for online retailers with data from 2010–2012. Furthermore, as the frequency of price changes increases, their size is also getting smaller, 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 found that “online sellers adjust their prices more often than offline retailers, but by roughly the same amounts.”

In Table 2, I show implied durations by sector. These results show that the changes are bigger in categories of goods where online retailers tend to have larger marker shares, such as “Recreation and Electronics” and “Furnishings and Household Goods.” By contrast, “Food and Non-Alcoholic Beverages”—where only 0.4% of total sales took place online in 2016—had 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 $1/frequency$. The table shows the average using all months in each 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.

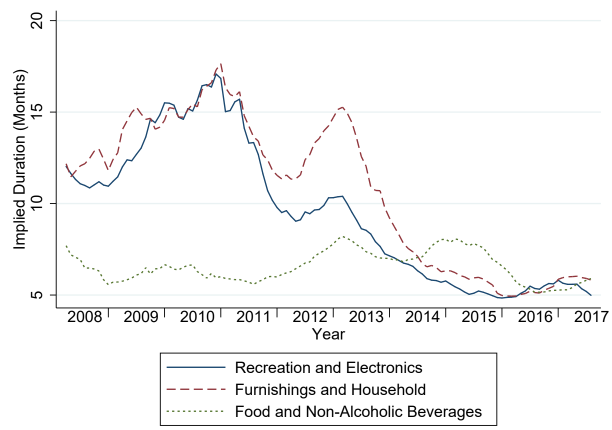
The timing of the fall in implied durations also seems to coincide with the timing of Amazon's expansion in different sectors. This can be seen in Figure 2, where I plot the implied duration every month for the three main categories discussed above. The implied duration of "Recreation and Electronics" 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 more aggressively expand into groceries with its "Amazon Fresh" platform.[14] According to the

[13]These 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.

[14]Amazon also acquired Whole Foods in 2017. Haddon and Nassauer (2016) report that traditional grocers such as Walmart and Kroger have aggressively expanded their online services in recent years.

US Census Bureau, e-commerce 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 these patterns are intriguing, they do not provide direct evidence that the changes are related to online competition. To more formally test this connection, 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 each good can be found on Amazon (used as a proxy for the degree of online competition). More details on how this database was constructed were provided in Section II.

Table 3 shows the results of a regression of the 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 each of the sectors from Table 2 for which I have online data.

The first column shows that products found on Amazon tend to have approximately 20% shorter implied durations. After controlling for category fixed effects, the goods "Found on Amazon" had an average of 5.45 days lower duration compared to an unconditional level of approximately 28 days. The unconditional implied duration is lower than the estimates in Table 2 because these are daily prices that 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	-3.63	-41.18	-1.55	-8.33	-5.71
	(0.46)	(0.75)	(4.78)	(0.76)	(6.38)	(0.59)
Constant	27.95	30.97	94.98	22.42	59.25	23.43
	(0.60)	(0.40)	(2.61)	(0.50)	(3.92)	(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, 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").

At the sector level, the largest impact —both in days and in percentage terms—is in "Clothing and Footwear," a sector that also experienced intense competition between Walmart and Amazon in recent years.[15] The share of products that I was able to find on Amazon for this category is relatively low, reflecting both the heterogeneous product descriptions in clothing but also the fact that Walmart sells many "private-label" apparel brands in an attempt to distinguish itself from Amazon. All the other sectors have statistically significant reductions in implied duration, with the only exception being "Health and Medical" products, where Amazon does not yet have a major presence.[16]

One caveat with these results is that their validity rests upon the assumption that I am using a good proxy for online competition. Although the fixed effects control for omitted factors at the category level, it is possible that the "Found on Amazon" dummy is 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 is that the scrap-

[15]See Kapner (2017), Stevens (2018), and Boyle (2018).
[16]See Wingfield and Thomas (2017) and Langreth and Tracer (2018).

ing software is simply replicating what any customer would do if she wanted to compare prices: copy and paste the product description across websites. Another reason for confidence is that Amazon's search algorithm is likely to work better for product descriptions that are searched repeatedly on its website.[17]

The evidence in this section suggests that competition with online retailers has increased the frequency of price changes in US 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 see 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 of many online retailers —including Amazon—is that each good tends to have the same posted price regardless of the location of the buyer, a pricing strategy that is 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 noted that of the 10 largest US retailers selling online, only Walgreens and Walmart appeared to use zip codes to localize prices. 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 10 countries to find that nearly all had a single price online, which also coincided with the *offline* price in a randomly chosen location about 72% of the time. I also found that US 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 US Federal Trade Commission website states that customized prices are "generally lawful, particularly if they reflect the

[17] Amazon'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.

different costs of dealing with different buyers or are the result of a seller's attempts to meet a competitor's offering."[18] 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 face the potential anger of their customers, who may not consider it fair. 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."[19] The majority of online retailers appear to follow a similar approach, which is why a CEA report on "Differential Pricing" published in 2015 concluded that it was still being used in a "limited and experimental fashion."[20]

In practice, uniform posted prices would matter little if online retailers could price discriminate using different shipping costs. But 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 weight/size of the item, not the location of the buyer.[21] 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. Furthermore, DellaVigna and Gentzkow (2017) found evidence of uniform pricing even in unit-value prices that include coupons.

A growing number of papers are also documenting uniform pricing in *offline* retailers. DellaVigna and Gentzkow (2017) use the US Nielsen-Kilts scanner data for food, groceries, and mass-merchandise stores to conclude that "nearly-uniform pricing is the industry norm." In particular, they show that the variation of prices within chains is far smaller than the variation

[18] It 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).

[19] See CNN (2000) and Amazon.com (2000).

[20] CEA (2015).

[21] See Amazon.com (2018b).

between stores in different chains, even for store locations that have very different income levels or are in geographically segmented markets. The evidence for uniform prices in offline stores becomes clearer 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 reduces 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 costs should 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.[22]

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 found 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 US. The data,

[22]See 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.

described in more detail in Section II, include prices for over 10,000 identical 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 common in the literature. First, I calculate the share of identical prices for all bilateral comparisons between two stores of the same retailer. 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 (with 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 very high degree of uniform pricing. Prices are identical 91% of the time, while the average price difference between stores is only 1.61%. These findings are impressive if 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 only 5.49%. These results are similar with those on Cavallo (2017), where I found 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 the majority of the price differences across locations occurs in "Food and Beverages," the sector with the lowest share of online sales. DellaVigna and Gentzkow (2017) also found 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, in Table 5 I follow a similar approach to the previous section. I use the subset of grocery products sold by Walmart through 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 goods increases by 5.8 percentage points, from a level of 91% to almost 97%. A similar result can be obtained with the average price difference, which falls by 1.9 percentage points for goods found on Amazon, from a level of approximately 2.9% in the full sample.

In Columns 2 and 4, I show the effects of adding the number of zip codes sampled and the unemployment rate difference. I included the number of zip codes to help control for the possibility that the goods "Found on Amazon" might be national brands that are sold in multiple locations. The coefficient has the right sign but its impact 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 roughly need a 10 percentage point dif-

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

	Share of Identical		Average Price Difference	
Found on Amazon	0.058	0.055	-1.979	-1.891
	(0.008)	(0.008)	(0.306)	(0.309)
Zip Codes Sampled		0.002		-0.044
		(0.000)		(0.017)
UE Rate Difference		-0.006		0.386
		(0.002)		(0.071)
Constant	0.914	0.921	2.939	1.794
	(0.004)	(0.009)	(0.152)	(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: Fixed Effects at the COICOP 3-digits level.

ference 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 the behavior of Amazon. In the cross section, the more a good competes with Amazon, the higher the degree of uniform pricing. While I am not able 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 changes can increase the sensitivity of prices to various types of shocks. Consistent with this hypothesis,Gorodnichenko and Talavera (2017) found 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 if making prices more flexible *and* uniform, we would expect to see an increase in the price sensitivity to "nationwide" shocks. Examples of such shocks include changes in average gas prices or fluctuations in nominal exchange rates. [23]

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 the Walmart 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:

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

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; 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 rate,

[23] By "nationwide" I mean shocks common to all locations, though not necessarily common to all goods.

which is usually considered the "short-run pass-through" in the literature. The exchange-rate regression include only goods that are listed as "imported" on the Walmart website, about 30% of the total. This makes my results more comparable to those in Gopinath (2016) with prices at the border, where the country of origin information is also available. To measure the US exchange rate, I use a trade-weighted value of the US dollar against the currencies of a broad group of trading partners, with the US dollar as the base currency. An increase in the index is therefore a depreciation of the US dollar, and 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 more strongly 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% when a good can found on Amazon.

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

		Found on Amazon	
	Full Sample	No	Yes
Gas Prices (1 quarter)	0.22	0.19	0.28
	(0.02)	(0.02)	(0.03)
N	191,690	122,800	68,890
r2	0.17	0.17	0.16
Exchange Rate (2 quarters)	0.32	0.26	0.44
	0.03	0.04	0.05
N	61,340	39,296	22,043
r2	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 TWEXB is inverted so that an increase is a depreciation of the US dollar and the sign of the pass-through estimates are consistent with those reported in the exchange-rate pass-through literature. This table shows the results using fixed-effects estimator at the individual product level and COICOP 3-digit category, and reports the contemporaneous (1-quarter) pass-through for gas prices, and the sum of the contemporaneous and first lag (2 quarters) of the change in the TWEXB.

These results do not establish causality, but the high sensitivity of prices to both variables, and the finding that it increases when a good 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, and difference and system GMM methodologies that use the lag structure to try to control for endogeneity in these variables. I also obtain similar results if I run the regression with both gas prices and exchange rates at the same time.

V.B Price Sensitivity over Time

Online competition increases the pass-through of aggregate shocks in 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 rates pass-through, for which I have better data and a variety of methods used in the literature that can be applied. My goal here is to study how pass-through has changed over time, regardless of the specific methodology used to measure it.

In Table 7, Panel A, I start by running regression (1) using online price indices computed with online data from a large number of multi-channel retailers in the US from 2008 to 2017.[24] One advantage of these data is the large number of multi-channel retailers and sectors included in these indices. The other is the long time series, which allows me to split the sample into two periods, from 2008 to 2012 and from 2013 to 2017. All available COICOP 3-digit sector price indices are included, with the exception of those including gas prices.

[24] I use sector-level price indices computed by PriceStats using 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 are constant over time and do not affect pass-through estimates.

Table 7: Price Sensitivity to Exchange Rate 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	0.12	0.25
	(0.05)	(0.07)	(0.06)
Long-Run (2 years)	0.31	0.04	0.44
	(0.09)	(0.37)	(0.12)
Panel B: Matched Relative Prices (2 sectors, 7 countries)			
Food & Beverages	0.38	0.23	0.45
	(0.01)	(0.05)	(0.02)
Electronics	0.83	0.79	0.91
	(0.03)	(0.14)	(0.07)

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

A major limitation in the regressions in Panel A is that these price indices include goods that are domestically produced, which may not only dampen the level of the coefficients but also affect their changes over time if the composition of imported and domestic goods changes. Furthermore, without information about the country of origin, I am unable to control for shocks in foreign production cost that may be correlated 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 in levels using matched-product prices across countries, as in Gorodnichenko and Talavera (2017):

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

where $p_{i,t}^{us}$ denotes the price of good i at time t in the U.S., z is another country, $e_t^{us,z}$ 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.[25].

At the retail level, using relative prices has the advantage that we implicitly control for production costs and other good-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 that are 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.

In Panel B of Table 7, I show 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, there is is a significant increase in the pass-through over time in both categories. 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.

Such high levels of pass-through are not commonly found at the retail level. Burstein and Gopinath (2014) estimate a long-run passthrough in tradable CPI prices of just 13% in the US until 2011.[26] Instead, the 44%

[25]The absolute version of the law of one price would further require that $\alpha^{us,z}$ be equal to zero

[26]Using a different method, Gopinath (2016) reports a long-run CPI pass-through of 0.052 in the U.S., a number close to what I found with online prices in the period 2008-

of long-run pass-through in Panel A for the period 2013-2017 is closer to the Gopinath (2016) found for U.S. import prices "at-the-dock".[27] Online competition, by increasing the frequency and uniformity of price changes, is making retail prices become far more sensitive to exchange rates than in the past.

VI Conclusions

Online competition can affect 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. In this paper, I study pricing behaviors for large multi-channel retailers in the US in the past 10 years, and show that online competition increases both the frequency of price changes and the degree of uniform prices across locations. When combined, these changes 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 monetary policy and those interested in inflation dynamics, the implication is that retail prices are becoming less "insulated" from these common nationwide shocks. Fuel prices, exchange-rate fluctuations, or any other force affecting costs that may enter the pricing algorithms used by these firms are more likely to have a faster and larger impact on retail prices that in the past. In terms of cost shocks, a natural extension of my work would be to measure the retail price pass-through from the recent increase in U.S. tariffs. Demand side shocks, which are not covered in this paper, are also a promising area for future research. Gorodnichenko et al. (2018b) found no evidence of a high-frequency price response to macroeconomic announcement shocks 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 type of demand shocks are likely to have the greatest impact on aggregate inflation dynamics.[28]

2012.

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

[28]See 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 how pricing algorithms can be implemented in an online retailer.

For monetary models and empirical work, my results 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 last remaining costs for price adjustments appears to be fairness concerns, as in the work by Rotemberg (1982) and Kahneman et al. (1986). This topic has received relatively little attention in the price stickiness literature.[29] The evidence in this paper suggests that fairness is currently more important for price differences between locations than for changes over time. But what people consider as being "fair" in terms of pricing can change across countries, sectors, and time. 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.

[29] More 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 with the highest and lowest unemployment rates for February 2018 in each state (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 kept only zip-codes that are fully within a county, and then selected the zip-code with the largest population in each county. Finally, I selected the zip-codes with the highest and lowest unemployment 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

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

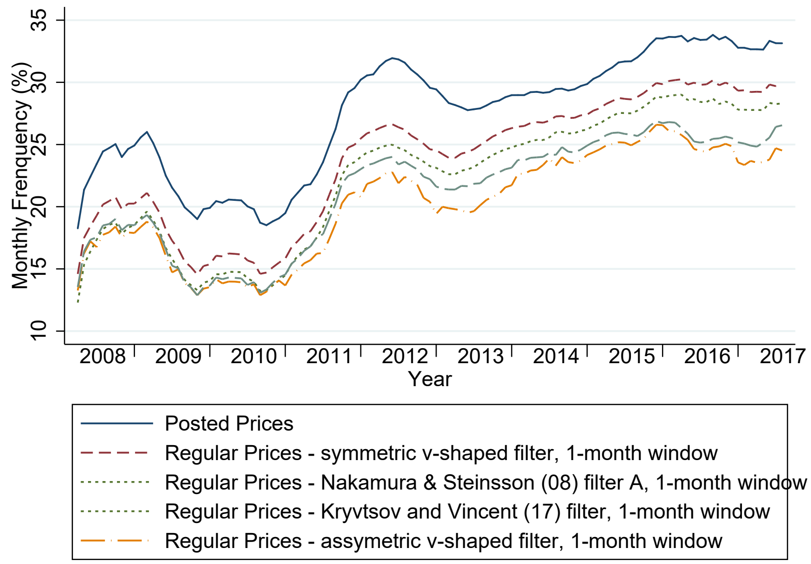

Figure A2: Monthly Frequency of Price Changes by COICOP Sector

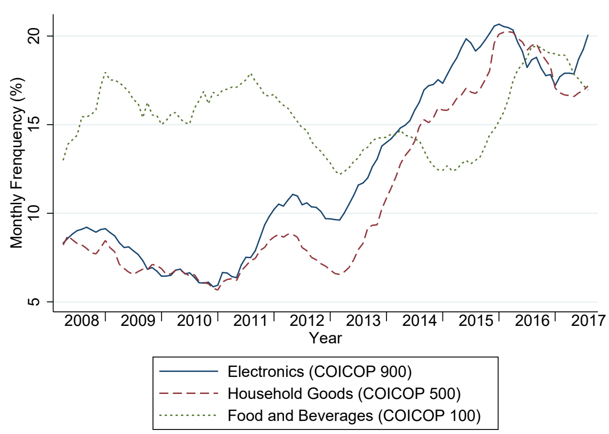

Figure A3: Implied Duration of Price Changes

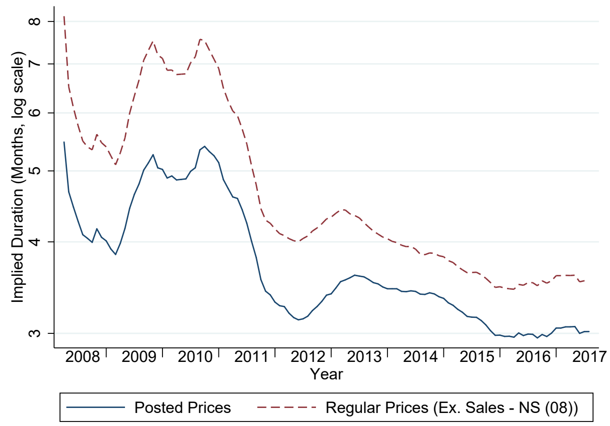

Figure A4: Mean Absolute Size of Price Changes

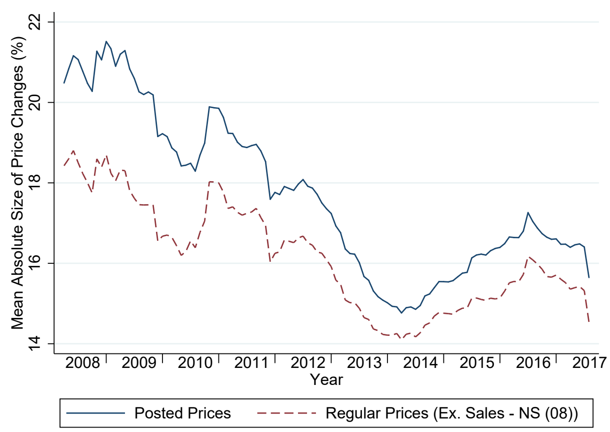

Figure A5: Average Monthly Frequency by Retailer and Sector