More Amazon Effects: Online Competition and Pricing Behaviors

Alberto F. Cavallo

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 United States, 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 United States 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 microprice 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 ("multichannel 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) 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 100 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 multichannel 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 2008-10 to approximately 3.65 months in 2014-17, 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 percent 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), suggesting 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 2016-18 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 multichannel 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 microdata were collected using web-scraping methods from the websites of large multichannel 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 multichannel 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 microdata 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 microdata 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.

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 United States 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. 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.i. 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 United States from 2008 to 2017, when the share of online sales grew from 3.6 percent to 9.5 percent of all retail sales, according to the Census Bureau.[10]

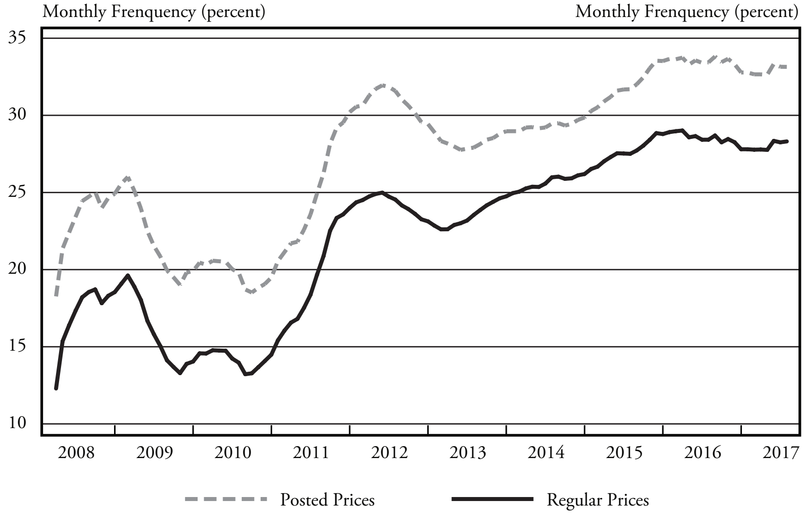
Chart 1 plots the monthly frequency of price changes of large multichannel retailers over time. This is computed as a weighted average of the number of non-zero price changes, divided by the total number of price-change observations, following standard methodologies in the literature. It is first calculated 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]

Panel A of Chart 1 shows that the monthly frequency of *posted* prices increased from 21 percent in 2008-10 to more than 31 percent in 2014-17. 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.

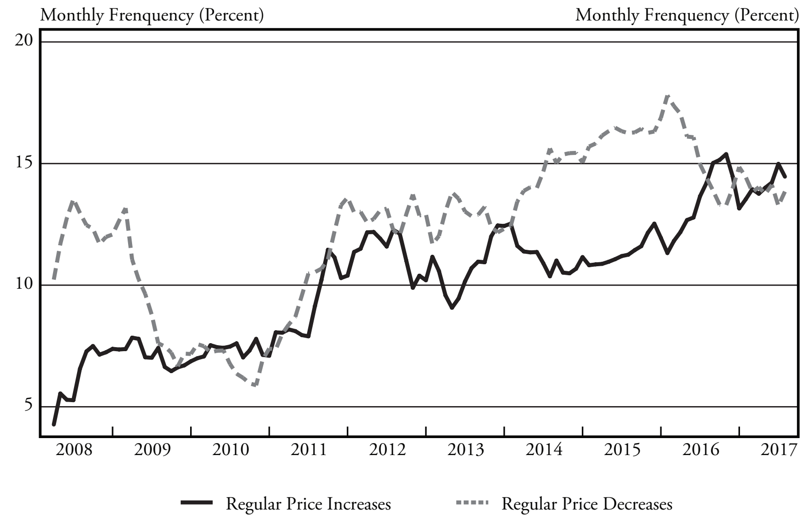
Papers such as Eichenbaum et al. (2011) and Kehoe and Midrigan (2008) argue that sale prices are less relevant for monetary policy, while Kryvtsov and Vincent (2016) find sales to be strongly cyclical in countries like the United States and the U.K. For the purposes of this paper, it is important to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

Chart 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 and Steinsson (2008). This chart shows the 12-month moving average of the monthly frequency. See the appendix for results with alternative sale algorithms.

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 percent in the years 2008-10 to almost 30 percent in 2014-17. The increase in frequency is even greater if I exclude the recession years of 2007-09. Consistent with Vavra (2013), Chart 1A shows a spike in the frequency of price changes in late 2008 and early 2009. Chart 1B 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.

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 2010-12. 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 percent to 15.02 percent. 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 marker 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 percent of total retail sales in 2016—have a much more stable behavior over time.

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

	Period Averages		
	2008-10	2011-13	2014-17
Frequency of Price Changes (percent)	15.43	22.39	27.39
Implied Duration (months)	6.48	4.47	3.65
Frequency of Price Increases (percent)	6.89	10.27	12.49
Frequency of Price Decreases (percent)	8.94	12.12	14.96
Absolute Size of Price Changes (percent)	17.45	16.24	15.02
Size of Price Increases (percent)	18.3	17.09	15.42
Size of Price Decreases (percent)	-16.79	-14.71	-14.02
Share of Price Changes under 1pc	6.59	5.23	8.01
Sales as Share of Price Changes (percent)	4.02	3.98	3.29

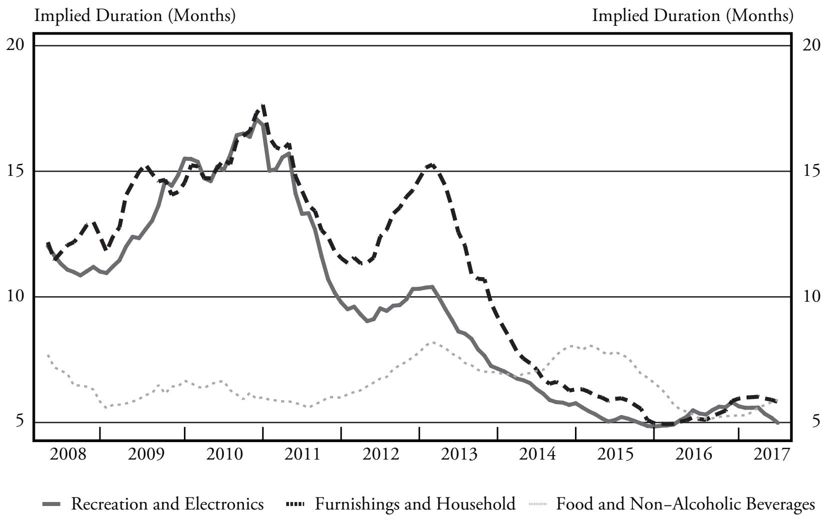
Table 2
Implied Duration of Regular Price Changes by Sector

	Period Averages		
	2008-10 (months)	2011-13 (months)	2014-17 (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 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 Chart 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

Chart 2
Monthly Implied Duration of Regular Price Changes by Sector



with its "Amazon Fresh" platform.[14] According to the U.S. Census Bureau, online sales in food and beverages stores grew 27 percent in 2016, almost twice as fast as the 14 percent estimated for e-commerce as a whole.

III.ii. 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 percent shorter implied durations, with goods "Found on Amazon" having an implied duration of posted

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 and using prices collected from 2016-18. The variable "Found on Amazon" is a dummy that identies 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 three-digit category (for example, COICOP 1.1.1 corresponding to "Bread and Cereals"). Standard errors are in parentheses.

prices that is 5.45 days shorter than the unconditional level of approximately 28 days.[15]

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 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 10 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 more than 85 percent 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 matches the offline price at a randomly chosen location about 72 percent 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 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 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.i. Comparison between Amazon and Multichannel 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 multichannel retailers that sell online in the United States. The data, 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 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 one of three 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).

Panel A of Table 4 shows that Amazon has a high degree of uniform pricing. Prices are identical 91 percent of the time, with an average price difference between stores of only 1.61 percent. 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 multichannel retailers were available only in an average of 22 ZIP codes.

Still, multichannel retailers are not far behind: their share of identical prices is 78 percent, while the average price difference is 5.49 percent. 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 percent of the time, ranging from 66 percent in drugstores to 96 percent 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 percent, 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 percent, while the average price difference nearly doubles to 2.92 percent. By contrast, the prices for electronics have nearly perfect uniform pricing in all the retailers I sampled.

IV.ii. 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

Table 4
Evidence of Uniform Pricing in Large U.S. Retailers

	Share of Identical		Average Price Difference	
	Other Retailers	Amazon	Other Retailers (percent)	Amazon (percent)
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	9,469	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	6,588	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	1,578	191		
Average ZIP Codes	42	100		

"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 5.8 percentage points, from a level of 91 percent to almost 97 percent. A similar result is obtained for the average price difference, which falls by 1.9 percentage points for goods found on Amazon, from about 2.9 percent 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

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: The dependent variables are measured using prices collected from multiple ZIP codes in March 2018. The variable "Found on Amazon" is a dummy that identies 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 three-digit category. Standard errors are in parentheses.

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 percent tends to reduce the share of identical prices by 0.6 percent. Assuming a linear relationship, we need a 10 percentage point difference 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 percent increase in the difference of unemployment would raise the average price difference by about 4 percent.

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 multichannel 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.i. 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:

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

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 sum of the coefficients for two lags of the change in the nominal exchange 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 percent in a single quarter, and it rises from 19 percent to 28 percent for goods that can be easily found on Amazon. The short-run exchange-rate pass-through is 32 percent and rises from 26 percent to 44 percent for products that can be found on Amazon.

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.ii. 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.

Table 6
Short-Run Pass-Through into Walmart's Prices (2016-18)

		Found on Amazon	
	Full Sample	No	Yes
Gas Prices (one quarter)	0.22	0.19	0.28
	(0.02)	(0.02)	(0.03)
Observations	191,690	122,800	68,890
R-squared	0.17	0.17	0.16
Exchange Rate (two quarters)	0.32	0.26	0.44
	(0.03)	(0.04)	(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 three-digit category and reports the contemporaneous (first-quarter) pass-through for gas price changes and the sum of the contemporaneous and first lag (two quarters) of the nominal exchange rate changes. Standard errors are in parentheses.

In Table 7, Panel A, I start by running regression (1) using price indices computed with online data from a large number of multichannel retailers in the United States from 2008 to 2017.[25] One advantage of these data is the large number of multichannel 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 three-digit sectors are included, with the exception of gas price indices.

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 percent to 25 percent. The long-run (eight quarters) effect is higher at 31 percent and also increases over time, from an insignificant 0.04 percent in 2008-12 to a statistically significant 44 percent in recent years.

A major limitation of the regressions in Panel A is that these price indices include nontradables 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

Table 7
Price Sensitivity to Exchange Rates Over Time

		By Period	
	Full Sample	2008-12	2013-17
Panel A: Online U.S. Price Indexes (All goods excluding fuel)			
Short-Run (two quarters)	0.16 (0.05)	0.12 (0.07)	0.25 (0.06)
Long-Run (two years)	0.31 (0.09)	0.04 (0.37)	0.44 (0.12)
Panel B: Matched Relative Prices (two sectors, seven countries)			
Food and 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 multichannel 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.

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):

$$\ln\left(p_{i,t}^{us}/p_{i,t}^{z}\right)=\alpha^{us,z}+\beta\ln\left(e_{t}^{us,z}\right)+\in_{i,t}^{us,z} \qquad (2)$$

where $p_{i,t}^{us}$ denotes the price of good i at time t in the United States, 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 microdata 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 United States, 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 percent versus only 38 percent 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 percent in 2008-12 to 45 percent in 2013-17. Similarly, the pass-through for "Electronics" rises from 79 percent to 91 percent between the same periods.

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 percent in the United States until 2011.[27] The 44 percent long-run pass-through in Panel A for 2013-17 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 multichannel retailers in the United States 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 policymakers 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 that 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 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.

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Appendix

ZIP Codes Selected for Uniform Pricing Data

Using BLS and Census Bureau data, I selected the ZIP codes in each state with the highest and lowest unemployment rates for February 2018 (the last nonpreliminary month of data available at the time the data were merged.) The unemployment data from BLS is available at the county level, so I merged it with a ZIP code county correspondence table from the Census Bureau. 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 ZIP code 02138 (my location) and 98101 (Amazon's Seattle headquarters).

Appendix Tables

Table A1
Behavior of Posted and Regular Prices in Large U.S. Retailers

	Period Averages		
	2008-10	2011-13	2014-17
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
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
A: Gas Prices (one 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)
B: Exchange Rates (two quarters)			
OLS	0.47 (0.03)	0.44 (0.03)	0.52 (0.04)
Fixed Eeffects	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 three-digit category levels.

Appendix Charts

Chart A1
Monthly Frequency of Price Changes with Different Sales Filters

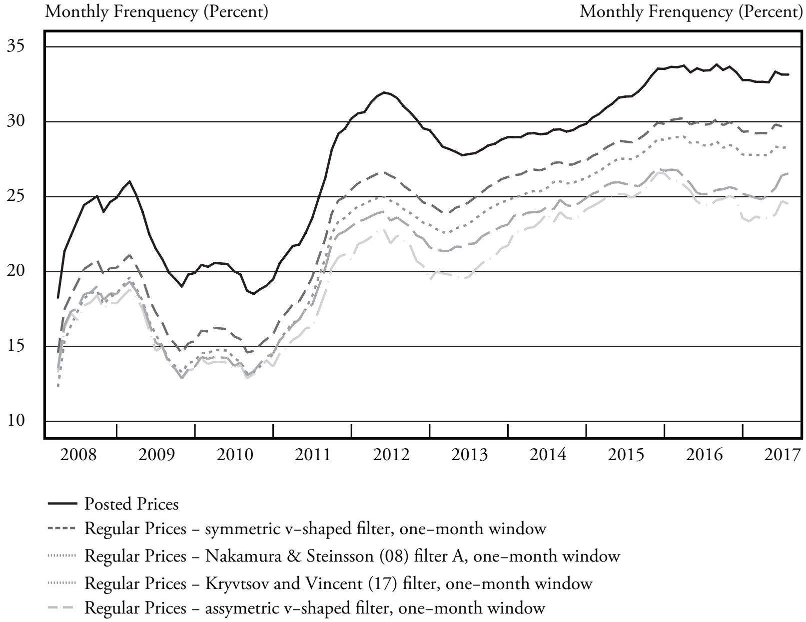


Chart A2
Monthly Frequency of Price Changes by COICOP Sector

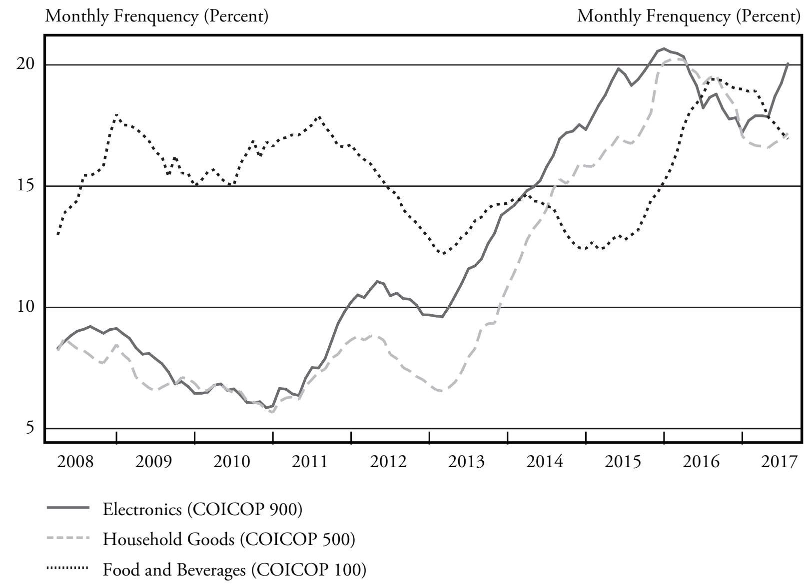


Chart A3
Implied Duration of Price Changes

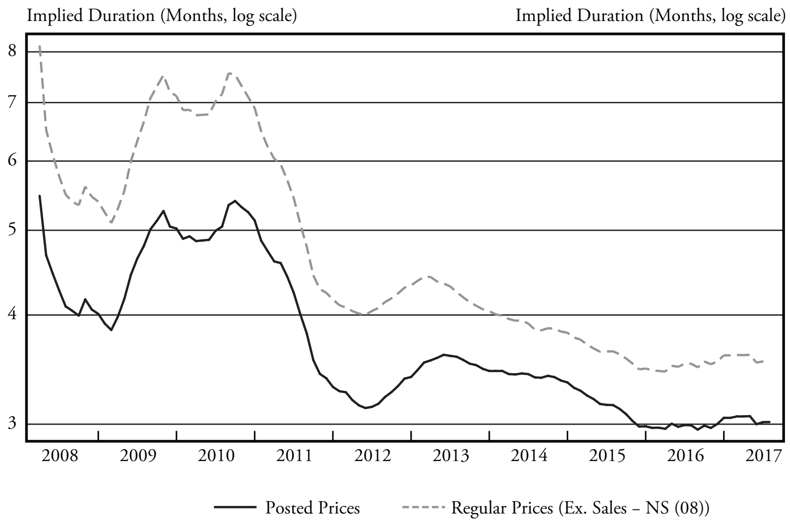


Chart A4
Mean Absolute Size of Price Changes

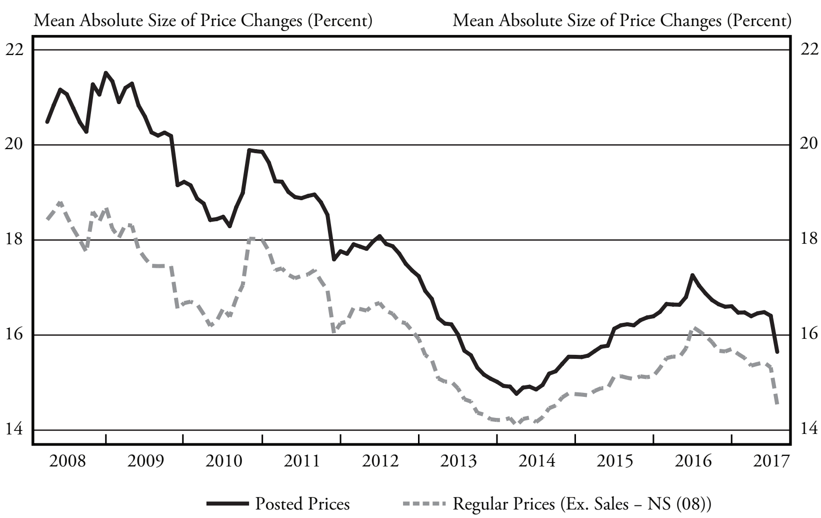
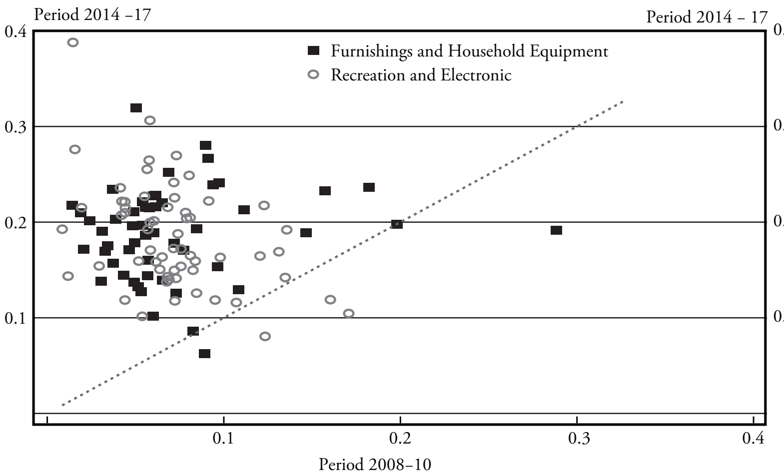


Chart A5
Average Monthly Frequency by Retailer and Sector



Endnotes

[1]See 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.

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

[3]See 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).

[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 three-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 U.S. ELI classification structure.

[5]See Mims (2017).

[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 United States and found a similarly high frequency of price changes.

[7]See Angwin and Mattioli (2012).

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

[9]See 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).

[10]See *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. 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.

[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 appendix Chart A1.

[13]These results are not driven by changes in the composition of retailers sampled over time. Chart 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 also aggressively expanded their online services in recent years.

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

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

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

[18]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.

[19]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).

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

[21]CEA (2015).

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

[23]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 United States and other countries.

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

[25]I 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.

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

[27]Using a different method, Gopinath (2016) reports a long-run CPI pass-through of 0.052 in the United States, a similar number to the one I found for online prices in 2008-12.

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

[29]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 the type of pricing algorithms that can be implemented by online retailers.

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

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Commentary: More Amazon Effects: Online Competition and Pricing Behaviors

Yuriy Gorodnichenko

I. Introduction

The job of a proverbial central banker is supposed to be straightforward: she has one tool (the nominal interest rate) and she must hit one target (2 percent inflation per year). But, of course, it is not so simple in real life. Economies are relentlessly battered by shocks and, thus, a central banker should be constantly tracking ever-changing conditions. Yet, even when central banks are on guard 24/7, they may contemplate more basic questions: What price index should they target and how should they measure their preferred price index? These could appear to be classic academic questions with little bearing for day-to-day policymaking but, in fact, these questions have significant implications in the current economic environment.

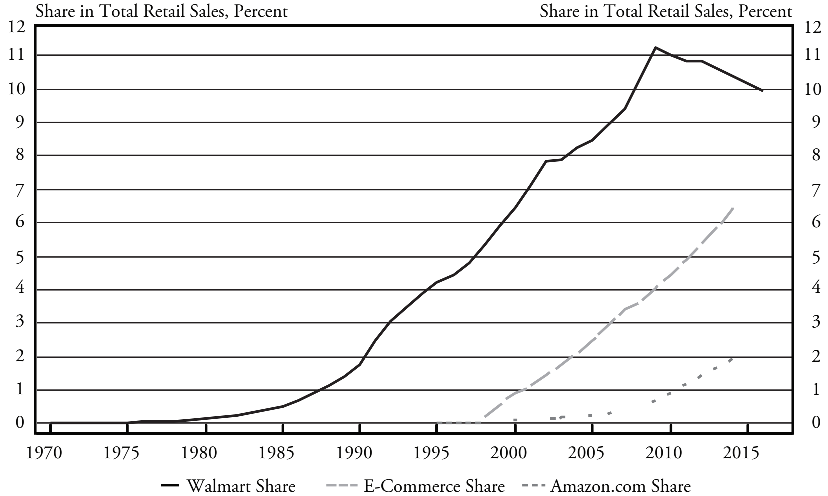
Indeed, the Fed and other central banks in developed countries consistently undershot their inflation targets in recent years thus raising concerns about central banks' ability to deliver on their promises. Furthermore, the record low levels of unemployment and the glaring lack of inflation in the United States appear to undermine the Phillips curve, a central tenet of how monetary policy influences macroeconomic outcomes.

One explanation of these puzzles is that inflation is mismeasured because of changes in the retail sector. Specifically, this theory posits that by offering lower prices, Amazon.com and other e-commerce outlets in the last 10 years or so have exercised a strong downward pressure on prices similar to what was experienced in the 1980s and 1990s with the rising dominance of Walmart and other discount retail chains (Chart 1). Because these changes in the market structure are transitory (i.e., at some point the market share of Amazon.com and similar stores will stabilize), the "underlying" inflation may be higher. In other words, if one removes this one-time "Amazon" effect, some notion of "true" inflation is potentially higher than the current inflation rate and so central banks should not be concerned about the low inflation of recent years. Opponents of this theory, however, may appeal to the findings of the Boskin Commission (see Boskin et al. 1998 for a summary): a rapid expansion of discount stores like Walmart was not properly accounted for in the CPI (due to outlet substitution bias) and, as a result, the CPI overstated inflation by 0.1 percentage point per year. If so, the true inflation now is lower than the CPI inflation suggests.

Although what is the net effect of e-commerce on aggregate inflation remains to be established, we can still learn a great deal from the evolution of pricing behavior of stores facing the likes of Amazon.com to prepare central banks for the maybe not-so-distant future where e-commerce is *the* key force in retail. Alberto Cavallo's paper is an important step in this direction.

I draw two main conclusions from his analysis. First, consistent with earlier studies, he finds that Amazon's prices are a lot more flexible than prices of conventional, brick-and-mortar stores. More importantly, he documents that this forces Walmart (and presumably other traditional retailers) to adjust prices more often for products that are also offered on Amazon.com. As result, via strategic complementarity, Amazon.com can have more influence on how prices are set than is suggested by Amazon.com's market share. This means that consumer prices may be more sensitive to cost shocks than thought before. Second, while traditional retailers have some scope for variation of prices across geographical locations (i.e., a bottle of Pepsi may cost more in

Chart 1
Retail Shares



Notes: The chart reports the share of sales for selected retailers in total retail sales. Shares for Walmart and Amazon.com are computed as the ratio of each company's revenue (reported in Compustat) to total retail sales. Total retail sales and e-commerce retail sales are from the U.S. Census Bureau.

New York than in Detroit), online stores effectively offer the same price across locations thus pushing uniform pricing to the extreme.

This is an excellent paper. Alberto is careful to not venture into speculations about what these facts mean for monetary policy. But my role as a discussant is more permissive and so I will make several claims about why central bankers should care about this paper.

II. More Flexible Prices

New Keynesian economics has long recognized the tremendous heterogeneity in price rigidities across sectors and its implications (Haltiwanger and Waldman 1991, Carvalho 2004, Nakamura and Steinsson 2008). A basic conclusion from this line of work is that central banks should try to target a price index that overweighs sticky prices for two reasons. First, sticky prices incorporate more information about future inflation. Intuitively, "flexible" prices may move rapidly in response to transitory shocks but firms which change their prices less frequently have to be more forward looking in their pricing decisions because they are stuck with chosen prices for a while. At the same time, central banks may have lags in observing price data and monetary policy itself influences the economy only with a lag. Thus, by responding to higher-frequency price changes, a central bank can destabilize rather than stabilize the economy. In contrast, because sticky prices react to more persistent shocks, they provide an operational target (Eusepi et al. 2011). Second, cross-sectional price dispersion, which is the main cost of business cycles in the New Keynesian models, is largely driven by sticky prices (Aoki 2001). As a result, the central bank can improve welfare by stabilizing inflation of sticky prices, which, via strategic complementarity, can also stabilize inflation of flexible prices. Consistent with these insights, central banks often target "core" inflation that excludes commodity (food, energy) prices, which are highly volatile. Relatedly, Eusepi et al. (2011) propose a price index that explicitly weighs sectors by their price stickiness and there are similar alternatives (e.g., the Federal Reserve Bank of Atlanta published Sticky-Price CPI developed by Bryan and Meyer 2010).

What if e-commerce makes consumer prices as flexible as commodity prices?

One can entertain several implications. First, central banks may have to recalibrate their targeted measures of inflation. If pass-through for online prices is as high as it is for food and energy prices, one could imagine that, in the limit, the core inflation measure would become *CPI All Items Less Food, Energy and Amazon*. Relatedly, one may expect that central banks in large, developed countries will have a weaker grip on inflation, especially in the short run, since price dynamics will increasingly be driven by short-run forces outside their control. As a result, central banks in these countries may encounter similar challenges as those faced by central banks in small open economies face (Fraga et al. 2003) and may have more difficulty in establishing or maintaining their credibility.

Second, central banks are constrained in their ability to combat recessions in the current ultra-low interest rate environment. This constraint can be exacerbated by increasingly flexible prices. For example, De Long and Summers (1986) and, more recently, Eggertson and Krugman (2012) argue that price flexibility may be destabilizing. Intuitively, sticky prices can help avoid deflationary spirals: a negative shock pushes prices down but, because prices are not flexible, deflationary pressure is attenuated. Thus, increasingly flexible prices will require countercyclical policy to be more aggressive precisely at a time when central banks have only limited ammunition.

Third, modern New Keynesian models imply that the main cost of inflation is the cross- sectional dispersion of prices. For positive steady state inflation, this dispersion is increasing in price stickiness. Furthermore, the weight on inflation volatility in the second-order approximation of consumer utility is increasing in price stickiness. Therefore, if e-commerce makes prices more flexible, policymakers should care less about inflation and, instead, put a higher weight on the volatility of output.

Finally, the standard New Keynesian model emphasizes pricing frictions as a key mechanism of how changes in nominal interest rates affect the economy. Obviously, there are other channels for how central banks can influence the economy but a move to a flexible-price world would mean that central banks need to rethink their analytical frameworks and change operations.

III. Uniform Pricing

Central bankers are mandated to manage macroeconomic outcomes but, inevitably, regional variation in economic performance enters policy discussions implicitly or explicitly (Coibion and Goldstein 2012, Beraja et al. 2017, Cœuré 2017). Regional variation in prices provides one mechanism to smooth out (at least partially) regional shocks without much input from aggregate policies. Indeed, retailers and manufacturers can vary their profit margins in response to changes in local economic conditions. Consistent with this insight, Beraja et al. (2016) document robust evidence that states with higher unemployment have lower inflation. Uniform pricing, however, limits the scope of this adjustment mechanism: If Detroit is hit hard by a recession relative to other parts of the United States, Amazon.com is unlikely to give a special discount to consumers in Detroit. In theory, other margins of adjustment (wages, migration, etc.) can compensate for uniform pricing. In practice, these margins likely have little power as painfully illustrated by the experience of the eurozone during the 2008 global financial crisis. Even for countries like the United States, these margins may be less active than before. For example, Molloy et al. (2011) and others document that internal migration in the United States fell considerably since the 1980s. Grigsby et al. (2018) report considerable wage rigidities (especially downward, a tangible constraint during downturns). In such an economy, recessions may be prolonged and costly because it takes more time for resources to reallocate.

One potential solution is for monetary policy to be more countercyclical, but this may be difficult given the likely future constraints from the zero bound. An alternative solution is for monetary policy makers to adopt tools that can be more targeted to specific regions, industries, or populations. To this end, Coibion et al. (2018) propose management of expectations as an alternative to conventional policies relying on changes in nominal interest rates. Intuitively, similar to advertising campaigns, communication policies can be tailored to a specific industry/region/population so that the perceived real interest rate moves at a subnational level, a task that is hard to achieve with nominal interest rates alone.

IV. Additional Forces

E-commerce not only changes how firms set prices but also how consumers do their shopping. With some oversimplification, a typical shopping trip for a consumer making purchases in a conventional store can be split in two stages. First, the consumer chooses a store that ex ante offers the best prices for a bundle of goods that the consumer desires. Second, after coming to the chosen store, the consumer adjusts his basket in response to observed prices. Given that consumers buy many things conditional on coming to a store, retailers can use cross subsidies to maximize total profit. A classic strategy for stores in this context is to lure consumers by offering them discounts on some goods and potentially charging high prices on other goods that are bundled with the discounted items.

Internet shopping has a different structure. First, consumers decide what they want to purchase. Second, they search the internet for the best deal. As a result, the ability of stores to bundle goods is more limited. Furthermore, because the search for the best deal online is particularly easy, the elasticity of demand with respect to price becomes high. Indeed, even going from the lowest price to the second lowest price in online markets is associated with a large decline in quantities.[1] As a result, a large market share in e-commerce does not necessarily translate into high markups because consumers are not terribly attached to an online retailer. Consistent with this prediction, profit margins of Walmart (more than 20 percent) are much higher than profit margins of Amazon.com (less than 4 percent).

These patterns have several implications for central banks. First, small markups limit the ability of retailers to absorb cost shocks and so the pass-through for online retailers should be higher. Second, because the Phillips curve in estimated DSGE models is quite flat, most of the variation in inflation is attributed to "markup" shocks. While these shocks should not be interpreted literally as variation in market power, these models may face greater skepticism because large variation in "markups" would be inconsistent with very low levels of price markups in the data (that is, there is little space for variation in markups for online retailers like Amazon.com). Third, greater elasticity of demand typical for online retailers entails greater strategic complementarity which in turn means a flatter Phillips curve.

There are other potential changes in shopping behavior that may be relevant for central banks. For example, the advent of big-box/warehouse stores has led to less frequent shopping trips and more prevalent purchases of goods in bulk (Coibion et al. 2017). As a result, spending inequality measured on short histories of purchases (e.g., the Diary Survey in the U.S. Consumer Expenditure Survey) has been drifting up since the 1980s. Online shopping can reverse this trend as consumers do not have to buy goods in bulk to get disco unted prices. Because the distributional consequences of monetary policy have become more important both in a positive (Coibion et al. 2017, Auclert 2017) and normative (Yellen 2014, Mersch 2014) sense, policy discussions should be cognizant of this potential change in the direction of the trend.

Finally, the emerging prevalence of e-commerce offering low prices can create new opportunities for consumers to switch their shopping outlets over the business cycle. For example, Coibion et al. (2015), Nevo and Wong (2015) and others document that households actively exploit price differentials across stores and "trade down" in recessions (e.g., switch from "Safeway" to "Walmart"). One may predict that this switching will be amplified in the future because switching to an online store is particularly easy. As a result, aggregate "true" inflation may be more cyclically sensitive than suggested by headline CPI inflation. Furthermore, such store switching reduces the weight on inflation volatility in micro-founded New Keynesian models because store switching reduces the cost of price dispersion.

V. Limits of E-Commerce

Although internet offers seemingly unbounded opportunities for retailers and the stock market believes that the future of retail belongs to the likes of Amazon.com, I have several reasons to believe that Amazon.com (and more generally e-commerce) will not take over the world and prices of consumer goods will not be as flexible as commodity prices. First, Cavallo documents that Amazon.com changes the pricing behavior of Walmart. But strategic complementarity is a two-way street: Walmart can slow down Amazon's price changes. Indeed, the conventional New Keynesian wisdom is saying that, in presence of strategic complementarity, flexible-price firms should mimic the behavior of sticky-price firms. Thus, although it is most remarkable that Amazon.com can reverse the flow of causality, one may expect that as long as brick-and-mortar stores remain a fact of our shopping lives, online stores should not deviate too much from conventional retailers characterized by sticky prices. Relatedly, stores selling goods offline *and* online have similar prices offline and online (Cavallo 2017). Hence, as Amazon.com and others move to conventional retail, they may be forced to set their prices in a way that is closer to how prices are set by traditional retailers.

Second, a great appeal of online retail is dynamic pricing, that is, the ability of firms to set prices every instant depending on demand and supply conditions. Indeed, online retailers are uniquely positioned to collect vast amounts of data about consumers and to employ algorithmic pricing at very high frequencies (they do not face physical costs of nominal price adjustment, "menu" costs). A few industries (e.g., airlines and hotels) embraced this opportunity but many industries did not follow the suit. For example, Amazon.com continues to have rather sticky prices of books and other printed media (Boivin et al. 2012) despite having an overwhelming dominance in the market. Furthermore, although online prices change more frequently than prices in conventional stores, early evidence (Gorodnichenko et al. 2018) suggests that online prices are as unresponsive to monetary policy shocks and macroeconomic news shocks as offline prices. In fact, it is rather puzzling why we do not see more dynamic pricing. Perhaps, prices remain sticky because of psychological costs of alienating consumers by breaking implicit price contracts (Blinder 1994, Rotemberg 2011) even if they can change every second.

Third, the logic of internet markets characterized by easy search and absence of classical "menu" costs suggests that we should observe little (if any) price dispersion for a precisely defined good. Indeed, if there is a market where the law of one price must hold, e-commerce is that market. Yet, many studies (e.g., Ellison and Ellison 2009, Gorodnichenko et al. 2014) document that cross-sectional price dispersion for online markets is large and is comparable to that for offline markets. For example, on Aug. 11, 2018, Google Shopping showed that prices (including shipping and taxes) for Samsung Galaxy S9 (64 GB, Midnight Black, Unlocked) varied from $603 to $878 across sellers with reviews (the price at Amazon.com was $680), see Table 1. More generally, by many metrics online markets are as imperfect as offline markets. What determines these surprising patterns is an area of active research.

Fourth, there are exogenous and endogenous barriers for Amazon.com and other online retailers to overtake some markets. For example, many services cannot be delivered over the internet (health care, education, housing, etc.) but they account for roughly a half of consumer spending. Perhaps, some day Amazon.com will find a way to make a flu shot or a haircut with a drone but for now prices in the service sector will likely remain as rigid as they have been in the past. There are also signs that firms attempt to protect themselves from e-commerce

Table 1
Prices for a Specific Product on Google Shopping

Samsung Galaxy S9 - 64 GB – Midnight Black – Unlocked
$634 online ***** 2,907 product reviews

Sellers	Seller Ratings	Details/ Special Offers	Base Price	Total Price
BuyVPC.com	97% positive (200)		$765.98 +$70.85 tax. Free shipping	$836.83
PCNation	96% positive (1,839)		$758.51 +$56.89 tax. Free shipping	$815.40
CompSource	95% positive (655)		$744.75 +$55.86 tax. Free shipping	$800.61
Sam's Club	94% positive (692)		$790.90 +$79.85 tax and $7.60 shipping	$878.35
B&H Photo -Video-Audio + Show all 2	93% positive (188,962)	Used	$633.50 Free shipping. No tax	$633.50
Electronicsforce.com	93% positive (700)		$603.19 Free shipping. No tax	$603.19
BLINQ.com	92% positive (4,858)	Refurbished	$652.99 +$60.40 tax. Free shipping	$713.39
NothingButSavings.com	92% positive (390)		$725.01 +$52.56 tax. Free shipping	$777.57
Best Buy + Show all 2	92% positive (228)		$669.99 +$61.97 tax. Free shipping	$731.96
Newegg.com	88% positive (68,262)		$732.34 +$67.74 tax. Free shipping	$800.08
Walmart + Show all 2	86% positive (1,993)		$699.99 +$64.75 tax. Free shipping	$764.74

Note: Information retreived from website Aug. 11, 2018.

competition. For instance, conventional retailers can have goods sold exclusively by these retailers (e.g., Walmart and Costco use private labels Great Value and Kirkland). One may anticipate that this kind of behavior will be increasingly widespread. Indeed, many manufactures sell exclusively via their online and offline stores (e.g., Apple and IKEA do not sell their products via Amazon.com or other online retailers) which have rather rigid prices (Cavallo et al. 2014).

VI. Concluding Remarks

Walmart reshaped the landscape of retail in the 1980s and 1990s. Now a new revolution in retail is being led by Amazon, eBay, Overstock and other online shops. In this new world, menu costs are negligible, search for best prices is cheap and easy, and the geographical location of consumers and stores is largely irrelevant. Undoubtedly, these characteristics of e-commerce will make prices more flexible and more uniform across locations, although consumer prices will not converge in their properties to commodity prices. What does this mean for central banks?

My tentative analysis suggests several predictions. First, monetary policy should be more aggressive in combatting recessions. Second, central banks should likely put a higher weight on volatility of output as more flexible prices lead to smaller distortions in the allocation of resources. Third, holding everything else constant, inflation will likely become more volatile and cyclically sensitive, more dominated by transitory shocks, and potentially move difficult to control in the short run. Fourth, central banks will possibly need to redefine their targets and operations to respond to the evolving nature of price setting in the retail sector. Perhaps, central banks will need to develop new tools to make their policies more targeted.

Of course, these changes will not happen overnight but central banks will be well advised to prepare themselves early on. Indeed, despite the growing importance of e-commerce, the properties of online prices are still relatively understudied. Somewhat surprisingly, efforts to collect online price data are largely confined to individual academics like Cavallo but this kind of endeavor requires considerable investment and institutional support. Since statistical agencies appear to show little appetite to gather price quotes and volumes of sales for e-commerce, central banks should fill in this void. Having such data will help us better understand the nature of online markets and adjust policies accordingly.

Author's Note: I thank Oli Coibion for comments on an earlier version of this discussion.

Endnote

[1]The European Commission (2014) finds that 74 percent of all shoppers in the European Union use internet comparison tools to compare prices and find the cheapest price.

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General Discussion: More Amazon Effects: Online Competition and Pricing Behaviors

Chair: Lisa D. Cook

Ms. Evans: A really interesting paper. My question goes to the nature of the data. I think from what you said you're scraping websites and essentially getting the sticker price, not the realized price the consumer pays which would incorporate things like free shipping, coupon codes, rewards programs, etc. In a sense, that doesn't matter, since you're looking at volatility. But if those change over time, or if they vary by geography, then it could really change your results, right? My question is about the nature of the prices. Is it sticker price, does it incorporate all these other things, and if not, how do you think that impacts your results?

Mr. Williams: I've got a couple of comments picking up on Yuriy Gorodnichenko's comments. One is when we talk about inflation measures, when thinking about monetary policy, an important thing to remember is goods make up a little less than a third of consumer spending. So we tend to talk a lot about the thing that we can measure, and the things that are changing, but services make up about two-thirds of consumer spending in the PCE price index. I wouldn't extrapolate so much from goods prices, in terms of inflation measures and monetary policy.

And second, my conclusion is a little different than Yuriy's. I wouldn't think about excluding things. I think the right way to think about it is the way we actually do think about it, which is like the trimmed mean inflation rate which takes out naturally the things that are volatile. I mean, that's just a pretty much neutral way to deal with the issue, that over time there's a change in the frequency that prices change. Similarly the New York Fed has a measure that basically underweights goods and services where the prices change more quickly. So we do have these price indices and we use them regularly. And what's nice about them is that over time, as these developments continue, these measures, I think, will capture that, as opposed to trying to come up with a new measure that excludes Amazon or something. But this is a terrific paper.

Mr. Spriggs: When you're looking at the price changes that quickly, are you also giving us some clues as to what we may be doing wrong with the CPI anyway? John Williams just mentioned one issue, which is it's very dominated by housing. Many of us have a problem because of that because housing prices are driven by people at the high end of the income distribution and therefore give a misleading picture of what inflation is really doing if you're thinking about medium people. But your indication of this quick price convergence, are you able to detect the other problem that people think, which is that people quickly go to the lower price of some sort of option, and this response on the part of consumers would mean that the current way that we estimate the CPI is probably off? We're really overestimating inflation because now consumers can react much quicker to lower price alternatives.

Ms. Gopinath: I think this is a terrific paper in terms of the wealth of data that is being brought to this question, and I can see there are many more papers coming out that compare online prices and brick-and-mortar-store prices. My question/kind of concern would be about the measures that you have of exchange rate pass-through. You report a number like 44 percent into these retail prices and you said these seem similar to at the dock prices. But the reason for my skepticism is the following. One is that you're looking at all prices and these are not just imported goods. So the pass-through that you're looking into in retail prices is not just the goods that are being imported from outside, but these include domestic prices. So the U.S. imports of GDP is over 15 percent. The 44 percent number seems really large. One possible reason for that could be that besides exchange rates, you don't have any other cost control in there, and I think it would be useful if you put in a few more of those controls to absorb the effect.

Mr. Carstens: Excellent paper. For monetary policy, a key issue is the pass-through, even with more countries now having a flexible exchange rate. I will be very interested in hearing your answer to Gita Gopinath's question, but I have two additional questions on pass-through. Did you find if the pass-through response is symmetric to appreciation and depreciation? And second, in terms of the frequency of price adjustments, is the exchange rate development symmetric? Do Amazon and others adjust their prices with the same frequency when the currency appreciates as when it depreciates?

Mr. Cavallo: Thank you Yuriy for the discussion, it was very thorough. And thank you for all your questions. I will try to answer most of them. The coupons I get are the ones that apply to all consumers. When you see an item on sale, and it applies to everyone, that is something I can observe in my data. But if people have personalized coupons or loyalty cards, that is not in my data, just like it is not on the CPI data either. You are right that the frequency of that personal coupons over time could have an impact on some my results and the way we measure inflation. I will say though, for example, some of the facts like uniform pricing—there's a paper by Levine and Gentzkow looking at scanner data that does incorporate personal coupons and loyalty discounts, and they also find that there's pervasive uniform pricing even when you include them.

John Williams raises a great point. I am not claiming this applies to services. One nice thing that could be done with these data is to improve those estimates of flexible versus sticky price indexes that you mentioned. Those are calculated by taking the sectors that are considered to be flexible or sticky based on past data in academic works. We can improve them by measuring those sectoral estimates more frequently. I think it would be even better if we can take every category of goods and say: these are the individual goods that are flexible, these are the ones that are sticky, and then build indices that can split the data at a finer level of disaggregation.

On the question about the CPI: in this paper I am not trying to solve the CPI's measurement problems. I do have other work where I discuss how this type of data could help us in things like quality adjustments. You specifically pointed out the fact that people may substitute to other goods. Pete Klenow has a very interesting paper where he uses online data and also quantities and he makes specifically the point that if you take into account quantities, our measured inflation changes. But my data only has price information.

Gita, I think you are absolutely right. There are a lot of domestic goods here and relatively few controls. I am working on another paper that will look specifically at the level of the pass-through estimates, and try to see whether these high numbers are driven by the type of data or the way that I am measuring pass-through. I hope that I will have answers soon, and this also applies to the question by Agustín Cartens: I do not have any results to give you about the symmetry at this stage. Still, I want to highlight that my goal in this paper was to show how pass-through is changing over time, and connect it to the increase in the frequency of price changes. So while changing the regression affects the measured level of pass-through, it does not affect the finding that it has increased significantly over time.

Mr. Haltiwanger: You actually kind of partly touched upon where I wanted to go. I wanted to bring up the work of Redding and Weinstein who really have emphasized recently the importance of having the P and the Q data, and particularly they would argue that they built what they called the Unified Price Index and it differs dramatically from standard price indices with a huge product variety effect, turnover effect, and consumer valuation bias. And my sense is those terms would be very sensitive to what you are talking about today. So basically, do you think, if we're going to take into account the effects that you are talking about, we need the P and the Q data to be able to figure out quantitatively. And it's also the case, even just a more limited question, you did need to use weights in various parts of your paper today and those weights are pretty crude. So the question is how sensitive do you think your results are to those weights?

Mr. Fischer: This was really a very interesting and very impressive work. How much work is being done on the transformation from this to policy? We heard lots of adjectives in the description, but is there anything in which a model is being set out and your estimates are used, and if something changes by "x" percent, there is some parameter in policy that ought to change by "y" percent? Do we have that worked? Does somebody have an example of that? Because you can see this thing working by having an appendix which is, what does this do to policy, and just stick the things in and outcomes. Be a heck of a lot more wide awake for what's happening to the cost of the university education for example. Thanks.

Ms. Forbes: I want to expand on one of your findings, which I think is very important, but which you passed over quickly, and which could appear to contradict the conventional wisdom. That is your finding that pass-through has increased over time in the United States. This would have first-order implications for thinking about inflation dynamics and monetary policy. The conventional wisdom cited by people in this literature, however, is that pass-through has actually decreased over time around the world. So what's going on? Where is this disconnect? The conventional wisdom is true. If you look at cross-country data, pass-through has decreased over time. But if you look under the covers, which we learned is important yesterday, and break out composition effects, the decrease in pass-through around the world has occurred entirely in emerging markets. Inflation has come down in emerging markets, inflation volatility has fallen in emerging markets, and both of those trends are correlated with a large fall in pass-through. But in advanced economies you have instead seen an increase in pass-through. Now you have provided a potential explanation of why this has occurred. I think this is potentially very important and it also makes us think differently about the conventional wisdom that pass-through has fallen.

Ms. Boone: I have two very quick comments. The first—and forgive me for saying that from a European standpoint—it is very U.S. focused. I was wondering whether you have the database on the capacity of running such data for China or for Europe, but it's particularly China I guess where the development is even higher. And similarly, a comment to Yuriy, who I'm not really sure I fully understand what you are suggesting for monetary policy when you highlight that there will be less geographical prices variation. I understood, but correct me if I'm wrong, that you were suggesting that monetary policy should adapt to the fact that geographical price were less of an indicator. This reminded me very much of what's happening in Europe where I think we tend to think that we should look at prices in aggregate and not use monetary policy to particularly target those price fluctuations which are local or rather national, that the proper policy to address that is fiscal policy.

Mr. Blinder: I want to join the praise for the paper. It's a really fascinating paper. First, a very simple, straightforward question. Your basic time series graph at the end shows a big dip that looks like a recession. That's not what we're measuring there, but I'm just wondering if you have any idea of what in the world happened there? Second, near the end of your presentation, you talked about an idea that you hear a lot from businesses about they don't want to antagonize their customers. You were using that idea spatially—that we didn't want customers to find out it costs less in Detroit and more in Cleveland. I'm thinking about the same idea in a time series context, about the deltas. The survey that I and co-authors conducted decades ago, which you mentioned, quizzed a lot of companies on price changes. When we asked them why they didn't change more frequently, the answer often was—and this is a time series dimension—that we don't want to antagonize our customers. That idea was not where we started. We started with theories that came out of the academic literature, and that was not one of them. But when we pre-tested the questionnaire in the field, we found company after company saying that. And I am wondering whether you think that's disappearing because of the online influence?

Mr. Frenkel: I find Cavallo's paper stimulating and interesting. I would like to make a point that relates the degree of pass-through to the credibility of the monetary authority. Typically, in high-inflation countries, in which the credibility of the central bank is very low, a change in the exchange rate is transmitted immediately into prices. Thus, a nominal depreciation of the currency does not improve competitiveness (the real exchange rate) since the pass-through into higher prices and wages is immediate. In contrast, when the credibility of the central bank is high, a depreciation of the currency does not get transmitted immediately into prices and wages since the credible monetary authority is expected to take actions preventing the translation of exchange rate changes into prices. This would be the case in countries which follow an inflation targeting strategy with credibility. The data employed by Cavallo applies to the United States, which is categorized by low inflation. It would be interesting to apply Cavallo's approach to other cases, in which inflation is high and explore the dependence between the degree of pass-through and the credibility of the monetary authority.

Mr. Furman: Three points. The first is a potentially testable implication which is we know the Phillips curve is very strong across MSAs. You could look at how that strength has changed over time because this would say it should have become less strong over time. Second, I'm a little bit puzzled at how this fits in with the big puzzle we all have which is that the Phillips curve has become more horizontal. This would seem to imply the Phillips curve has become more vertical at the national level, and I wanted to know what you think about that. Then the third, I don't think it's hugely important, but in terms of a causal identification of the Amazon effect, you don't know if the products that Amazon lists are ones that change price more frequently versus it having a causal effect and how would you try to instrument or sort that question out?

Ms. Cook: I'll take the chair's prerogative and ask my own question, and I'll pile on with respect to pass-through. So, Brynjolfsson and Liu have this paper that says that eBay's exports have increased by 17.5 percent due to AI in translation search costs being reduced. So, how would this change how you think about monetary policy and its effectiveness with respect to Jacob Frenkel's comments related to declining versus increasing pass-through?

Mr. Cavallo: Thank you, I will have to limit some of my answers due to the time. In the case of John Haltiwanger and his question on weights: what I can tell you is I have used weights at the level that are published by the BLS. If I look at very narrow categories, I still find these effects, so I don't necessarily think it' going to change much if we had better weights. But it will be interesting to try to combine these online data with scanner datasets to see how much individual product weights matter.

Stanley Fisher asked about use of this data for policy, particularly in modelling applications. I do not think online data is currently being used much in this context. I am certainly hoping that this conference will help me convince other people to start using this for policy type of analysis that you are proposing.

Then on pass-through, Kristin Forbes is right. I think the conventional wisdom is that pass-through has been decreasing. In this particular paper there are many things I am abstracting from, including the nature of shocks and how they have changed over time, which is something Kristin has recently written about. I am instead trying to identify one structural parameter that usually tends to move very slowly, but that I think the Amazon competition is now affecting a lot: the frequency of price adjustments. In many of our models, if you increase the frequency, no matter the assumptions we make or the shocks that we have, we can expect to see more pass-thorough. That is my point so far. The question on the level or nature of pass-through in different conditions is certainly something that I hope to work more in the future.

For the question about China, if we look at those scatterplots with preliminary results across categories and countries, I do find a significant increase in the frequency of changes for electronics in China. But there's certainly a lot more work that I need to do on the international dimension.

Alan Blinder asked about the big dip in the frequency of price changes around 2010. I believe the anomaly is actually the increase in the frequency that we see at the beginning of my sample, in 2008 and 2009. In the paper, you can see estimates for both price decreases and increases. The rise in overall frequency in those two years is entirely driven by more flexible price decreases, which is something we would expect to happen during a recession. So my interpretation is that the frequency went back to normal in 2010, back to a level which closely resembles what previous papers found using historical CPI data. There is clearly a limitation here: I do not have data before 2008. On the question about antagonizing customers, I think you are right. If you take my results literally, people today are not antagonized when they see prices changing very frequently over time. Maybe Amazon has played a role in changing perceptions of fairness in pricing frequency. You can also think of the example of Uber or Lyft and how transportation prices were set in the past. It used to be a case of we were expecting prices to be always the same, regardless of whether it rained or not. Now we have become used to the idea that it makes sense for these companies to increase their prices during a storm. I believe the perception of fairness is affected by experience, and that is why in the paper I argue that we need to look at other sectors and countries to understand how this happens.

In response to Jacob Frenkel, I agree that the credibility of the central bank is important but it is not something I have explored much here. In the appendix I have removed the crisis years and then split the sample again from 2011 to 2017, and I find very similar results. But there's definitely a lot to learn from the comparison with other countries in the future.

Finally, Jason Furman asked about the horizontal Phillips curve. This is related to something Yuriy mentioned in his discussion. He has a paper where he shows that retailers do not change their prices quickly in response to policy announcements. This is likely because the retailers are not interested in the announcement per se, but rather on the actual observable change in demand and costs that they experience. My results suggest that retailers will adjust their prices quickly when those changes occur. In other words, the explanation for the horizontal Phillips Curve and the lack of inflation today is not that prices are sticky: they are in fact getting more flexible over time. Instead, I believe it has more to do with the types of shocks that some of these retailers are experiencing, such as the falling gas prices and the dollar appreciation that I discussed today, as well as other factors such as wage stickiness which I have not addressed in this paper.