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Price Setting in Online Markets: Does IT Click?

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Abstract:
Using a unique dataset of daily U.S. and U.K. price listings and the associated number of clicks for precisely defined goods from a major shopping platform, we shed new light on how prices are set in online markets, which have a number of special properties such as low search costs, low costs of monitoring competitors' prices, and low costs of nominal price adjustment. We document that although online prices are more flexible than offline prices, they nevertheless exhibit relatively long spells of fixed prices, large size, and low synchronization of price changes, considerable cross-sectional dispersion, and low sensitivity to predictable or unanticipated changes in demand conditions. Qualitatively, these patterns are similar to those observed for offline prices, a finding that suggests a need for more research on the sources of price rigidities and dispersion.

JEL Classifications: E3

Keywords: online markets, prices, price dispersion

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1 Introduction

Internet firms such as Google, Amazon, and eBay are revolutionizing the retail sector, as there has been an explosion in the volume and coverage of goods and services sold online. In 2013, Amazon alone generated $74.5 billion in revenue—approximately the revenue of Target Corporation, the second largest discount retailer in the United States—and carried 230 million items for sale in the United States—nearly 30 times the number sold by Walmart, the largest retailer in the world. While virtually nonexistent 15 years ago, e-commerce sales stood at $263.3 billion and accounted for 5.6 percent of total retail sales in the U.S. economy in 2013. The rise of e-commerce has been truly a global phenomenon. Between 2006 and 2011, the average annual growth rate of global online retail sales was 13 percent (A.T. Kearney 2012), and global e-commerce sales are expected to reach $1.4 trillion by 2015 (Cisco 2011). While visionaries of the internet age are utterly bold in their predictions, one can already exploit special properties of online retail, such as low search costs, low costs of monitoring competitors' prices, and low costs of nominal price adjustment, to shed new light on some perennial questions in economics and the workings of future markets.

We use a unique dataset of daily price listings for precisely defined goods (at the level of unique product codes) from a major shopping platform (SP) to examine price setting practices in online markets in the United States and the United Kingdom, two countries with a developed internet retail industry. This dataset covers an exceptionally broad spectrum of consumer goods and sellers over a period of nearly two years. Importantly, we have the number of clicks for each price listing, giving us a measure of how relevant listings are for consumers. We document a number of stylized facts about the properties of online prices (frequency of price adjustment, price synchronization across sellers and across goods, size of price changes) and compare our findings to results reported for price data from conventional, brick-and-mortar stores. Similarities or differences in the properties of prices across online and offline stores inform us about the nature and sources of sluggish price adjustment, price discrimination, price dispersion, and many other important dimensions of market operation.

Our main result is that online prices (especially prices with a large number of clicks) are more flexible than prices in conventional stores. Yet, the difference in the properties of prices across internet and brick-and-mortar stores is quantitative rather than qualitative. That is, despite the power of the internet, the behavior of online prices is consistent with smaller but still considerable frictions, thus calling into question the validity of popular theories of sticky prices and, more generally, price setting. By some metrics, prices of goods sold online could be as imperfect as prices of goods sold in regular markets.

Specifically, we find that, despite small physical costs of price adjustment, the duration of price spells in online markets is about 7 to 20 weeks, depending on the treatment of sales. While this duration is considerably shorter than the duration typically reported for prices in brick-and-mortar stores, online prices clearly do not adjust every instant. The median absolute size of a price change in online markets, another measure of price stickiness, is 11 percent in the United States and 5 percent in the United Kingdom, comparable to the size of price changes in offline stores. Sales in online markets are about as frequent as sales in conventional stores (the share of goods on sale is approximately 1.5–2 percent per week) but the average size of sales (10–12 percent or less in the United States and 6 percent or less in the United Kingdom) is considerably smaller. We use rich, cross-sectional variation of market and good characteristics to analyze how they are related to various pricing moments. We find, for example, that the degree of price rigidity is smaller when markets are more competitive; that is, with a larger number of sellers, the frequency of price changes increases and the median size decreases.

Although the costs of monitoring competitors' prices and the costs of search for better prices are extraordinarily low in online markets, we observe little synchronization of price changes across sellers, another key statistic for non-neutrality of nominal shocks. In particular, the synchronization rate is approximately equal to the frequency of price adjustment, suggesting that by and large online firms adjust their prices independently of their competitors. Even over relatively long horizons, synchronization is low. We also fail to find strong synchronization of price changes across goods within a seller; that is, a typical seller does not adjust prices of its goods simultaneously. Finally, we document that the synchronization rates of sales across goods for a given seller and across sellers for a given good are similar to the frequency of sales.

In line with Warner and Barsky (1995), we find some evidence that prices in online stores respond to seasonal changes in demand during Thanksgiving and Christmas, which is similar to the behavior of prices in regular stores. We also show that there is large variation in demand, proxied by the number of clicks, over days of the week or month. For example, there are 33 percent more clicks on Mondays than on Saturdays. Yet, online prices appear to have little, if any, reaction to these predictable changes in demand, a finding that is inconsistent with the predictions of Warner and Barsky (1995). We also do not find strong responses of online prices to the surprise component in macroeconomic announcements about aggregate statistics such as the gross domestic product (GDP), consumer price index (CPI), or unemployment rate. These findings are striking because online stores are uniquely positioned to use dynamic pricing (that is, instantaneously incorporate information about changes in demand and supply conditions).

We document ubiquitous price dispersion in online markets. For example, the standard deviation of log prices for narrowly defined goods is 23.6 log points in the United States and 21.3 log points in the United Kingdom. Even after removing seller fixed effects, which proxy for differences in terms of sales across stores, the dispersion remains large. We also show that this high price dispersion cannot be rationalized by product life cycle. Specifically, a chunk of price dispersion appears at the time a product enters the market and price dispersion grows (rather than falls) as the product becomes older. Price dispersion appears to be best characterized as spatial rather than temporal. In other words, if a store charges a high price for a given good, it does so consistently over time rather than alternating the price between low and high levels. In addition, price dispersion can be related to the degree of price stickiness, intensity of sales, and returns to search.

To underscore the importance of clicks, we also calculate and present all moments weighted by clicks. Such weighting tends to yield results consistent with a greater flexibility of online markets relative to conventional markets: price rigidities decline, cross-sectional price dispersion falls, synchronization of price changes increases. For example, using weights reduces the median duration of price spells from 7–12 to 5–7 weeks. Yet, even when we use click-based weights, online markets are far from completely flexible.

Comparing prices in the United States and the United Kingdom offers additional insights.[1] High penetration of online trade in the two countries is largely due to availability of credit cards, a history of mail order and catalogue shopping, and an early arrival of e-retailers, such as Amazon and eBay. Yet, there are important differences between the two markets. For example, population density is eight times higher in

[1]In 2011, the value per head of business-to-consumer (B2C) e-commerce in the United Kingdom was £1,083, up 14 percent from £950 in 2010, making it the leading nation in terms of e-commerce; see Ofcom (2012).

the United Kingdom than in the United States; thus, it is easier to organize fast and frequent deliveries in the United Kingdom. We find that, despite the differences between the markets, price setting behavior is largely the same in the two countries.

Although e-commerce has been growing rapidly, there are only a few studies that focus on price adjustment in the sector. The data used in these studies typically cover a limited number of consumer goods in categories that feature early adoption of e-trade, such as books and CDs (Brynjolfsson and Smith 2000), or span a short period of time, usually not exceeding a year (Lünnemann and Wintr 2011). In spite of increasing efforts to scrape more and more prices online to broaden data coverage (Cavallo and Rigobon 2011, Cavallo 2012, Cavallo, Neiman, and Rigobon 2014), we are aware of just one dataset that contains information on the quantity margin.[2] In contrast, the SP data used in this paper combine broad coverage of consumer goods with information on the number of clicks each price quote received at the daily frequency for almost two years, a degree of data coverage that has not been within the reach of researchers in the past.

High-quality data for online prices are not only useful to estimate price rigidity and other properties of price adjustment in online commerce but also allow comparing the behavior of prices online and offline. Empirical studies on price stickiness usually document substantial price rigidity in brick-and-mortar retail stores (Klenow and Kryvtsov 2008, Nakamura and Steinsson 2008, Klenow and Malin 2010). Theoretical models explain it with exogenous time-dependent adjustment (Taylor 1980, Calvo 1983), menu costs (Sheshinski and Weiss 1977, Mankiw 1985), search costs for consumers (Benabou 1988, 1992), costs of updating information (Mankiw and Reis 2002), or sticker costs[3] (Diamond 1993). However, none of these explanations appears plausible for online markets, where costs of monitoring competitors' prices, search for a better price, or adjusting a price quote on a platform are significantly smaller. Yet, we observe a fair amount of price stickiness in online markets.

Why prices are sticky is important for real effects of nominal shocks. For example, in the standard New Keynesian model with staggered price adjustment, nominal shocks change relative prices and, hence, affect real variables (Woodford 2003).[4] On the other hand, Head et al. (2012) construct a model with price stickiness coming from search costs that delivers monetary neutrality. Overall, our results suggest that standard macroeconomic models of price rigidities, which emphasize menu costs and search costs, are likely incomplete. We do indeed observe more flexible prices in online markets, where these costs are much smaller, but qualitatively the behavior of online prices is similar to the behavior of offline prices. Since popular mechanisms rationalizing imperfect price adjustment in traditional markets do not fit well with e-commerce, more research is required to understand sources of price rigidities and dispersion.

The rest of the paper is structured as follows. The data are described in the next section. Section 3 provides estimates of the frequency, synchronization, and size of price changes and sales and compares them to pricing moments in brick-and-mortar stores. Section 4 examines properties of price dispersion in online markets. This section also explores how product entry and exit are related to observed price dispersion

[2] Baye et al. (2009) use data from the Yahoo! Kelkoo price comparison site to estimate the price elasticity of clicks. They document significant discontinuities in click elasticity at the minimum price in the PDA market. Their data cover 18 models sold by 19 different retailers between September 2003 and January 2004.

[3] That is, inability of firms to change the price for inventories.

[4] In this model, price stickiness, in addition, leads to inflation persistence that is inherited from the underlying process for the output gap or marginal cost. Modifications of this model that include shocks to the Euler equation, indexation of price contracts, or "rule-of-thumb" behavior give rise to intrinsic inflation persistence; see Fuhrer (2006, 2010).

and other pricing moments. Section 5 looks at the variation of prices over time, including conventional sales seasons and days of the week and month, and then focuses on price responses to macroeconomic shocks at high frequencies. Concluding remarks are in Section 6.

2 Data

We use data[5] from a leading online shopping platform on daily prices (net of taxes and shipping costs) and clicks for more than 50,000 goods in 22 broadly-defined consumer categories in the United States and the United Kingdom between May 2010 and February 2012. This dataset is a stratified random sample of observations with at least one click per day obtained directly from the shopping platform; hence, it is reliable and unlikely to have measurement error associated with scraping price observations from the internet. Broad product coverage allows us to expand our understanding of how online markets work, which up until now has been shaped largely by data on electronics, books, or apparel. Moreover, as a good is defined at the unique product level, similar to the Universal Product Code (UPC), this dataset is comparable to those used in the price-stickiness literature (for example, scanner data) and therefore allows us to compare price setting in online and brick-and-mortar stores. Having a large sample of sellers (more than 27,000), we can look at price setting through the lens of competition between stores, analyze price dispersion across them, and examine the effect of market characteristics on price adjustment. Next, since the data are recorded at a daily frequency, we can study properties of prices at high frequencies. Last and foremost, information on clicks can be used to focus on products that are relevant for online business. Unfortunately, we do not have information on actual sales, local taxes, shipping costs, names of sellers, or sellers' costs. Although the sample period is long relative to previous studies of online markets, it is not long enough to accurately measure store entry and exit, product turnover, or price behavior at longer horizons. Overall, we use the most comprehensive dataset on online prices made available to researchers by a major online shopping platform.

Shopping Platform The shopping site that donated the data is a huge and growing price comparison platform, which utilizes a fully commercialized product-ads system and has global operational coverage (including countries such as Australia, Brazil, China, the Czech Republic, France, Germany, Italy, Japan, the Netherlands, Spain, Switzerland, the United Kingdom, and the United States). Information available to consumers on the platform includes a product description and image, the number of reviews, availability, and minimum price across all participating stores. Consumers are also offered an option to browse other items in the same product category. Information about sellers—name, rating, number of reviews, base price, total price with tax and shipping cost, and a link to the seller's website—is located below the description. The on-screen order of the sellers is based on their quality rank (computed using reviews, click-through rate, etc.) and the bid price per click. Consumers can sort the sellers by the average review score, base price, or total price. The platform also provides information (but not the price) about nearby brick-and-mortar stores that offer the same product.

The seller specifies devices, language, and geographical location where the ad will appear, as well as a cost-per-click bid and maximum daily spending on the ad. The seller may be temporarily suspended if

[5] All tables and figures in this paper are based on proprietary data, provided on condition of nondisclosure, unless specified otherwise.

Table 1. Data Coverage

Category	United States: Number of Goods (1)	United States: Number of Sellers (2)	United Kingdom: Number of Goods (3)	United Kingdom: Number of Sellers (4)
Media	14,370	3,365	14,197	1,136
Electronics	7,606	8,888	7,693	2,967
Home and Garden	5,150	6,182	5,311	1,931
Health and Beauty	4,425	3,676	4,425	1,362
Arts and Entertainment	2,873	2,779	2,945	963
Hardware	2,831	3,200	2,770	1,042
Toys and Games	2,777	3,350	3,179	1,073
Apparel and Accessories	2,645	2,061	2,761	797
Sporting Goods	2,335	2,781	2,392	950
Pet Supplies	1,106	1,241	1,145	295
Luggage and Bags	1,077	1,549	1,037	679
Cameras and Optics	978	2,492	978	842
Office Supplies	849	1,408	792	651
Vehicles and Parts	575	1,539	620	390
Software	506	1,041	545	593
Furniture	334	1,253	338	408
Baby and Toddler	160	654	169	301
Business and Industrial	67	324	48	116
Food, Beverages, and Tobacco	67	174	69	97
Mature	43	385	30	20
Services	26	119	50	112
Not Classified	*1,976*	*3,465*	*1,273*	*1,039*
Total	***52,776***	***27,308***	***52,767***	***8,757***

Source: Authors' calculations based on proprietary data, provided on condition of nondisclosure.

daily spending reaches the cap or the monthly bill is not paid on time. Remarkably, there is no explicit cost of an impression (a listing display) or a price change! The seller pays for clicks only—although there is an implicit cost of having a low click-through rate (number of clicks divided by number of impressions) associated with an increase in the bid price required to reach the same on-screen position in the future. The SP's rules represent both opportunities (no direct costs) and limitations (bad reviews or low click-through rate if unsuccessful) of price experimentation on the platform and, overall, favor dynamic pricing. The seller's information set consists of the number of clicks for a given period, the number of impressions, the click-through rate, the average cost per click, the number of conversions (specific actions, such as purchase on the seller's website), the cost per conversion, and the total cost of the ad—all are available through the seller's ad-campaign account. The SP explicitly recommends that its sellers remove ads with a click-through rate smaller than 1 percent in order to improve their quality rank (which can be monetized through a lower bid price for the same on-screen rank in the future).

Coverage The sample covers 52,776 goods sold across 27,308 online stores in the United States and 52,767 goods across 8,757 stores in the United Kingdom in 2,055 narrowly defined product categories, which are aggregated into 22 broad categories (for example, costumes, vests, and dresses are subcategories in "Apparel and Accessories," while hard drives, video cards, motherboards, and processors are subcategories in "Electronics"). Importantly, this dataset includes not only electronics, media, and apparel (categories studied before), but also product categories that have not been studied before, such as home and garden equipment, hardware, or vehicles. A list of broad product categories, together with the corresponding number of sellers and goods, is provided in Table 1. Some key results presented in this paper are available at the category level in the appendix.

Notation We use p_{ist} and q_{ist} to denote the price and number of clicks, respectively, for good i offered by seller s at time t. Time is discrete, measured with days or weeks, and ends at T, the last day (week) observed. We denote the set of all goods, all sellers, and all time periods as $\mathscr{G} = \{1, \ldots, N\}$, $\mathscr{S} = \{1, \ldots, S\}$, and $\mathscr{T} = \{1, \ldots, T\}$, respectively, with N being the number of goods in the dataset and S the number of sellers. Subscripts i and s indicate a subset (or its cardinality) that corresponds to a given good or seller. For instance, $N_s \leq N$ is the number and $\mathscr{G}_s \subseteq \mathscr{G}$ is the set of all goods sold by seller s, while $S_i \leq S$ is the number and $\mathscr{S}_i \subseteq \mathscr{S}$ is the set of all sellers that offer good i. We denote averages with a bar and sums with the corresponding capital letter—for example, $\bar{p}_{is} = \sum_t p_{ist}/T$ is the average price charged by seller s for good i over the entire sample period and $Q_{it} = \sum_{s \in \mathscr{S}} q_{ist}$ is the total number of clicks that good i received across all sellers in week t.

Aggregation We use the number of clicks as a proxy for sales, at least partially bridging the gap between the studies of online markets, which do not have such information, and brick-and-mortar stores, which use quantity or sales weights to aggregate over products. We find that a relatively small number of products and sellers on the SP obtain a disproportionately large number of clicks. To emphasize the difference between price-setting properties for all products and sellers (available for scraping) and those that actually generate some activity on the user side, we employ three different weighting schemes to aggregate the frequency, size, and synchronization of price changes, as well as cross-sectional price dispersion, over goods and sellers. First, we compute the raw average, with no weights used. Second, we use click weights to aggregate across sellers of the same product but then compute the raw average over products. We refer to this scheme as within-good weighting. Third, we use clicks to aggregate across both sellers and products (referred to as between-good weighting). More specifically, let f_{is} be, for example, the frequency of price changes for good i offered by seller s, and Q_{is} the total number of clicks. The three aggregate measures (denoted by $\bar{f}$, $\bar{f}^{\mathrm{w}}$, and $\bar{f}^{\mathrm{b}}$, respectively) are computed as follows:

$$
\begin{aligned}
\bar{f} &= \sum_i \frac{1}{N} \sum_s f_{is} \frac{1}{S}, \\
\bar{f}^{\mathrm{w}} &= \sum_i \frac{1}{N} \sum_s f_{is} \cdot \underbrace{\frac{Q_{is}}{\sum_s Q_{is}}}_{\substack{\text{within-good} \\ \text{weights}}}, \qquad (1) \\
\bar{f}^{\mathrm{b}} &= \sum_i \underbrace{\frac{\sum_s Q_{is}}{\sum_i \sum_s Q_{is}}}_{\substack{\text{between-good} \\ \text{weights}}} \cdot \sum_s f_{is} \cdot \underbrace{\frac{Q_{is}}{\sum_s Q_{is}}}_{\substack{\text{within-good} \\ \text{weights}}}.
\end{aligned}
$$

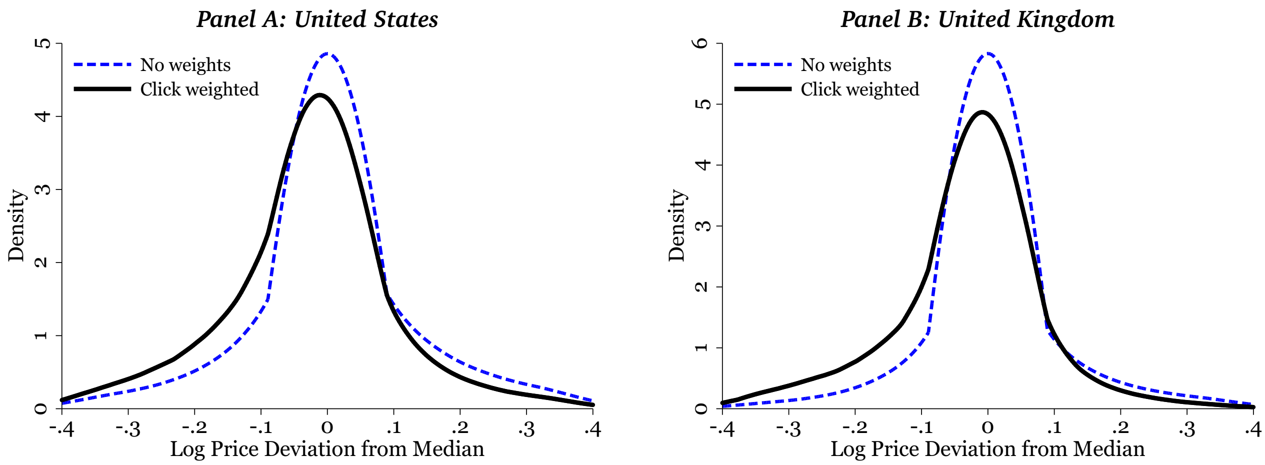
Empirically, the difference between $\bar{f}$ and $\bar{f}^{\mathrm{w}}$ is often much smaller than the difference between either of them and $\bar{f}^{\mathrm{b}}$, as many products have only one seller. However, the within-good weighting appears more important if we look only at products with a sufficiently large number of sellers. We use $\bar{f}^{\mathrm{b}}$ as our preferred measure, since it is the closest among the three to the corresponding brick-and-mortar measure and incorporates information on the relative importance of goods in the consumption basket of online shoppers.

Table 2. Distribution of Prices, local currency

	Mean Log Price		Mean Price					
	Mean (1)	Standard Deviation (2)	5th Percentile (3)	25th Percentile (4)	Median (5)	75th Percentile (6)	95th Percentile (7)	Number of Goods (8)
				Panel A: United States				
No weights	3.37	1.53	4	11	25	71	474	
Within-good weights	3.37	1.53	4	11	24	70	466	52,776
Between-good weights	4.15	1.51	7	22	61	192	852	
				Panel B: United Kingdom				
No weights	3.13	1.56	3	8	19	57	381	
Within-good weights	3.13	1.56	3	8	19	56	377	52,767
Between-good weights	3.82	1.44	5	17	48	134	473	

Notes: Columns (1)–(2) show moments of the distribution of the average (for a good) log price, $\overline{\log p_i}$, Columns (3)–(7) of the average price, $\bar{p}_i$, and Column (8) the total number of goods, N.

Figure 1. Price Distribution and Clicks



Notes: The blue dashed line shows the distribution of the log price deviation from the median across sellers, and the black solid line shows the between-good click-weighted distribution of that deviation.

Price Distribution Table 2 reports percentiles of the distribution over goods of the average price for a good, $\bar{p}_i$, together with the mean and the standard deviation of the average log price, $\overline{\log p_i}$. The median good in the sample costs around \$25 in the United States and £19 in the United Kingdom. About a quarter of goods cost \$11 or less; products that cost \$100 or more represent around 20 percent of the sample. Goods that obtain more clicks tend to be more expensive: the median price computed using the between-good weights is \$61 and £48 in the United States and the United Kingdom, respectively.

To illustrate the importance of clicks for measuring prices effectively paid by consumers, for each good we compute the average (over time) log deviation of the price of seller s, p_{ist}, from the median price across sellers, $\widetilde{p}_{it}$:

$$\bar{\rho}_{is} = \frac{1}{T} \sum_t \log\left(p_{ist}/\widetilde{p}_{it}\right). \tag{2}$$

Figure 1 plots the density of deviations without weights and with the between-good weights based on the number of clicks, Q_{it}. Applying the weights shifts the distribution to the left by approximately 10 percent; that is, sellers with price substantially below the median product price receive a larger number of clicks.

3 Price Stickiness

Price-adjustment frictions should be smaller for online stores than for brick-and-mortar stores. For example, changing the price does not require printing a new price tag and is therefore less costly. In a similar spirit, consumers can compare prices across retailers without leaving their desks (smaller search costs). As a result, we should observe a higher frequency and smaller size of price changes in online markets. At the same time, lower costs of monitoring competitors' prices should lead to a higher synchronization of price changes across sellers and across goods, thus diminishing nominal non-neutrality. This section challenges these conjectures by showing that online markets are not that different from their conventional counterparts after all.

3.1 Regular and Posted Prices

Previous work (see Klenow and Malin 2010 for an overview) emphasizes the importance of temporary price cuts ("sale prices") for measuring the degree of price rigidities. However, Eichenbaum, Jaimovich, and Rebelo (2011) point out that sale prices carry little weight at the aggregate level because they likely represent a reaction to idiosyncratic shocks. Hence, we make a distinction between posted prices (that is, prices we observe in the data) and regular prices (that is, prices that exclude sales).

In contrast to scanner data, our data set does not have sales flags and therefore we use filters as in Nakamura and Steinsson (2008), Eichenbaum, Jaimovich, and Rebelo (2011), and Kehoe and Midrigan (2012) to identify temporary price changes.[6] We consider a price change to be temporary if the price returns to its original level within one or two weeks. As the dataset contains missing values, we identify sales with and without imputation. Consider the following price series: {\$2, n.a., \$1, \$2}, where "n.a." denotes missing values. In the "no imputation" case, we assume that "n.a." breaks the price series so that we have one series of consecutive observations {\$2} and another series of consecutive observations {\$1, \$2}. In this case, there is one "regular" price change from \$1 to \$2 in the second series because \$1 is not preceded by \$2. In the "imputation" case, we drop "n.a." and consider {\$2, \$1, \$2} as the time-series.[7] In this case, there is one period with a sale price (the price temporarily falls from \$2 to \$1 and then returns to the initial level of \$2) and there are no regular price changes. We report statistics for the two assumptions separately.

Table 3 reports the frequency and size of sales. In the United States, the mean weekly frequency of sales (columns 1 and 5), without weights, is in the range of 1.3–2.2 percent, depending on the filter. This weekly frequency is comparable to the frequency of sales reported for prices in regular stores. There is substantial heterogeneity in the frequency across products: we do not find sales in more than a half of the products (see column 3). When we focus on goods that receive more clicks (use between-good weights), sales occur more often: the mean frequency is 1.7–2.7 percent depending on computation technique. The median size of sales is 10.5–11.9 percent with equal weights and 4.4–5.3 percent with between-good weights. These sizes are smaller than the size of sales in regular stores (about 20–30 percent). Using our "imputation" procedure for missing values tends to generate a higher frequency and size of sales. The magnitudes are

[6] We use both ∨- and ∧-shaped filters to account not only for temporary price cuts but also for temporary price increases (for example, due to stockout).

[7] In this example, our "imputation" filter drops one "n.a." value. In practice, our filters for "n.a." values can drop up to five missing values.

Table 3. Frequency and Size of Sales

	One-Week Filter				Two-Week Filter				
	Mean Freq. (1)	Standard Deviation (2)	Med. Freq. (3)	Med. Size (4)	Mean Freq. (5)	Standard Deviation (6)	Med. Freq. (7)	Med. Size (8)	Number of Goods (9)
Panel A: United States									
No Imputation									
No weights	1.3	3.1	0.0	10.5	1.9	3.9	0.0	10.5	10,567
Within-good weights	1.5	3.2	0.0	4.8	2.2	4.1	0.0	5.4	10,567
Between-good weights	1.7	1.9	1.4	4.4	2.6	2.5	2.2	4.8	10,567
With Imputation									
No weights	1.6	3.5	0.0	11.9	2.2	4.2	0.0	11.9	21,452
Within-good weights	1.8	3.7	0.0	5.2	2.6	4.4	0.0	5.8	21,452
Between-good weights	1.9	1.9	1.6	4.7	2.7	2.4	2.4	5.3	21,452
Offline Stores	1.9	*n.a.*	*n.a.*	29.5					
Panel B: United Kingdom									
No Imputation									
No weights	0.9	2.9	0.0	5.7	1.3	3.7	0.0	5.7	4,464
Within-good weights	1.0	3.0	0.0	2.3	1.5	3.8	0.0	2.6	4,464
Between-good weights	1.3	1.7	1.0	2.5	1.8	2.3	1.4	2.9	4,464
With Imputation									
No weights	1.1	3.3	0.0	6.2	1.6	4.0	0.0	5.9	10,754
Within-good weights	1.2	3.4	0.0	2.2	1.7	4.1	0.0	2.5	10,754
Between-good weights	1.4	1.8	1.0	2.5	2.0	2.4	1.5	3.2	10,754
Offline Stores	0.3	*n.a.*	*n.a.*	7.0					

Notes: Column (1) reports the average weekly frequency of sales across goods (percent), Column (2) the standard deviation of the frequency across goods, Column (3) the frequency for the median good, and Column (4) the absolute size of sales for the median good measured by the log difference between the sale and regular price (multiplied by 100). In all the four columns, we identify sales using the one-week, two-side sale filter (see the text). Columns (5)–(8) report the same statistics for the two-week sale filter. Column (9) reports the number of goods. The statistics for offline stores are from Nakamura and Steinsson (2008) for the U.S. and Kryvtsov and Vincent (2014) for the U.K.; the mean frequency is converted to the weekly rate.

Table 4. Synchronization of Sales

	Across Sellers of the Same Good			Across Goods by the Same Seller		
	Mean (1)	Standard Deviation (2)	Median (3)	Mean (4)	Standard Deviation (5)	Median (6)
Panel A: United States						
No Imputation						
No weights	0.8	5.2	0.0	2.1	9.6	0.0
Within-good (-seller) weights	1.0	6.3	0.0	2.4	11.4	0.0
Between-good (-seller) weights	1.8	4.7	0.2	2.1	1.0	2.4
With Imputation						
No weights	1.1	6.6	0.0	2.7	10.8	0.0
Within-good (-seller) weights	1.2	7.0	0.0	2.6	11.0	0.0
Between-good (-seller) weights	1.6	3.7	0.3	2.2	1.1	2.7
Panel B: United Kingdom						
No Imputation						
No weights	1.0	6.4	0.0	2.7	11.1	0.0
Within-good (-seller) weights	1.1	7.3	0.0	2.9	12.7	0.0
Between-good (-seller) weights	1.3	3.2	0.0	2.3	5.8	2.0
With Imputation						
No weights	0.8	5.5	0.0	3.7	14.2	0.0
Within-good (-seller) weights	0.8	5.7	0.0	3.7	14.7	0.0
Between-good (-seller) weights	1.9	5.3	0.1	2.1	3.4	2.1

Notes: Column (1) reports the mean synchronization of price changes across sellers, Column (2) the standard deviation of this measure across goods, and Column (3) the synchronization for the median good. Columns (4)–(6) report the same statistics for the synchronization of price changes across goods.

similar for the United Kingdom.

We also report the degree of synchronization of sales (across sellers for a given good or across goods within a given seller), which can be informative about the nature of sales.[8] For example, sales could be strategic substitutes (low synchronization) or complements (high synchronization), they could be determined by seller-specific factors (low synchronization) or aggregate shocks (high synchronization).[9] We find (Table 4) that the synchronization of sales across sellers is below 2 percent in each country. The synchronization of sales across goods within a seller is less than 3 percent in the United States and 4 percent in the United Kingdom. Because the degree of synchronization is similar to the frequency of sales, we conclude that synchronization of sales is low.

3.2 Frequency and Size of Price Changes

Frequency We compute the frequency of price adjustment per quote line as the number of nonzero price changes divided by the number of observed price changes.[10] This measure is then aggregated to the good level. Based on the frequency of price adjustment, we also compute the implied duration of price spells under the assumption of constant hazards. Specifically, let $\varphi_{ist} = \mathbb{I}\{q_{is,t} > 0\}\mathbb{I}\{q_{is,t-1} > 0\}$ be the indicator function whether a price change (either zero or not) is *observed*, $\Pi_{is} = \sum_t \varphi_{ist}$ the number of observed price changes per quote line, and $\chi_{ist} = \mathbb{I}\{|\Delta \log p_{ist}| > 0.001\}$ the indicator function for a nonzero price change. Then, the frequency of price adjustment per quote line is the number of nonzero price changes divided by the number of observed price changes,

$$f_{is} = \frac{\sum_t \chi_{ist}}{\Pi_{is}}. \tag{3}$$

We aggregate this measure to the good level by taking the raw, $\bar{f}_i$, and click-weighted, $\bar{f}_i^{\mathrm{w}}$, average across quote lines with at least five observations for a price change:

$$\bar{f}_i = \frac{1}{\sum_{s\in\mathscr{S}_i} \mathbb{I}\{\Pi_{is} > 4\}} \sum_{s\in\mathscr{S}_i} f_{is}\mathbb{I}\left\{\Pi_{is} > 4\right\}, \tag{4}$$

$$\bar{f}_i^{\mathrm{w}} = \frac{\sum_s f_{is}\mathbb{I}\left\{\Pi_{is} > 4\right\}Q_{is}^{\varphi}}{\sum_s \mathbb{I}\{\Pi_{is} > 4\}Q_{is}^{\varphi}}, \tag{5}$$

where $Q_{is}^{\varphi} = \sum_t q_{ist}\varphi_{ist}$. The former measure is referred to as "no weights" and the latter as "within-good weights." The "between-good" measure reports the distribution across goods of $\bar{f}_i^{\mathrm{w}}$ with $W_i = Q_i^{\Pi}/\sum_{i\in\mathscr{G}} Q_i^{\Pi}$ used as weights, where $Q_i^{\Pi} = \sum_{s\in\mathscr{S}_i} \mathbb{I}\{\Pi_{is} > 4\}Q_{is}^{\varphi}$. The implied duration of price spells is then computed

[8] We define the sale synchronization rate as the mean share of sellers that put a particular product on sale when another seller of the same good has a sale. In particular, if B is the number of sellers of good i and A of them have sales, the synchronization rate is computed as $(A-1)/(B-1)$. See Section 3.4 for more details.

[9] Guimaraes and Sheedy (2011) propose a model of sales that are strategic substitutes. Alternatively, Anderson et al. (2013) present evidence that sales are largely determined by seller-specific factors and best described as being on "autopilot" (not related to aggregate variables and not synchronized).

[10] This measure is analogous to the one used by Bils and Klenow (2004), Klenow and Kryvtsov (2008), and Nakamura and Steinsson (2008). In line with Eichenbaum, Jaimovich, and Rebelo (2011), price changes smaller than 0.1 percent are not counted as price changes. We exclude quote lines with fewer than five observations.

Table 5. Frequency and Size of Price Changes

	No Imputation			With Imputation			
	No Weights (1)	Within Weights (2)	Between Weights (3)	No Weights (4)	Within Weights (5)	Between Weights (6)	Offline Stores (7)
Panel A: United States							
Posted Price							
Median frequency, percent	14.0	16.7	19.3	7.2	9.3	16.3	4.7
Implied duration, weeks	6.6	5.5	4.7	13.4	10.2	5.6	20.8
Median absolute size, log points	11.0	10.7	11.2				10.7
Regular Price							
Median frequency, percent	8.8	10.8	14.5	6.3	8.0	13.5	2.1
Implied duration, weeks	10.9	8.7	6.4	15.5	12.1	6.9	47.1
Median absolute size, log points	10.9	10.6	10.9				8.5
Panel B: United Kingdom							
Posted Price							
Median frequency, percent	12.8	13.0	20.0	5.9	5.9	17.0	4.6
Implied duration, weeks	7.3	7.2	4.5	16.5	16.4	5.4	21.2
Median absolute size, log points	5.1	5.0	8.5				11.1
Regular Price							
Median frequency, percent	7.7	7.7	15.8	5.0	5.1	14.7	3.2
Implied duration, weeks	12.5	12.5	5.8	19.5	19.3	6.3	30.7
Median absolute size, log points	5.0	4.9	7.6				8.7

Notes: Column (1) reports the frequency and size of price changes when missing values are dropped and no weights are applied. Columns (2) and (3), instead, aggregate using within- and between-good weights, respectively. Columns (4)–(6) report the analogous statistics when missing values are imputed (if the next available observation is within four weeks and there is no price change). Column (7) shows the corresponding statistics from Nakamura and Steinsson (2008) for the U.S. and Kryvtsov and Vincent (2014) for the U.K., converted to the weekly frequency. Regular prices are identified using the one-week filter for sales.

as

$$\bar{d}_i = -\frac{1}{\ln\left(1-\bar{f}_i\right)}. \tag{6}$$

The first two rows in each panel of Table 5 show the estimated frequency of price changes and the corresponding implied duration. In the United States, the median implied duration of price spells varies from 7 to 13 weeks when no weights are applied, from 6 to 10 weeks when weights across sellers are applied, and from 5 to 6 weeks when we use weights across sellers and goods. When we apply the one-week sale filter, the duration of price spells increases by 15–60 percent. The magnitudes are similar for the United Kingdom. We also find that the frequency of price increases is approximately equal to the frequency of price decreases (see Appendix).

Price spells for online stores appear significantly shorter than for brick-and-mortar stores (by one-third for posted prices and by two-thirds for regular prices). However, with spells of up to four months, online prices are far from being completely flexible, pointing toward price-adjustment frictions other than the conventional nominal costs of price change. At the same time, goods that receive a large number of clicks have more flexible prices—with the average duration of only 5–7 weeks for regular and posted prices.

Size Using our notation in the previous section, we can write the average absolute size of price changes for good i as follows:

$$\overline{\left|\Delta \log p_i\right|} = \frac{1}{\sum_{s\in\mathcal{S}_i}\sum_t \chi_{ist}} \sum_{s\in\mathcal{S}_i}\sum_t \left|\Delta \log p_{ist}\right| \cdot \chi_{ist}. \tag{7}$$

Next, let $Q_i^\chi = \sum_{s\in\mathscr{S}_i}\sum_t q_{ist}\chi_{ist}$ be the total number of clicks when a nonzero price change occurs. The within-good weighted average of this measure can be written as

$$\overline{\left|\Delta\log p_i\right|}^{\mathrm{w}} = \sum_{s\in\mathscr{S}_i}\sum_t \underbrace{\frac{q_{ist}\chi_{ist}}{Q_i^\chi}}_{\substack{\text{within-good}\\ \text{weights}}} \left|\Delta\log p_{ist}\right|. \tag{8}$$

Finally, the between-good weighted results are based on the weighted distribution of $\overline{|\Delta\log p_i|}^{\mathrm{w}}$ with weights $W_i = Q_i^\chi / \sum_{i\in\mathscr{G}} Q_i^\chi$, implemented in a similar fashion as for the frequency of price adjustment.

The last row of each panel in Table 5 reports the absolute size of price change. In the United States, online sellers change their prices on average by 11 percent. This magnitude is remarkably stable and close to that for brick-and-mortar stores. The fact that online sellers adjust their prices more often than their offline counterparts but by roughly the same amount indicates the presence of implementation costs of price change. Incidentally, regular and temporary changes are approximately of the same size. In the United Kingdom, the size of price change is smaller (approximately 5 percent), but it approaches the U.S. statistics when between-good weights are applied (8.5 percent). Price decreases are slightly smaller (in both countries) and more frequent (in the United States) than increases (see Appendix).

3.3 Do Prices Change Mostly during Product Substitution?

Nakamura and Steinsson (2012) emphasize that product substitution is potentially an important margin of price adjustment and that focusing on goods with short product lives and no price changes can overstate the degree of price rigidity ("substitution bias"). In the context of online prices, Cavallo, Neiman, and Rigobon (2014, henceforth, CNR) scraped price data from selected online retailers (Apple, IKEA, H&M, and Zara) and documented three facts related to the substitution bias: (1) most products do not change their prices throughout the lifetime (77 percent in the U.S. sample); (2) the median duration of product life is short (15 weeks); and (3) products that live longer are more likely to have at least one price change (a product observed for more than two years is 39 percentage points more likely than the average product to have at least one price change).

To assess the importance of product substitution for measurement of price rigidities in online markets, we first compute the share of products with a constant price over their lives and compare these products to products with at least one price change. In the United States, 11.9 percent of goods have a constant price within their life span (column 1 of Table 6)—this is significantly lower than 77 percent found by CNR. Moreover, goods with no price change account for only 1 percent of total clicks. When we look at products in apparel that are offered by one seller only (hence, a sample of goods that is more similar to those in H&M or Zara), the share of goods with no price changes rises to 31 percent and the corresponding share of clicks to 26 percent (column 3). When we further remove jewelry and watches, which represent a large share of "apparel and accessories" in our data but are not key for H&M and Zara, the magnitudes further increase to 42 and 31 percent, respectively (column 5). We observe a similar pattern in the United Kingdom. Hence, the prevalence of goods with no price changes in the CNR data appears to be determined by their sample of goods and sellers.

In the next step, we compare (Table 6) goods with and without price changes along four dimensions:

Table 6. Price Adjustment and Product Substitution

	All Products		Apparel, One Seller		—excl. Jewelry and Watches	
	Constant Price (1)	Price Changes (2)	Constant Price (3)	Price Changes (4)	Constant Price (5)	Price Changes (6)
Panel A: United States						
Share of goods, percent	11.9	88.1	31.0	69.0	42.4	57.6
Share of clicks, percent	1.3	98.7	25.7	74.3	30.8	69.2
Average number of clicks per quote	1.5	1.7	1.5	1.4	1.7	1.7
Average number of price quotes	9.1	12.2	8.6	10.7	7.7	10.6
Average number of sellers	1.3	5.1	1.0	1.0	1.0	1.0
Duration of product life, weeks	36.2	57.2	27.9	37.4	22.3	30.3
nontruncated observations only	32.2	43.3	24.7	34.0	20.5	27.1
Total number of goods	3,119	23,060	192	428	78	106
Panel B: United Kingdom						
Share of goods, percent	17.0	83.0	29.5	70.5	34.1	65.9
Share of clicks, percent	3.3	96.7	25.5	74.5	34.3	65.7
Average number of clicks per quote	1.8	1.7	1.4	1.3	1.6	1.4
Average number of price quotes	8.7	10.8	8.0	9.6	8.3	8.9
Average number of sellers	1.2	3.4	1.0	1.0	1.0	1.0
Duration of product life, weeks	28.5	45.3	24.5	34.4	19.0	27.4
nontruncated observations only	26.0	35.7	21.1	29.9	15.8	23.8
Total number of goods	2,467	12,005	142	340	61	118

Notes: The table compares the sample of goods with a constant price (odd-numbered columns) and goods with at least one price change (even-numbered columns). Columns (1) and (2) are for the entire sample, Columns (3) and (4) for products in "apparel and accessories" that have only one seller (like those in H&M and Zara), and Columns (5) and (6), in addition, exclude jewelry and watches. Only quote lines with five or more price quotes are considered. To compare, the share of products with any price changes in Cavallo, Neiman, and Rigobon (2014) is 23 percent for the entire U.S. sample (21 percent for H&M and 3 percent for Zara).

Table 7. Price Stickiness by Duration of Product Life

	No Weights				Click Weighted				
	Frequency, percent			Duration	Frequency, percent			Duration	
Duration of Product Life	Mean (1)	Standard Deviation (2)	Median (3)	of Spells, weeks (4)	Mean (5)	Standard Deviation (6)	Median (7)	of Spells, weeks (8)	Number of Goods (9)
Panel A: United States									
Less than six months	18.4	22.9	11.9	7.9	19.6	17.8	17.1	5.3	1,262
Six months to a year	17.8	18.7	13.6	6.8	18.2	13.4	16.4	5.6	1,961
More than one year	17.9	17.4	14.1	6.6	18.1	11.4	17.0	5.4	1,593
Panel B: United Kingdom									
Less than six months	22.6	29.2	11.1	8.5	19.6	23.0	14.3	6.5	988
Six months to a year	20.7	25.5	12.1	7.7	18.8	17.5	16.8	5.5	912
More than one year	19.8	21.6	12.5	7.5	19.7	14.3	20.7	4.3	459

Notes: Columns (1)–(3) report the mean, standard deviation, and median frequency of price adjustment across goods with a specified duration of life, Column (4) the corresponding implied duration of price spells, Columns (5)–(8) the same statistics with between-good click weights, and Column (9) the number of goods.

(1) the average number of clicks for a price quote; (2) *observed* duration of product life; (3) the number of price quotes with a click; and (4) the number of sellers. While these two groups of goods are similar in terms of (1), we see considerable differences in all other dimensions. In the United States, goods with at least one price change, on average, span over 57 weeks, have 12 price quotes, and 5 sellers as opposed to 36 weeks, 9 quotes, and 1 seller for goods with no price changes.[11] The U.K. data look remarkably similar in this regard. Hence, goods with no price changes have a smaller duration of life (similar to the results in CNR) and are more likely to be sold by just one retailer (hence, the difference between this paper and CNR).

Finally, to establish the relationship between observed price stickiness and duration of product life, we compare the frequency of price adjustment and the duration of spells for goods with nontruncated product lives (that is, goods which appear for the first time after our sample period starts and exit the market before

[11] We find similar results when we exclude goods with truncated entry/exit. See Appendix Table F1.

the end of our sample period). We find (Table 7) that, in our sample, the frequency of price changes is similar across the bins of goods with different product lives. Hence, there is little support in the data for the idea that product life is a major determinant of price rigidity. Specifically, although products that live longer are more likely to have their price changed within their life span, this pattern is not due to a higher per-period probability of price change for these goods.

3.4 Synchronization

Measurement To measure the extent to which stores change prices simultaneously, we define the synchronization of price changes across sellers as the mean share of sellers that change the price for a particular good when another seller of the same good changes its price. In other words, if A is the number of sellers of good i that change their prices at time t and B is the number of all sellers of good i at t, the synchronization rate is $(A-1)/(B-1)$, provided $A>0$ and $B>1$. The synchronization rate ranges between zero (no synchronization) and one (perfect synchronization). More formally, the synchronization rate, $\bar{z}_i$, for good i is computed as the time average of nonmissing values of

$$z_{it} = \frac{\left(\sum_{s\in\mathscr{S}_{it}} \chi_{ist}\right)-1}{S_{it}-1}, \tag{9}$$

where $S_{it} = \#\mathscr{S}_{it} \leq S$ is the number of sellers and $\chi_{ist} = \mathbb{I}\{|\log p_{ist}| > 0.001\}$ is the indicator function for a price change.

This measure of synchronization assigns equal weights to all sellers. To the extent that online markets have lots of inactive fringe sellers, this measure can understate the degree of synchronization among main players. To address this potential problem, we consider the following within-good, click-weighted measure of synchronization of price changes:

$$z_{it}^{\mathrm{w}} = \frac{\left(\sum_{s\in\mathscr{S}_{it}} q_{ist}\chi_{ist}\right)-\bar{q}_{it}^{\chi}}{\left(\sum_{s\in\mathscr{S}_{it}} q_{ist}\right)-\bar{q}_{it}^{\chi}} = \frac{\left(\sum_{s\in\mathscr{S}_{it}} \chi_{ist}\right)-1}{S_{it}\frac{\bar{q}_{it}}{\bar{q}_{it}^{\chi}}-1}, \tag{10}$$

where $\bar{q}_{it}^{\chi}$ is the average number of clicks over sellers that change the price and $\bar{q}_{it}$ is the average number of clicks over all sellers for the same good and time.[12] This synchronization rate uses the number of stores that changed their price (minus one) in the numerator, exactly as for z_{it}, and the "*effective*" (as opposed to *actual* for z_{it}) number of stores (minus one) in the denominator—the number of stores that would generate the same total clicks if sellers that did not change the price on average received the same number of clicks as stores that did, $S_{it}\cdot(\bar{q}_{it}/\bar{q}_{it}^{\chi})$. The within-good, click-weighted measure of synchronization, $\bar{z}_i^{\mathrm{w}}$, is the weighted time average of z_{it}^{w} where the weights are $Q_{it}/\sum_t Q_{it}$ and Q_{it} is the number of clicks for periods with well-defined z_{it}^{w}. The between-good, weighted average is then calculated as the weighted mean of $\bar{z}_i^{\mathrm{w}}$ with weights $W_i = \sum_t Q_{it}/\sum_t \sum_{i\in\mathscr{G}} Q_{it}$. To calculate the synchronization rate across goods, we just swap subscripts for sellers and goods in the above formulas.

Sellers may fail to synchronize price changes at the weekly frequency, but may be able to do so at lower frequencies. Measuring synchronization over horizons longer than one week, however, is more

[12] That is, $\bar{q}_{it}^{\chi} = \sum_{s\in\mathscr{S}_{it}} q_{ist}\chi_{ist}/\sum_{s\in\mathscr{S}_{it}} \chi_{ist}$ and $\bar{q}_{it} = \sum_{s\in\mathscr{S}_{it}} q_{ist}/S_{it}$.

complex: for an h-week period, a given week can take any of the h positions in the period depending on when the period starts.[13] To resolve this ambiguity about start dates, we compute the upper bound of synchronization at horizon h. Specifically, we split our sample into nonoverlapping periods of duration h and compute the synchronization rate using the method we described above. We then shift the start date for each period by one week and repeat the exercise. We do this h times and report the maximum synchronization rate across the different starting dates.[14]

To put the measured synchronization rates into perspective, we report synchronization rates that one would observe if price adjustment followed Calvo (1983). In particular, let $\bar{f}^{\mathrm{b}}$ be the median frequency of price adjustment computed with between-good click weights (our benchmark), then the Calvo synchronization rate at horizon h is $1-(1-\bar{f}^{\mathrm{b}})^{h+1}$. This is a useful benchmark: there is no synchronization of price changes in the Calvo pricing, yet the measured synchronization rate is not zero, because some price changes just coincide in time.

Synchronization across Sellers Synchronization of price changes across sellers is remarkably low in both countries (see columns 1–4 of Table 8). The average synchronization rate for posted prices (no weights) is about 10 percent in the United States and 15 percent in the United Kingdom; more than a half of products in each country have zero synchronization. The average rate is even smaller for regular prices (no weights): 8 and 12 percent in each country, respectively; hence, sales are more synchronized than regular price changes. Although synchronization is higher when aggregated using between-good weights—in the United States the median is 15 percent for posted prices and 13 percent for regular prices, and in the United Kingdom the values are 18 and 14 percent, respectively—it is still significantly lower than one could have expected. Can this result be explained by timing? For example, although the cost of monitoring competitors' prices in online markets is low, sellers might still need some time to collect and analyze information, as well as to make decisions about price changes. Yet, even at the three-month horizon, no more than 60 percent of competitors adjust their price (see column 4 of Table 8). Moreover, the curve representing the synchronization rate over the time horizon (Panels A and C of Figure 2) lies below the curve for the Calvo pricing and is significantly flatter. This pattern suggests significant heterogeneity across sellers: some sellers are relatively attentive and change their prices often, while other sellers ("zombie" sellers) almost never react to changes in competitors' prices.[15]

Bhaskar (2002), Olivei and Tenreyro (2007), and others emphasize that nominal shocks should have limited real effects if price changes are synchronized. In a limiting case, if price adjustment is perfectly synchronized, real effects of nominal shocks can last at most as long as the duration of price spells. Our evidence suggests that price changes in online markets are rather staggered over time, which is consistent with potentially tangible monetary non-neutrality.

Synchronization across Goods If firms do not adjust prices simultaneously with their competitors, do they at least synchronize price changes across goods *they* sell? Such cross-good synchronization is at the heart of popular theories of multiproduct firms (Midrigan 2011, Alvarez and Lippi 2014), which claim that

[13]For example, consider synchronization over three weeks. Week t could be a part of three three-week periods that start at different times: $\{t-2, t-1, t\}$, $\{t-1, t, t+1\}$, and $\{t, t+1, t+2\}$.

[14]We are grateful to Nicolas Vincent for pointing out that the measure based on overlapping windows would suffer from downward bias.

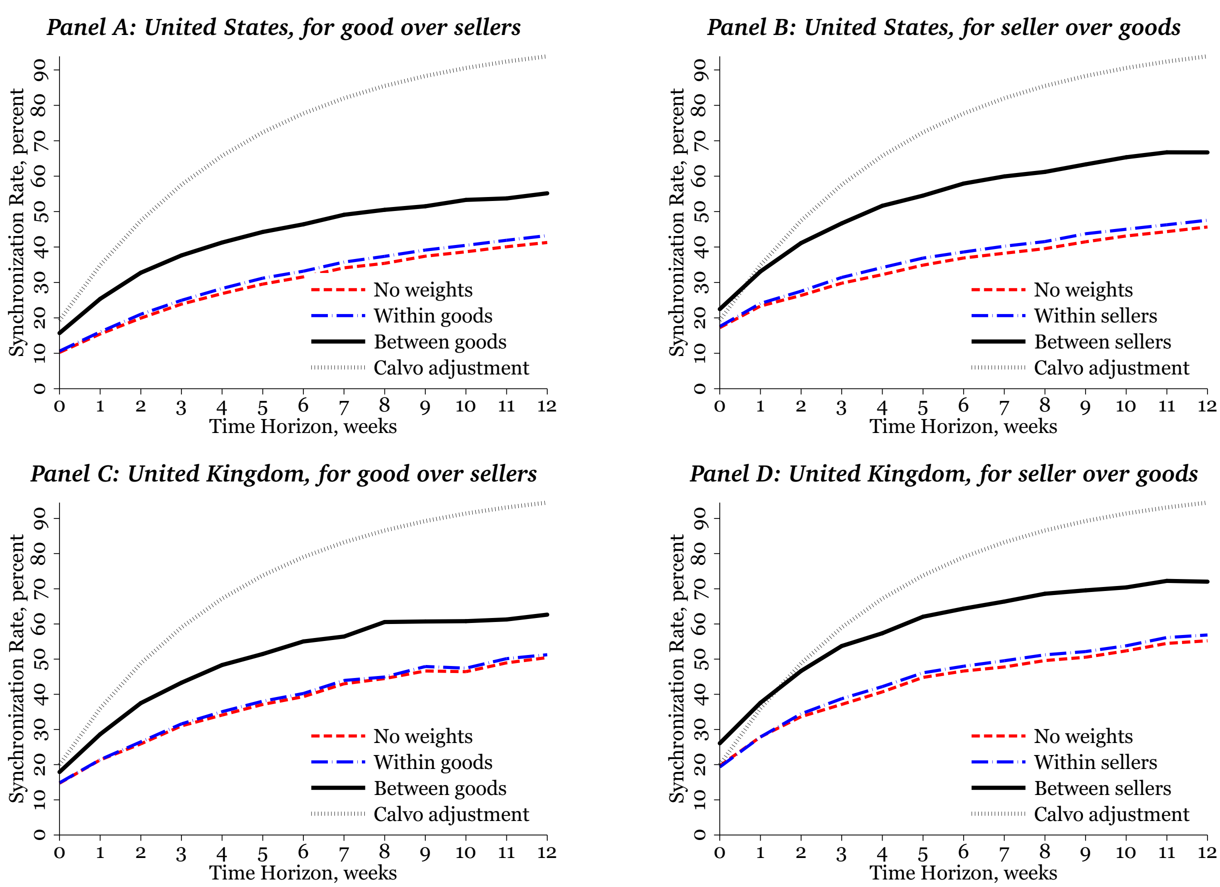
[15]This result also holds for regular prices; see the appendix.

Table 8. Synchronization Rate, percent

	Synchronization across Sellers: Mean (1)	Standard Deviation (2)	Median (3)	At Three-Month Horizon (4)	Synchronization across Goods: Mean (5)	Standard Deviation (6)	Median (7)	At Three-Month Horizon (8)
Panel A: United States								
Posted Price								
No weights	10.2	18.6	0.0	41.3	17.2	27.4	1.6	45.7
Within weights	10.6	19.2	0.0	43.2	17.6	28.3	1.2	47.6
Between weights	15.7	10.0	15.1	55.2	22.5	11.6	24.9	66.7
Regular Price								
No weights	7.8	16.4	0.0	40.6	14.7	25.7	0.0	46.1
Within weights	8.2	17.0	0.0	42.2	15.2	26.7	0.0	48.1
Between weights	12.8	8.6	12.6	52.8	18.3	10.3	20.3	64.3
Panel B: United Kingdom								
Posted Price								
No weights	14.7	24.8	0.0	50.4	19.7	26.5	8.2	55.2
Within weights	14.8	25.2	0.0	51.3	19.3	26.8	8.3	56.9
Between weights	17.9	11.1	17.9	62.6	26.1	16.7	26.0	72.0
Regular Price								
No weights	12.1	22.9	0.0	50.5	16.6	24.7	5.0	54.9
Within weights	12.4	23.4	0.0	51.6	16.5	25.0	4.9	56.0
Between weights	15.6	10.5	14.3	62.9	22.4	15.3	21.2	69.6

Notes: Columns (1)–(3) report the mean, standard deviation, and median of the weekly synchronization *for a good across sellers*. Column (4) reports the upper bound of synchronization at the three-month horizon. Columns (5)–(8) report the same measures for the weekly synchronization *for a seller across goods*. Regular prices are identified based on the one-week, two-side filter.

Figure 2. Synchronization Rate for Posted Prices by Time Horizon



Notes: Panels A and C report the upper bound synchronization *across sellers* at the week-*h* horizon, while Panels B and D synchronization *across goods*. The red dashed line aggregates using the raw average, the blue dash-dot line uses within-good/seller click weights, and the black solid line, between weights. The black dotted line shows synchronization under the assumption of fixed probability of price adjustment, as in Calvo (1983), based on the between-good click-weighted median frequency.

Table 9. **Frequency and Synchronization of Posted-Price Increases and Decreases**

	No Weights			Between Weights			
	Mean (1)	Standard Deviation (2)	Median (3)	Mean (4)	Standard Deviation (5)	Median (6)	Number of Goods (7)
Panel A: United States							
Frequency of							
Price changes	17.8	17.4	14.0	19.8	11.2	19.3	14,483
Price increases	8.3	9.7	5.9	8.9	5.4	8.6	14,483
Price decreases	9.5	11.0	6.5	10.9	6.9	10.1	14,483
Cross-Seller Synchronization of							
Price changes	10.2	18.6	0.0	15.7	10.0	15.1	9,937
Price increases	5.4	14.4	0.0	6.6	5.5	6.3	8,281
Price decreases	5.9	14.7	0.0	9.8	7.2	10.3	8,365
Cross-Good Synchronization of							
Price changes	17.2	27.4	1.6	22.5	11.6	24.9	2,344
Price increases	11.9	23.5	0.0	10.0	5.6	13.0	1,897
Price decreases	11.1	22.1	0.0	13.4	6.9	17.5	1,765
Panel B: United Kingdom							
Frequency of							
Price changes	20.4	24.1	12.8	20.4	13.8	20.0	6,623
Price increases	10.4	14.2	5.6	9.8	7.2	9.0	6,623
Price decreases	10.0	13.3	5.3	10.6	7.8	10.4	6,623
Cross-Seller Synchronization of							
Price changes	14.7	24.8	0.0	17.9	11.1	17.9	3,867
Price increases	8.7	19.2	0.0	8.3	7.1	8.1	3,122
Price decreases	8.4	19.1	0.0	11.1	8.8	10.3	3,066
Cross-Good Synchronization of							
Price changes	19.7	26.5	8.2	26.1	16.7	26.0	1,258
Price increases	14.3	23.7	3.3	13.2	9.5	15.3	1,045
Price decreases	12.1	20.9	0.9	15.1	9.3	16.4	1,012

Notes: The table reports estimates of the frequency and synchronization of posted-price increases and decreases. See notes to Tables 5 and 8.

multiproduct firms with a fixed cost of changing all their prices can explain the prevalence of small price changes in the data, a fact that conventional menu-cost models (Golosov and Lucas 2007) cannot explain. We find little support for this theory in the online-market data. Price synchronization across goods within a seller is low and similar to the synchronization rates across sellers for a given good (columns 5–8 of Table 8). In the United States, the average synchronization rate is 17 percent, without weights, and 23 percent when between-seller weights are applied (15 and 18 percent for regular prices). In the United Kingdom, the synchronization rates are slightly higher: 20 and 26 percent, unweighted and weighted, for posted prices; 17 and 22 percent for regular price). The unweighted median rates are all below 10 percent (and very close to zero in the U.S. data). At the three-month horizon (see column 8 of Table 8 and Panels B and D of Figure 2), the share of goods with price changes is still below 60 percent (75 percent with between-seller weights)—not much higher than a corresponding measure of cross-seller price synchronization.[16]

Synchronization of Price Increases and Decreases In the textbook theory of oligopolistic markets, sellers that face a kinked demand curve are more likely to follow a decrease in competitors' prices (to protect their market share) than an increase. Instead, in models of market segmentation into loyal customers and bargain hunters (Guimaraes and Sheedy 2011), substantial temporary price decreases (sales) are not synchronized, as firms prefer to avoid direct competition for bargain hunters. We do not, however, find

[16]Many online stores sell goods in multiple categories. The measured synchronization across goods may be weak because stores can synchronize price changes within categories but not across categories. To assess the quantitative importance of this explanation, we calculate the synchronization rate across goods within a category for each seller and then aggregate category-level synchronization rates to the store level. Irrespective of whether we use a narrow or broad definition for categories, we continue to find low synchronization rates, which are similar to our benchmark measure.

much evidence for either claim in the online-market data. Table 9 suggests that (*i*) the synchronization rates for price increases and decreases are of the same order of magnitude and (*ii*) the difference between the two is largely driven by underlying differences in the frequency of price adjustment (that is, whenever price increases are more frequent than decreases, they are also more likely to be synchronized). These conclusions also hold for regular prices (see Appendix).

3.5 Predictors of Price Stickiness

Market and good characteristics could be related to the heterogeneity of price stickiness across products. We focus on four statistics that summarize market competition, structure, and consumer search intensity: (1) the number of sellers that offer a given product; (2) market concentration measured by the click-based Herfindahl index; (3) market size approximated by clicks; and (4) the median product price.[17] The first two statistics measure the degree of competition across sellers. The third statistic can be related to returns to correct, profit-maximizing pricing: a larger market means larger profits from charging the right prices. The last statistic can be a proxy for the intensity of consumer search: the absolute return to search is higher for more expensive products.[18] After aggregating the data to the good level, we regress the frequency, size, and cross-seller synchronization of price changes on these four variables, controlling for category fixed effects and clustering standard errors at the narrow-category level. For each measure of price stickiness, we consider three weighting schemes: the simple average; the within-good, click-weighted average; and the between-good, click-weighted average.

Results in Table 10 suggest that all these characteristics have some explanatory power. Markets with more sellers are characterized by more flexible prices (higher frequency, lower size, and higher cross-seller synchronization of price changes). Market size, measured by the number of clicks, is associated with more (rather than less) price stickiness. Finally, price flexibility increases in the median price for low- and moderate-price goods; however, very expensive products on the platform tend to have stickier prices. We conclude that properties of online markets such as product demand, product price, and the intensity of competition across sellers have strong association with the degree of price stickiness.[19]

4 Price Dispersion

Price dispersion is not only a key statistic entering welfare calculations (see Woodford 2003), but also a key moment that can help to explain the sources of sticky prices and the nature of competition. For example, Sheremirov (2014) shows that many popular macroeconomic models predict a tight link between price dispersion and the degree of price rigidity. In a similar spirit, establishing whether price dispersion is spatial (some stores consistently charge more or less than others for the same good) or temporal (a store's price moves up and down in the price distribution over time) can help to distinguish between popular theories of price dispersion in the industrial organization literature. With the rising availability of supermarket scanner data for brick-and-mortar stores, properties of price dispersion have received a lot of attention

[17] All variables are in logs except for the Herfindahl index, which is between zero and one—computed at the good-level as $HI_i = \sum_{s\in\mathscr{S}_i}(Q_{is}/Q_i)^2$, where $Q_{is} = \sum_t q_{ist}$ is the total number of clicks for good i and seller s and $Q_i = \sum_s Q_{is}$ is the total number of clicks for good i.

[18] To allow for a nonlinear relationship between the median price and the measures of price stickiness, we include a polynomial of order two in this variable.

[19] Table F3 in the appendix shows that the conclusions are largely the same for regular prices.

Table 10. Predictors of Posted-Price Stickiness

Predictors	Weights:	Frequency of Price Changes, *percent* No (1)	Within (2)	Between (3)	Absolute Size of Price Changes, *log points* No (4)	Within (5)	Between (6)	Cross-Seller Synchronization Rate, *percent* No (7)	Within (8)	Between (9)
Panel A: United States										
Log number of sellers		9.1^{***}	10.8^{***}	10.7^{***}	−1.1	−1.3	-1.3^{*}	2.5^{***}	2.6^{***}	2.8^{***}
		(0.5)	(0.7)	(0.6)	(0.8)	(0.8)	(0.7)	(0.7)	(0.7)	(0.6)
Concentration, Herfindahl index, (0, 1]		19.2^{***}	24.5^{***}	24.9^{***}	-6.6^{***}	-7.4^{***}	-6.6^{***}	10.6^{***}	12.7^{***}	13.3^{***}
		(2.7)	(3.2)	(2.8)	(1.7)	(1.7)	(1.5)	(2.9)	(3.1)	(2.9)
Log total clicks		-5.3^{***}	-4.4^{***}	-4.2^{***}	0.3	0.3	0.3	-1.0^{***}	-0.8^{*}	-0.6^{*}
		(0.4)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.4)	(0.4)	(0.4)
Log median price		1.2	0.3	0.1	-9.1^{***}	-9.4^{***}	-9.2^{***}	1.8^{**}	1.9^{***}	2.0^{***}
		(0.9)	(0.8)	(0.7)	(0.9)	(0.7)	(0.7)	(0.8)	(0.7)	(0.6)
Log median price, squared		−0.1	−0.1	−0.1	0.7^{***}	0.7^{***}	0.7^{***}	−0.1	−0.1	-0.1^{*}
		(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
R^2		0.08	0.08	0.09	0.11	0.11	0.12	0.05	0.04	0.05
N		14,483	14,483	14,483	17,053	17,053	17,053	9,937	9,937	9,937
Panel B: United Kingdom										
Log number of sellers		4.8^{***}	6.0^{***}	6.8^{***}	−1.0	−1.0	-1.3^{*}	3.5^{**}	3.4^{**}	3.8^{***}
		(1.4)	(1.5)	(1.4)	(0.7)	(0.7)	(0.7)	(1.5)	(1.5)	(1.4)
Concentration, Herfindahl index, (0, 1]		21.7^{***}	25.2^{***}	25.7^{***}	-7.1^{***}	-7.2^{***}	-7.6^{***}	11.9^{**}	13.3^{**}	13.3^{**}
		(5.0)	(5.2)	(4.8)	(1.5)	(1.5)	(1.6)	(5.3)	(5.7)	(5.5)
Log total clicks		-3.1^{***}	-2.9^{***}	-2.9^{***}	0.8^{***}	0.9^{***}	1.0^{***}	-3.0^{***}	-2.9^{***}	-2.5^{***}
		(0.5)	(0.5)	(0.5)	(0.2)	(0.2)	(0.2)	(0.6)	(0.7)	(0.6)
Log median price		4.5^{***}	4.8^{***}	4.1^{***}	-3.8^{***}	-4.1^{***}	-4.4^{***}	2.9^{*}	2.9^{*}	3.1^{**}
		(1.3)	(1.2)	(1.2)	(0.6)	(0.6)	(0.6)	(1.6)	(1.5)	(1.3)
Log median price, squared		-0.5^{***}	-0.5^{***}	-0.4^{***}	0.3^{***}	0.4^{***}	0.4^{***}	−0.2	−0.2	−0.2
		(0.2)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.2)
R^2		0.08	0.08	0.08	0.07	0.08	0.08	0.05	0.05	0.05
N		6,623	6,623	6,623	9,092	9,092	9,092	3,867	3,867	3,867

Notes: The table presents estimates of the regression of the frequency (Columns 1–3), size (4–6), and cross-seller synchronization (7–9) of price changes on the given set of variables. “No weights” columns use the unweighted measures of price stickiness, raw median price across sellers, and assign equal weights to each observation in the regression. “Within weights” columns use the within-good click-weighted measures of price stickiness, weighted median price across sellers, but still assign equal weights to each good. “Between weights” columns further weight observations by the number of clicks obtained by each good. Concentration is measured with the Herfindahl index, normalized to be between zero and one. Category fixed effects are included but not reported. Standard errors clustered at the narrow-category level are in parentheses. *, **, and *** represent the 10, 5, and 1 percent significance level, respectively.

recently (Clark and Vincent 2014, Kaplan and Menzio 2014, Sheremirov 2014). Yet, little is known about price dispersion in online markets.[20,21]

In this section, we document that price dispersion in online markets has a number of unexpected properties. First, the magnitude is similar to, if not larger than, that for brick-and-mortar stores. Price dispersion remains sizeable even when the seller fixed effects are removed. Second, price dispersion cannot be explained by inactive sellers keeping their prices prohibitively high. The click-weighted measure of dispersion is only slightly smaller than the unweighted one. Third, price dispersion rises steadily during product life. It increases by a third within one-and-a-half years of the product introduction, and we show that this result is not due to a composition effect as we look at the sample of long-lived products separately. Finally, the data support spatial price dispersion, which is surprising, given that search in online markets is easy.

4.1 Intraweek Dispersion across Sellers

Measurement To distinguish between dispersion in the left tail of the price distribution—which generates more clicks—from that in the right tail, we use six different measures, which complement one another. Three of them—the *coefficient of variation (CV)*, *standard deviation of log prices*, and *range*—capture the whole spectrum of prices. Two other measures, the *gap* and *value of information (VI)*, capture price dispersion at the left tail. The gap is defined as the log difference between the two lowest prices and the *VI,* between the average and minimum price. The VI can be interpreted as the maximum markup a risk-neutral consumer would be willing to pay to obtain information about the seller with the best price versus buying from a seller picked at random (Varian 1980). To reduce the influence of extreme observations, we also compute the *interquartile range (IQR)*—the log difference between the 75th and 25th percentile.[22] We use the CV and standard deviation of log prices as our preferred measures since (*i*) they capture the width of the entire price distribution and (*ii*) they are the ones most often reported in the literature on price dispersion. Once we compute a corresponding measure of price dispersion across sellers for each good i and week t (σ_{it}), we aggregate it to the good level by taking appropriate time averages ($\bar{\sigma}_i$ and $\bar{\sigma}_i^w$).

Dispersion Panels A and C of Table 11 report the cross-good raw average of $\bar{\sigma}_i$ (no weights), $\bar{\sigma}_i^w$ (within-good weights), and $\bar{\sigma}^b$ (between-good weights, that is, the click-weighted average of $\bar{\sigma}_i^w$) for each measure of dispersion for posted prices described above. As the share of identified weekly sales is small (within the 1.3–1.7 percent range; see Table 3) and a half of products in the dataset do not have sales at all, dispersion of regular prices is almost the same as dispersion of posted prices. To save space, we focus on results of posted prices and relegate results of regular prices to the appendix.

In the United States, the average gap between the two lowest prices is 28 log points, while the range is 41 log points. Together with the fact that, on average, the value of information is less than the gap,

[20] Dispersion of online prices has been studied for narrow markets such as books (Chevalier and Goolsbee 2003), CDs (Brynjolfsson and Smith 2000), consumer electronics (Baye, Morgan, and Scholten 2004), or travel (Clemons, Hann, and Hitt 2002). While analyses of these markets are informative, these markets are unusual in many respects (for example, the market is dominated by big sellers such as Amazon, prices tend to be very rigid) and hence generalization is not straightforward. To the best of our knowledge, there is no other study with a large coverage of goods sold online.

[21] However, online prices have been studied in the context of cross-border price dispersion and exchange-rate pass-through (Boivin, Clark, and Vincent 2012, Gorodnichenko and Talavera 2014).

[22] See Baye, Morgan, and Scholten (2004, 2010) for further discussion of price dispersion measures.

Table 11. Average Dispersion of Posted Prices across Sellers

	Coefficient of Variation, *percent* (1)	Standard Deviation of Log Price *log points* (2)	Value of Information, *log points* (3)	Interquartile Range, *log points* (4)	Range, *log points* (5)	Gap, *log points* (6)	Number of Goods (7)
			Panel A: United States, actual prices				
No weights	21.5	23.6	24.4	34.6	40.7	27.6	
Within-good weights	21.4	22.9	23.3	32.0	40.7	27.6	29,753
Between-good weights	19.9	20.3	24.8	26.1	50.1	21.1	
			Panel B: United States, prices net of seller fixed effects				
No weights		21.2	18.3	31.2	36.8	25.1	
Within-good weights		20.7	17.5	28.9	36.8	25.1	29,753
Between-good weights		17.5	18.6	22.5	43.8	18.8	
			Panel C: United Kingdom, actual prices				
No weights	19.4	21.3	20.4	31.3	34.3	26.7	
Within-good weights	19.4	20.7	19.2	28.8	34.3	26.7	17,715
Between-good weights	18.6	18.6	19.8	23.1	41.8	23.0	
			Panel D: United Kingdom, prices net of seller fixed effects				
No weights		16.5	13.3	24.2	26.9	20.4	
Within-good weights		16.0	12.6	22.2	26.9	20.4	17,715
Between-good weights		14.9	14.5	17.9	35.2	18.1	

Notes: Columns (1)–(6) report the average price dispersion for posted prices measured with the CV, VI, IQR, range, and gap, respectively. Column (7) reports the number of goods. The CV is computed as the ratio of the standard deviation to the mean and the range as the log difference between the highest and lowest price.

this suggests that there is more mass in the left tail than in the right one. This result is consistent with models that segment the market into loyal customers (those with a strong brand preference) and shoppers (bargain hunters who search for best prices), in which seller's optimal strategy is to offer a low price for the former and the reservation price for the latter (Morgan, Orzen, and Sefton 2006, Baye and Morgan 2009). Alternatively, if consumers face ex ante different information sets *à la* Varian (1980) (that is, some consumers are informed about price distribution, while others are uninformed and pick a seller at random) and there is heterogeneity in marginal costs across firms, then the most efficient firm will set the price equal to the marginal cost of the second most efficient firm (to attract informed customers), while every other firm will charge the monopoly price since the other firms face demand from uninformed customers only.

The CV is 22 percent and does not change materially when within- or between-good weights are applied (20 percent with between-good weights). This is similar to the estimates in Kaplan and Menzio (2014) and larger than in Sheremirov (2014)—two recent studies of price dispersion across brick-and-mortar stores.[23] The standard deviation of log prices is similar to the CV. In the United Kingdom the amount of price dispersion is roughly the same as in the United States: the CV is 19 percent (regardless of the weights used).

Dispersion Net of Seller Fixed Effects As suggested by Stigler (1961), some of the observed price dispersion may be due to differences in the shopping experience and terms of sale. This distinction is less likely to apply to shopping on the online platform since consumers deal directly with a seller only when they complete a transaction. Furthermore, if seller's reputation and differences in delivery and return policy matter, the importance of these factors is likely to be reduced in our setting because consumers get explicit credit-card guarantees from the issuer and "trusted seller" guarantees from the comparison site.

[23] Kaplan and Menzio (2014), using the Nielsen household panel for the period between 2004 and 2009, report the CV at the UPC level of 19 percent. Sheremirov (2014) uses the IRI scanner data for the 2001–2011 period and documents the average standard deviation of log prices as 10 log points. The difference between the two is likely to be due to sample composition—the IRI data are for grocery and drugstores only, while the Nielsen data also include warehouse clubs and discount stores, which can widen price distribution.

To address this potential issue more completely, we run the following regression:

$$\log p_{ist} = \alpha_i + \gamma_s + \varepsilon_{ist}, \tag{11}$$

where α_i and γ_s are good and seller fixed effects, respectively, and then report dispersion for the residual, which gives us price dispersion net of sellers' heterogeneity in shipping costs, return policies, etc.[24] In other words, since the terms of sale are unlikely to change much in a relatively short sample period, we can use seller fixed effects to capture the differences in reputation, delivery conditions, and return costs across sellers.

Seller fixed effects account for about 25–30 percent of variation in price dispersion across goods in the United States and about 40 percent in the United Kingdom (Panels B and D of Table 11). While store heterogeneity is a tangible source of price dispersion, the residual price dispersion remains high even when we use between-good weights: the standard deviation of log prices is 17.5 log points in the United States and 14.9 log points in the United Kingdom. These magnitudes are striking given how easy it is to compare prices for a precisely defined good across sellers in online markets.

4.2 Dynamic Properties

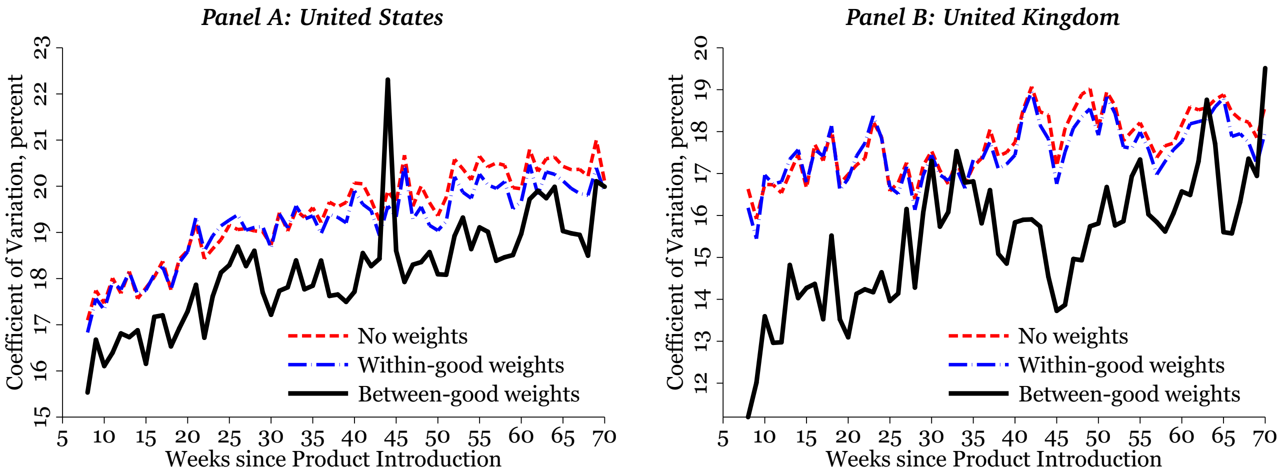
Dispersion over Product Life We may observe considerable dispersion of prices across sellers, as well as heterogeneity in the level of the dispersion across goods, because goods may be at different stages of their product lives. For example, in the absence of shocks, price dispersion should be falling over the course of product life as consumers learn about price distribution through search and firms collect information about their competitors' prices. If there is high dispersion of prices at the time a good is introduced, a high average level of price dispersion could reflect the prevalence of recently introduced goods rather than inability of online markets to eliminate arbitrage opportunities. Studying how price dispersion varies over product life can also inform us about the nature of price rigidities. For example, Cavallo, Neiman, and Rigobon (2014) find that the dispersion of prices across countries for a given good is effectively set at the time the good enters the market and remains relatively stable throughout the product life.

To examine the importance of this dimension, we compute the average price dispersion across products after h weeks since they appear in the dataset. We limit the sample to include only goods with the duration of product life of at least a year so that our results are not due to a composition effect (for example, if products that live longer have a higher or lower price dispersion than the average product).[25] Figure 3 suggests that price dispersion increases steadily during the product life. In the United States, the between-good weighted measure increases by a third within 70 weeks since the introduction, from 15 to 20 percent. In the United Kingdom, a corresponding increase in dispersion is even bigger, from 11 to 19 percent. Price dispersion for the unweighted measures increases as well, but at a smaller rate due to the level effect. Hence, while a chunk of price dispersion appears when a good is introduced, there is no evidence of price convergence over the good's product life, and heterogeneity in product lives cannot explain cross-sectional dispersion of prices.

[24] Controlling for time dummies does not affect the results.

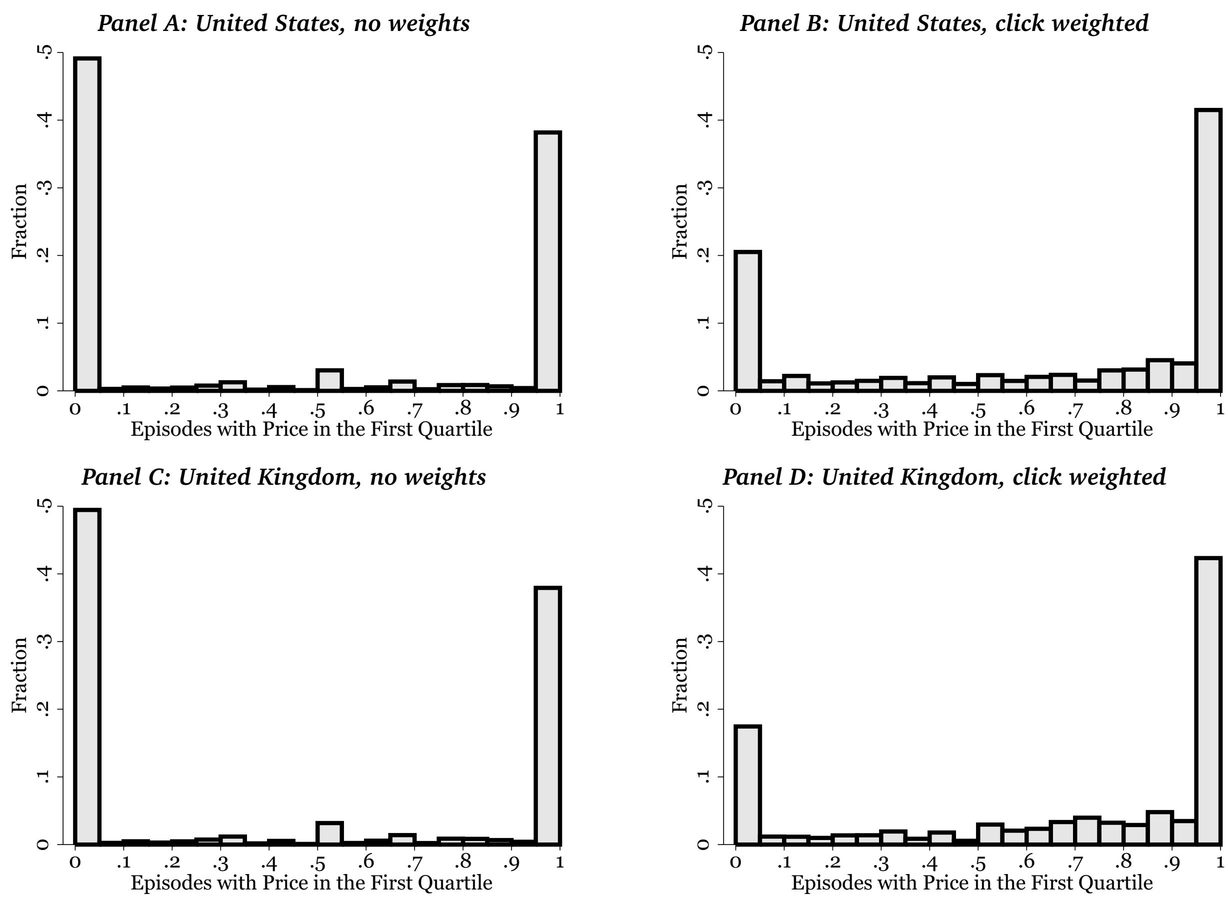
[25] We exclude products that enter within the first four weeks of the sample period because we do not know whether the product was introduced then or was unavailable due to a temporary stockout. We find similar results when we use alternative cutoffs for the minimum duration of product life. We also find similar results when we use dispersion net of seller fixed effects.

Figure 3. Cross-Seller Dispersion of Posted Prices over Product Life



Notes: The figure plots the raw and click-weighted mean over goods of the coefficient of variation for posted prices against the time passed since the product introduction. Goods introduced during the first seven weeks are cut off to account for truncated observations, and only goods with duration of life of more than a year are considered.

Figure 4. Is Price Dispersion Spatial or Temporal?



Notes: The figure reports the distribution of the share of episodes when a residual from Equation (11), ε_{ist}, is in the first quartile of the cross-seller price distribution in the number of episodes when it is either in the first or fourth quartile. Episodes when the price is within the interquartile range are omitted. Spatial price dispersion implies that the share should be either zero or one, while temporal price dispersion suggests a peak at 0.5.

Spatial and Temporal Dispersion Macroeconomic models of price rigidity usually generate temporal price dispersion. For example, in the Calvo model each firm is allowed to change the price randomly and therefore is equally likely to lag and lead other firms during an adjustment period. Over a sufficiently long period, a given firm should set its price below and above the average roughly the same amount of time. Sheremirov (2014) shows that, for reasonable parameterizations, popular menu-cost models make a similar prediction: when a firm adjusts in response to an inflationary shock, it sets its price above the average; as the price level steadily increases, the firm's price moves to the left in the price distribution and eventually falls below the average.

In contrast, many (but not all) models in the search or industrial organization literature produce spatial price dispersion (Reinganum 1979, MacMinn 1980, Spulber 1995). Burdett and Judd (1983) provide an example of a search model with temporal price dispersion.[26] Varian (1980) argues that over time consumers should learn whether a firm is high- or low-price, which should eliminate spatial price dispersion. Consistent with this prediction, Lach (2002) finds that price dispersion for brick-and-mortar stores is temporal. Given the ease of search for best prices in online markets, one might expect that most of price dispersion would be temporal rather than spatial.

Following Lach (2002), we calculate a fraction of episodes when a seller's price is in the left tail (defined as the first quartile) of the price distribution in the episodes when it is in either tail (the first or fourth quartile). If price dispersion is purely spatial, this fraction should be either zero or one.[27] If price dispersion is purely temporal, we should see a distribution of the fraction with support over the unit interval and a peak at the middle. Regardless of whether we use observed prices or prices net of seller fixed effects (ε_{ist}), we find strong support for spatial price dispersion (Figure 4): the data show clear spikes at zero and one and little mass in the middle. Using clicks as weights does not alter this finding. Thus, consumers appear to persistently ignore lower prices offered by other sellers and there is potentially significant segmentation of the market.

4.3 Predictors of Price Dispersion

Popular macroeconomic theories of price determination emphasize three broad sources of price dispersion. First, prices can be different across sellers because consumers face search costs. Second, prices may be different because they are set at different times and hence in response to different demand and supply conditions. This is the channel in models with sticky prices. Third, sellers can price discriminate among consumers (Guimaraes and Sheedy 2011, Coibion, Gorodnichenko, and Hong 2012, Kaplan and Menzio 2014, Sheremirov 2014). To explore the importance of these channels, we regress the standard deviation of log prices on variables measuring market power, returns to search, and price stickiness. To preserve space, we present results for between-good click-weighted data (Table 12) and relegate results for other measures and weighting schemes to the appendix.

We tend to find that a larger number of sellers and a smaller market size (measured by the number of clicks) are associated with a smaller price dispersion. The absolute magnitudes of the estimated coefficients on these two variables are similar. One may interpret this result as suggesting that price dispersion is

[26] For a comprehensive overview of search models of price dispersion, see Baye, Morgan, and Scholten (2010).

[27] For example, a spike at zero that is higher than a spike at one indicates that high-price sellers are less likely to have episodes of low prices than low-price sellers to have episodes of high prices.

Table 12. Predictors of Posted Price Dispersion

	Standard Deviation of Log Price						Net of Seller Fixed Effects					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: United States												
Log number of sellers	0.79					−3.24***	0.08					−3.61***
	(1.56)					(1.01)	(1.32)					(0.81)
Log total clicks	−0.15					4.76***	−0.34					4.19***
	(0.70)					(0.90)	(0.63)					(0.79)
Log median price	−4.83***					−3.94***	−4.00***					−3.16***
	(0.55)					(0.51)	(0.48)					(0.43)
Frequency of regular price changes		0.16***	0.26***	0.17***	0.27***	0.39***		0.14***	0.23***	0.15***	0.23***	0.34***
		(0.02)	(0.06)	(0.02)	(0.06)	(0.08)		(0.01)	(0.05)	(0.02)	(0.05)	(0.06)
Absolute size of regular price changes		0.09***	0.12***	0.11***	0.10***	0.29***		0.11***	0.11***	0.12***	0.10***	0.27***
		(0.02)	(0.03)	(0.03)	(0.04)	(0.06)		(0.02)	(0.02)	(0.02)	(0.03)	(0.05)
Frequency of sales			−0.48***		−0.54***	−0.31***			−0.35***		−0.43***	−0.27***
			(0.12)		(0.11)	(0.08)			(0.09)		(0.09)	(0.06)
Absolute size of sales			0.39***		0.40***	0.29***			0.35***		0.37***	0.27***
			(0.05)		(0.05)	(0.04)			(0.04)		(0.05)	(0.04)
Synchronization of posted price changes				−0.02	−0.06	−0.02				−0.01	−0.04	−0.00
				(0.02)	(0.04)	(0.03)				(0.01)	(0.04)	(0.03)
R^2	0.14	0.06	0.16	0.08	0.19	0.28	0.13	0.06	0.17	0.07	0.19	0.28
N	29,753	14,930	3,486	9,363	3,349	3,349	29,753	14,930	3,486	9,363	3,349	3,349
Panel B: United Kingdom												
Log number of sellers	−5.51***					−5.42***	−2.77***					−2.72***
	(1.37)					(1.42)	(0.94)					(0.89)
Log total clicks	1.61***					2.92***	0.62					1.59***
	(0.53)					(0.77)	(0.39)					(0.58)
Log median price	−4.15***					−3.01***	−2.73***					−2.26***
	(0.75)					(0.40)	(0.46)					(0.33)
Frequency of regular price changes		0.05	0.04	0.06	0.10**	0.17***		0.04**	−0.02	0.03	0.03	0.06
		(0.03)	(0.08)	(0.04)	(0.05)	(0.06)		(0.02)	(0.07)	(0.02)	(0.03)	(0.04)
Absolute size of regular price changes		0.06***	−0.05	0.03	0.02	0.11*		0.05***	−0.06	0.05***	0.02	0.05
		(0.02)	(0.10)	(0.02)	(0.04)	(0.06)		(0.01)	(0.10)	(0.02)	(0.03)	(0.04)
Frequency of sales			0.10		−0.20**	−0.27***			0.18		−0.11*	−0.14**
			(0.37)		(0.09)	(0.08)			(0.34)		(0.06)	(0.05)
Absolute size of sales			0.43**		0.27**	0.20*			0.43*		0.29**	0.24**
			(0.21)		(0.12)	(0.10)			(0.22)		(0.13)	(0.11)
Synchronization of posted price changes				−0.03**	−0.11***	−0.07***				−0.02*	−0.06***	−0.04**
				(0.02)	(0.02)	(0.02)				(0.01)	(0.02)	(0.02)
R^2	0.09	0.03	0.07	0.05	0.12	0.24	0.06	0.02	0.07	0.04	0.15	0.25
N	17,715	6,340	881	3,469	840	840	17,715	6,340	881	3,469	840	840

Notes: The table presents estimates of the regression of the standard deviation of log price and that net of seller fixed effects on a given set of variables, in rows. Variables and observations are weighted by clicks when possible; unweighted results are relegated to Appendix. Category fixed effects are included but not reported. Standard errors clustered at the narrow-category level are in parentheses. *, **, and *** represent the 10, 5, and 1 percent significance level, respectively.

increasing in the average number of clicks per seller. To the extent that the average number of clicks per seller signals market power, our results indicate that barriers to entry allow online stores to charge different prices and price discriminate among consumers, thereby generating increased price dispersion.

Consistent with predictions of models with search costs, a higher unit price, which proxies for higher returns on search, is associated with a lower price dispersion. The economic magnitude of the relationship is large: if good A is twice as expensive as good B, good A has a 6 to 8 log points lower dispersion of prices than good B.

In models of price stickiness (for example, Calvo 1983), the higher is the frequency of price adjustment, the smaller is price dispersion, because firms catch up with the price level faster when they are allowed to change their prices more often. While in models with menu costs the relationship between the frequency and price dispersion is more nuanced, Sheremirov (2014) shows that the correlation is negative for reasonable calibrations. In contrast to this theoretical prediction, we find a *positive* relationship between the frequency and price dispersion. At the same time, models with sticky prices predict a negative relationship between the frequency of price changes and the size of price changes so that the size of price changes may be interpreted as an alternative measure of price stickiness. If we focus on this alternative measure, then the estimated relationship between price stickiness and price dispersion is consistent with the predictions of sticky-price models: larger price changes are associated with larger cross-sectional price dispersion. The difference in the results for the frequency and size of price changes suggests that price changes in online markets may be motivated by reasons other than those emphasized by mainstream models of price setting. For example, a high frequency of price adjustment may reflect a noisier or more intensive process of price discovery, in which sellers frequently try different prices to probe the level and elasticity of demand, rather than being a result of fluctuations in marginal costs.

As we discuss above, sticky-price models generate price dispersion because of staggered price adjustment. If firms are allowed to synchronize their price changes, the cross-sectional price dispersion should disappear in these models. In line with this prediction, we find that synchronization tends to be negatively correlated with price dispersion.

While price discrimination can take a variety of forms, given data constraints, we use two approaches to capture the effects of price discrimination. First, we consider how the frequency and size of sales, a mechanism to discriminate across customers, are related to price dispersion.[28] Second, we study how removing seller fixed effects (a proxy for differences in terms of sales across stores) influences our estimates. We find that more frequent and smaller sales tend to be associated with lower price dispersion. Again, similar to the results for the frequency and size of regular price changes, the estimated coefficient on the size has a sign predicted by popular theories, while the estimate on the frequency of sales is surprising. Perhaps, this difference suggests heterogeneity in the purpose of sales across goods and markets. For example, a higher frequency of sales may occur in markets where high-price stores use sales to bring their prices closer to low-price competitors, while larger sales may be concentrated in markets where sellers have similar prices and use sales to differentiate themselves from the pack. We also find that removing seller fixed effects attenuates the estimates somewhat but does not affect the qualitative conclusions.

Obviously these results are not causal, but the estimates suggest that multiple sources of price dispersion are likely at play. Search costs, price stickiness, and price discrimination are predictors of the observed

[28] For example, Sheremirov (2014) finds that dispersion for conventional stores is lower for regular prices than for posted prices; thus, consistent with Varian (1980), one may interpret sales as a source of price dispersion.

price dispersion in online market. Controlling for one of the sources of price dispersion does not appear to change estimates on variables proxying for the other sources of price dispersion.

5 Dynamic Pricing

E-commerce has been long poised to adopt dynamic pricing: online sellers can, in principle, change their prices automatically in response to anticipated variation in demand (throughout the week, month, or year) or current market conditions (competitors' prices, number of customers, inventories, etc.). In fact, it is already widely used in a few industries. For example, airlines and hotels set their prices based on when a reservation is made, whether a trip includes a weekend stayover, and the number of available seats or rooms (see Bilotkach, Gorodnichenko, and Talavera 2010, 2012). Although dynamic pricing has obvious advantages (boosting profits through price discrimination, using price experimentation to obtain real-time estimates of demand elasticity), excessive use of dynamic pricing may alienate consumers and harm a firm's reputation. For example, dynamic pricing can undermine long-term seller-customer relationships and intensify competition, thereby putting pressure on profits.

From a macroeconomic perspective, dynamic pricing leads to increased price flexibility. Whether or not it also changes the effects of nominal shocks depends on what firms respond to. If firms adjust their prices only in response to transitory sector-specific shocks, increased price flexibility does not make monetary policy less powerful. If firms also react to changes in the current state of the economy, including policy-makers' decisions, dynamic pricing can lead to a lower degree of monetary non-neutrality. Under dynamic pricing, not only the frequency but also the timing of price changes matters. For example, Olivei and Tenreyro (2007) report that, due to uneven staggering of wage contracts, the effect of monetary-policy shocks on output depends on the quarter in which the shock occurs. One might expect that this effect would be amplified in online markets.

To shed new light on the use of dynamic pricing by online retailers, we consider different ways through which it can affect price flexibility. First, we look at *low-frequency* anticipated variation in demand due to holiday sales such as Black Friday and Cyber Monday (in the United States) or Boxing Day (in the United Kingdom). Second, we look at the reaction of prices to *high-frequency* variation in demand. We examine how online demand (proxied by the number of clicks) and prices vary over days of the week and month. We also investigate how online demand and prices react to the surprise component of macroeconomic announcements.

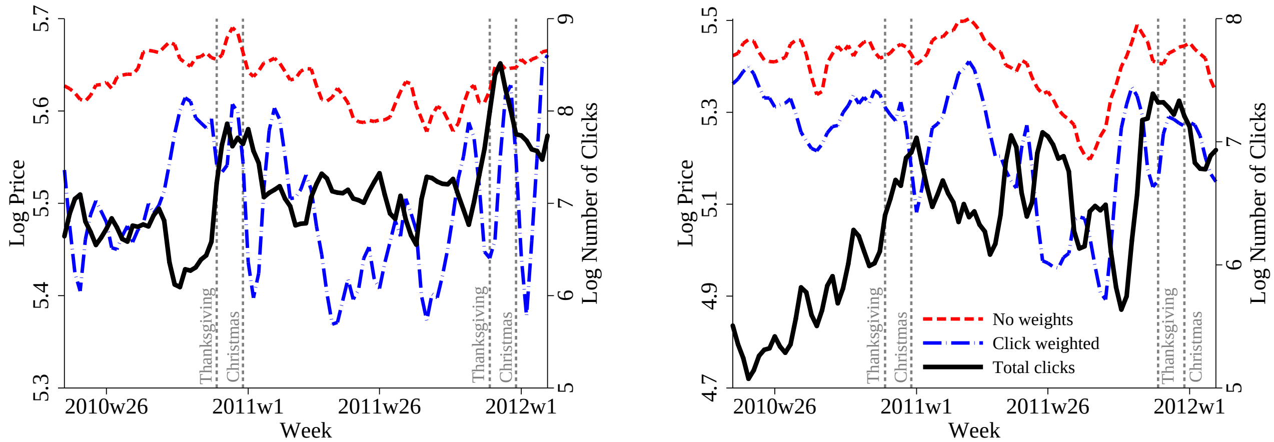
5.1 Variation in Demand Intensity

Holiday Sales To have long time-series and to keep exposition clear, we focus our analysis on a popular model of headphones that received many clicks in the sample. Figure 5 plots the time-series of the mean price over sellers in a given week, $\bar{p}_t = \sum_{s\in\mathscr{S}_t} p_{st}/S_t$, the click-weighted mean price, $\bar{p}_t^{w} = \sum_{s\in\mathscr{S}_t}(q_{st}/Q_t)p_{st}$, and the log of the total number of clicks, $\log Q_t = \log\sum_{s\in\mathscr{S}_t} q_{st}$. In each country and each year, the number of clicks goes up and the average price goes down during the holiday sales.[29] This finding is consistent with Warner and Barsky (1995), who find that brick-and-mortar stores choose to time

[29]Although in the United Kingdom people do not usually celebrate Thanksgiving, late November is a typical time to start Christmas shopping.

Figure 5. Average Price and Total Clicks for a Representative Good (headphones)

Panel A: United States *Panel B: United Kingdom*



Notes: The red dashed line is the average unweighted price across all sellers, the blue dash-dot line the click-weighted average, and the black solid line the log number of total clicks. Each time-series is a centered three-week moving average.

Table 13. Intraweek Variation in Prices and Clicks

	United States				United Kingdom			
		Log Deviation from Weekly Median, *log points*				Log Deviation from Weekly Median, *log points*		
	Click Share, *percent* (1)	Total Clicks (2)	Mean Price (3)	Weighted Mean Price (4)	Click Share, *percent* (5)	Total Clicks (6)	Mean Price (7)	Weighted Mean Price (8)
Monday	16.2	10.0	−0.1	−0.0	16.0	8.4	−0.1	−0.2
Tuesday	15.5	6.4	0.2	0.0	15.7	6.6	0.0	0.0
Wednesday	14.8	3.8	0.5	0.0	15.0	3.4	1.2	0.0
Thursday	14.3	0.0	1.4	0.1	14.8	0.0	2.0	1.5
Friday	13.3	−6.6	2.0	2.8	13.1	−8.9	3.2	3.3
Saturday	12.1	−16.0	−3.0	−0.8	11.8	−19.0	−2.0	−0.1
Sunday	13.8	−4.4	−5.4	−1.9	13.6	−6.6	−5.5	−4.9

Notes: Columns (1) and (5) report the share of clicks by day of the week, Columns (2) and (6) the median (across weeks) deviation of the number of clicks on that day from the median day within the same week, Columns (3) and (7) the same deviation for the raw mean price, and Columns (4) and (8) for the click-weighted mean price. Weeks are defined as Monday to Sunday to keep adjacent weekend days within the same week. Days before the first Monday and after the last Sunday in the sample are dropped. The sample period is between Monday, May 3, 2010, and Sunday, February 5, 2012.

price markdowns to periods of high-intensity demand. Notably, after the sales period, prices do not go back to their presale level but instead permanently settle at a new, lower value.

We observe a similar but weaker pattern when we aggregate across goods. Figure 6 shows that the frequency of regular price decreases rises relative to the frequency of regular price increases when we compare Thanksgiving or Christmas weeks with the weeks preceding or following the holiday season. Likewise, sales tend to be deeper and more widespread during the season. There seems to be no evidence that the size of regular price increases and decreases behaves differentially during the season than in off-season weeks. One should, however, take these observations with a grain of salt, since the time-series for these variables are noisy and we only observe two episodes of the holiday season.

Intraweek Variation Table 13 reports the deviation of log prices and total clicks from the weekly median, as well as the share of total clicks by day of the week. In each country, almost one-third of the total number of clicks occur on Mondays and Tuesdays—6 percentage points more than on Saturdays and Sundays, when the shopping activity on the platform is the lowest. In contrast, the shopping activity in brick-and-mortar

Figure 6. Price Adjustment during Holiday Sales, centered three-week moving average

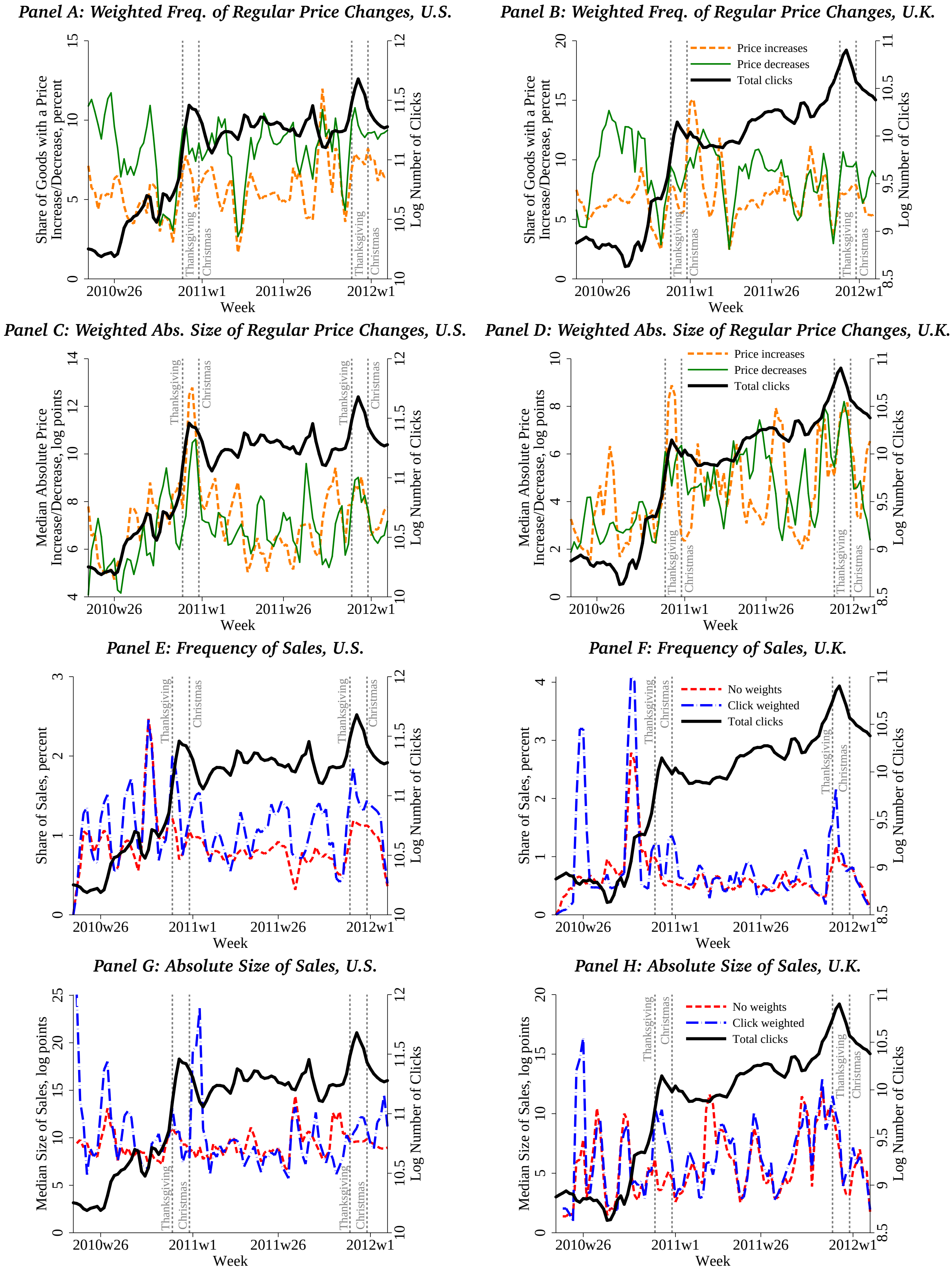
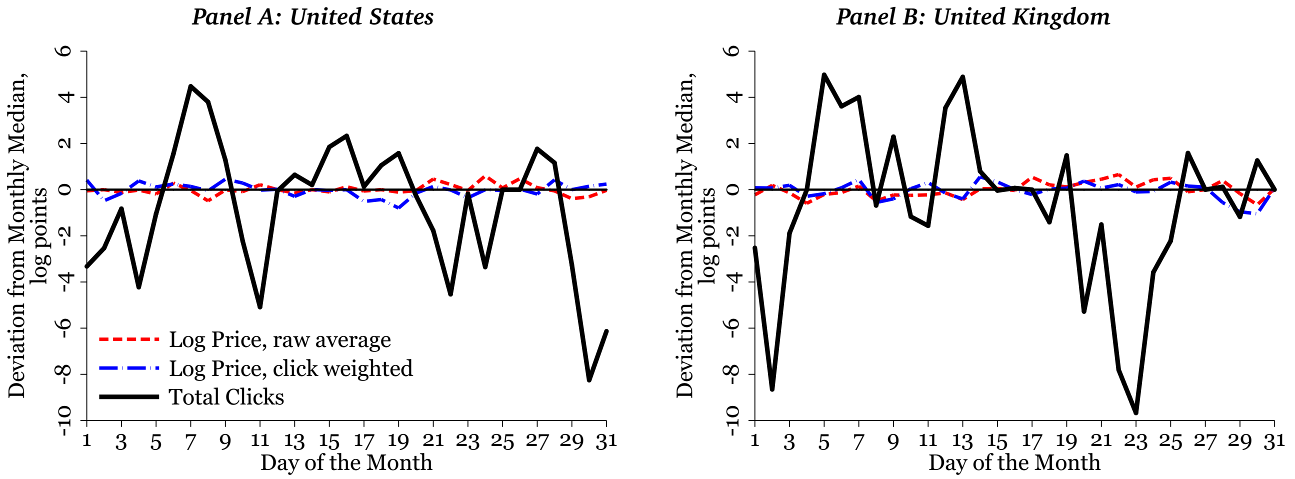


Figure 7. Intramonth Variation in Prices and Clicks



Notes: The red dashed line shows the median (over months) deviation of the raw mean log price on a given day from the median day of the same month, the blue dash-dot line shows the same deviation for the between-good, click-weighted mean, and the black solid line shows the deviation for the total number of clicks. The sample period is between May 1, 2010, and January 31, 2012.

stores is the highest on weekends (BLS 2014, Koustas 2014). In the United States, consumers generate 10 log points more clicks on Mondays than on the median day of the same week; on Saturdays, however, this measure is 16 log points lower than the median (8.4 and 19.0 log points, respectively, in the U.K. data). At the same time, Monday prices are within 0.2 log points from the median in both countries, while Saturday prices are 3 log points lower than the weekly median in the United States (2 log points in the United Kingdom). When the shopping intensity drops over the weekend, more high-price sellers receive no clicks at all, which explains most of the deviation in the raw mean price: click-weighted prices on Saturdays are only 0.8 and 0.1 log points lower than the median in each country, respectively. In summary, the intraweek variation is significantly smaller in prices than in the number of clicks, and the two are not perceptibly related. If anything, prices are slightly lower on the weekend, when the demand intensity on the online platform is lower, thereby contradicting the Warner-Barsky hypothesis.

Intramonth Variation Figure 7 shows that the intramonth variation of the number of clicks also significantly exceeds that of the average price. Specifically, we plot the median (over months) deviation of the total number of clicks as well as the raw and click-weighted mean price from the corresponding monthly median. While the number of clicks varies by 5 log points from each side of the median—at the extreme, the deviations can be almost 10 log points—both measures of price deviations are consistently within 1 log point of the median. In both countries, consumers are significantly more active in the first half of the month—and close to payday—than in the second half, with an additional spike in activity around the 15th day of a month in the United States (as some consumers are paid biweekly). In a pattern similar to the intraweek case, prices do not appear to respond to intramonth variation in demand.

5.2 High-Frequency Aggregate Shocks

Our results above support the view that online stores have only a limited reaction to anticipated changes in the intensity of demand for their products. Are sellers more responsive to unanticipated changes in aggregate economic conditions? To address this question, we explore how pricing moments and the number of clicks react to the surprise component of macroeconomic announcements at the daily frequency.

To measure these shocks, we use real-time data from Informa Global Markets (IGM),[30] which reports the actual release and median forecast of measures of economic activity such as capacity utilization, consumer confidence, core CPI, the employment cost index, GDP, initial claims, the manufacturing composite index from the Institute of Supply Management (ISM), leading indicators, new home sales, nonfarm sales, the producer price index (PPI), retail sales (total and excluding motor vehicles), and unemployment—14 series overall. We construct a *daily* shock for each series i as

$$\text{Shock}_t^i = \text{Actual Realization}_t^i - \text{Median Forecast}_t^i, \tag{12}$$

where t indexes days. To make units comparable across shocks, we standardize each shock series to have zero mean and unit standard deviation.

While macroeconomic announcements are not synchronized, each shock series has nonmissing values only 12 or fewer days per year (only initial claims are weekly and thus have about 50 nonmissing values per year). To enhance the statistical power of our analysis, we construct an aggregate shock series. Specifically, we estimate the loadings of these shocks on the change in consumption using the *monthly* data for the 1995–2012 period:

$$\Delta \log C_m = \alpha + \sum_{i=1}^{14} \beta_i \cdot \text{Shock}_m^i + \varepsilon_m, \tag{13}$$

where m indexes months and $\Delta \log C_m$ is the log change of monthly real personal consumption expenditures (FRED® code: PCEC96). The R^2 in this regression is 0.47, so the shocks account for a considerable variation in the monthly consumption growth rate. We then compute the aggregate shock as the *daily* predicted values of the consumption growth rate, $\widehat{\Delta \log C}_t = \hat{\alpha} + \sum_{i=1}^{14} \hat{\beta}_i \cdot \text{Shock}_t^i$.[31]

Next, we estimate the effect of our shock measures on the cross-sectional frequency and size of price changes and shopping intensity (number of clicks). Let f_t^{b} be the between-good, click-weighted frequency of price adjustment on day t. To allow for a delayed response to shocks, we also construct $\tilde{f}_t^{\text{b}} = \sum_{\tau=0}^{13} f_{t+\tau}^{\text{b}}/14$, the average weighted frequency of price adjustment within 14 days since day t. In a similar spirit, let $\overline{|\Delta \log p|}_t^{\text{w}}$ be the between-good, click-weighted average price change on day t and $\widetilde{|\Delta \log p|}_t^{\text{b}}$ the average value of the size of price changes between t and $t+14$. Since we expect a given shock to move prices in a certain direction, we consider price increases and decreases separately. Finally, Q_t is the total number of clicks on day t and $\tilde{Q}_t$ the average number of daily clicks between t and $t+14$. We project each moment at daily frequency on a set of dummy variables to remove the predictable variation of the moment across days of the week and days of the month. Then, we regress the residual from this projection on each individual shock separately and on the aggregate shock. Since we have relatively

[30] The data were collected by Money Market Services (MMS) up until 2003, when MMS merged with another leading financial analysis company, MCM, to form IGM. See Andersen et al. (2003) and Gurkaynak, Sack, and Swanson (2005) for more information about the data.

[31] We consider alternative ways to aggregate shocks. First, we use $\log(C_{m+h}/C_{m-1})$ as the dependent variable to allow shocks to have effects over h months rather than one month. This dependent variable gives higher weights to shocks that have delayed effects on consumption. Second, we use the *daily* percentage change in the S&P500 index as the dependent variable. While this variable is noisier than the consumption growth rate, it may provide a better measure of market expectations of how the economy reacts to the shocks. Using these alternative approaches does not affect our conclusions.

Table 14. Effects of Macroeconomic Shocks on Pricing

	On Impact							Two Weeks Ahead						
	Regular Price						Log	Regular Price						Log
	Frequency of		Absolute Size of		Sales		Number	Frequency of		Absolute Size of		Sales		Number
	Increases	Decreases	Inc.	Dec.	Freq.	Abs. Size	of Clicks	Inc.	Dec.	Inc.	Dec.	Freq.	Abs. Size	of Clicks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Capacity utilization	−0.05	−0.10	3.45	−0.91	−4.26	1.00	−0.10	−0.04	−0.23	0.49	−0.12	−0.68	−0.01	−0.08
	(0.48)	(0.53)	(1.22)	(1.47)	(3.32)	(2.63)	(0.12)	(0.28)	(0.29)	(0.75)	(0.92)	(2.10)	(0.32)	(0.13)
Consumer confidence	0.15	0.29	−4.36	0.16	0.00	0.21	0.11	0.40*	0.26	−0.62	−0.96	0.44	0.17*	0.05
	(0.54)	(0.49)	(3.98)	(1.14)	(1.82)	(0.29)	(0.12)	(0.24)	(0.26)	(0.65)	(0.85)	(1.17)	(0.10)	(0.11)
CPI, core	−0.67	−0.58	−1.00	3.38	−0.78	−3.50	0.11	−0.60	−0.58	0.24	−0.44	−0.81	−1.04	0.18
	(0.88)	(1.14)	(2.01)	(2.06)	(3.67)	(2.89)	(0.18)	(0.66)	(0.67)	(1.06)	(1.43)	(1.83)	(0.71)	(0.14)
Employment cost index	−0.02	0.25	−3.53	3.53	5.57	−0.56	0.01	0.06	0.06	−4.07**	−5.69*	1.14	−0.30	−0.15
	(1.67)	(1.43)	(3.06)	(3.83)	(5.08)	(3.95)	(0.24)	(0.84)	(0.73)	(1.73)	(3.07)	(2.66)	(0.36)	(0.18)
GDP	1.85	1.81	9.03	−22.89	−10.55	1.17	−0.24	−0.58	−0.22	10.70	14.97	−1.41	0.49	0.16
	(5.70)	(5.57)	(11.34)	(10.74)	(18.42)	(14.38)	(0.71)	(2.61)	(2.41)	(8.96)	(14.89)	(7.94)	(1.91)	(0.64)
Initial claims	−0.42	−0.29	0.67	−1.96	1.09	−0.52	−0.03	−0.27**	−0.28**	−0.10	−0.23	−0.65	−0.22*	−0.05
	(0.35)	(0.25)	(0.78)	(1.47)	(1.38)	(0.40)	(0.04)	(0.13)	(0.11)	(0.25)	(0.32)	(0.65)	(0.13)	(0.05)
ISM manufacturing index	0.14	0.00	−4.17	0.83	−1.60	0.74	0.10	0.13	0.14	−0.56	−0.65	2.38*	−0.08	0.09
	(0.35)	(0.45)	(4.33)	(2.29)	(3.40)	(0.78)	(0.13)	(0.19)	(0.20)	(0.54)	(0.81)	(1.42)	(0.31)	(0.11)
Leading indicators	−0.17	0.56	0.25	3.46	−3.09	3.34	0.09	0.40	0.15	0.22	0.00	1.02	0.10	0.09
	(0.55)	(0.64)	(1.37)	(1.40)	(2.31)	(4.13)	(0.11)	(0.39)	(0.28)	(0.70)	(1.05)	(1.24)	(0.40)	(0.14)
New home sales	−1.15	−0.46	−0.98	−7.03	5.76	−0.93	0.07	0.17	−0.12	−0.23	−0.86	1.28	−0.29	−0.04
	(1.56)	(1.24)	(0.84)	(11.38)	(4.24)	(0.66)	(0.28)	(0.60)	(0.55)	(0.94)	(1.06)	(2.06)	(0.31)	(0.26)
Nonfarm payrolls	0.85	1.09	−0.71	−0.48	−0.77	0.37	−0.11	0.18	0.26	−1.12*	−0.09	1.54	−0.33	−0.07
	(0.43)	(0.38)	(1.89)	(4.36)	(3.19)	(0.18)	(0.15)	(0.29)	(0.26)	(0.63)	(0.87)	(1.58)	(0.46)	(0.13)
PPI, core	−1.43*	−2.20	0.26	−0.76	−3.52	−0.19	0.01	−1.30***	−1.29***	0.04	−0.32	−0.65	−1.49**	−0.02
	(0.79)	(1.44)	(1.82)	(1.93)	(4.58)	(3.89)	(0.14)	(0.47)	(0.41)	(0.90)	(1.13)	(3.35)	(0.70)	(0.14)
Retail sales	0.27	0.65	−4.90	1.96	7.11	1.43	0.22	0.41	0.47	1.06	1.83*	1.60	1.45	0.24
	(1.33)	(1.56)	(2.47)	(1.82)	(4.55)	(2.38)	(0.29)	(0.86)	(0.86)	(0.80)	(1.03)	(2.52)	(1.51)	(0.25)
excluding motor vehicles	−0.16	−0.48	−2.51	1.89*	4.07	1.90	0.10	0.01	0.01	1.11***	1.50***	2.85	0.39	0.16
	(0.45)	(0.28)	(2.11)	(1.07)	(3.95)	(2.70)	(0.22)	(0.22)	(0.21)	(0.36)	(0.50)	(2.42)	(0.59)	(0.14)
Unemployment	0.11	0.25	−1.42	−3.93	1.55	−0.01	−0.06	−0.09	−0.11	−1.09**	−0.78	0.70	−0.05	−0.04
	(0.34)	(0.36)	(1.04)	(2.71)	(2.18)	(0.13)	(0.11)	(0.19)	(0.19)	(0.46)	(0.50)	(0.98)	(0.18)	(0.09)
Aggregate shock	***−0.17***	***−0.11***	***0.49***	***0.40***	***−0.57***	***−0.10***	***0.01***	***0.04***	***0.01***	***0.02***	***−0.26***	***−0.58***	***−0.01***	***−0.02***
	(0.19)	***(0.18)***	***(0.80)***	***(1.47)***	***(0.93)***	***(0.11)***	***(0.05)***	***(0.10)***	***(0.09)***	***(0.25)***	***(0.38)***	***(0.52)***	***(0.09)***	***(0.05)***

Source: Authors' calculations based on Informa Global Markets (IGM) data, combined with proprietary data from the online shopping platform, provided on condition of nondisclosure.
Notes: The table reports the estimates from regressions of pricing moment and clicks on high-frequency aggregate shocks. All variables and observations are click weighted when possible. All shocks are standardized to have zero mean and unit variance. Unweighted results are relegated to the appendix. The "two weeks ahead" results take the average over 14 days after the shock. The sample period is from May 1, 2010, to February 7, 2012. Bootstrap standard errors are in parentheses. *, **, and *** represent the 10, 5, and 1 percent significance level, respectively.

few nonmissing observations for each shock, we use bootstrap to estimate the average sensitivity of each moment to a shock and to calculate standard errors.

While Andersen et al. (2003), Gurkaynak, Sack, and Swanson (2005), and many others show that the surprise component in macroeconomic announcements moves asset prices at high frequencies, we find little evidence that the shocks have a consistently discernible effect on the moments on impact or within 14 days after a shock (Table 14). The vast majority of the estimates are not statistically or economically significant. None of the shocks moves the number of clicks, our proxy for demand. The aggregate shock, which has the largest number of nonmissing observations, does not have any significant estimates.

Obviously, the moments may be sensitive to other shocks, but our results suggest that prices of goods and services sold online are far from being as flexible as asset prices, exchange rates, bond yields, or commodity prices. In fact, online prices, after all, appear qualitatively similar to prices in conventional stores. Hence, the physical frictions of nominal price adjustment likely play only a minor role in the observed price stickiness.

6 Concluding Remarks

The internet offers seemingly limitless opportunities to the retail sector by enabling sellers to collect and process massive amounts of data to tailor prices and product characteristics to specific whims of consumers and ever-changing economic conditions. A popular view holds that prices for goods and services sold online should approach (if not now, then eventually) the flexibility of auction prices or stock prices. Indeed, the internet makes it trivial to compare prices across sellers: the best price is just a few clicks away, the physical location of online sellers is largely irrelevant, and numerous services advise online shoppers on when and where to buy a good they desire.

Using the unique richness of our dataset, which not only includes a very broad coverage of goods over a long time period but also provides a proxy (clicks) for quantities associated with price quotes, we find that online prices are more flexible than prices in brick-and-mortar stores. Furthermore, click-weighted pricing moments point to a greater flexibility for price quotes that matter to consumers. However, we also document that online prices demonstrate tangible imperfections such as stickiness, low synchronization of price changes, large cross-sectional price dispersion, and low sensitivity to predictable and unanticipated fluctuations in demand.

These findings have a number of implications. First, even if e-commerce grows to dominate the retail sector, price stickiness is unlikely to disappear because it does not seem to be determined exclusively by search costs and/or physical costs of changing a price sticker. Second, one should not disregard the effect of e-commerce on properties of the aggregate price level and inflation, as pricing in online markets does differ from that in brick-and-mortar stores. Third, macroeconomists should put more effort into developing theoretical models with alternative mechanisms generating price stickiness and other imperfections. Fourth, we anticipate that much can be learned from studying the price-setting of sellers that have a presence in both online and offline markets, as well as from more complete information about online sellers' inventories and costs.

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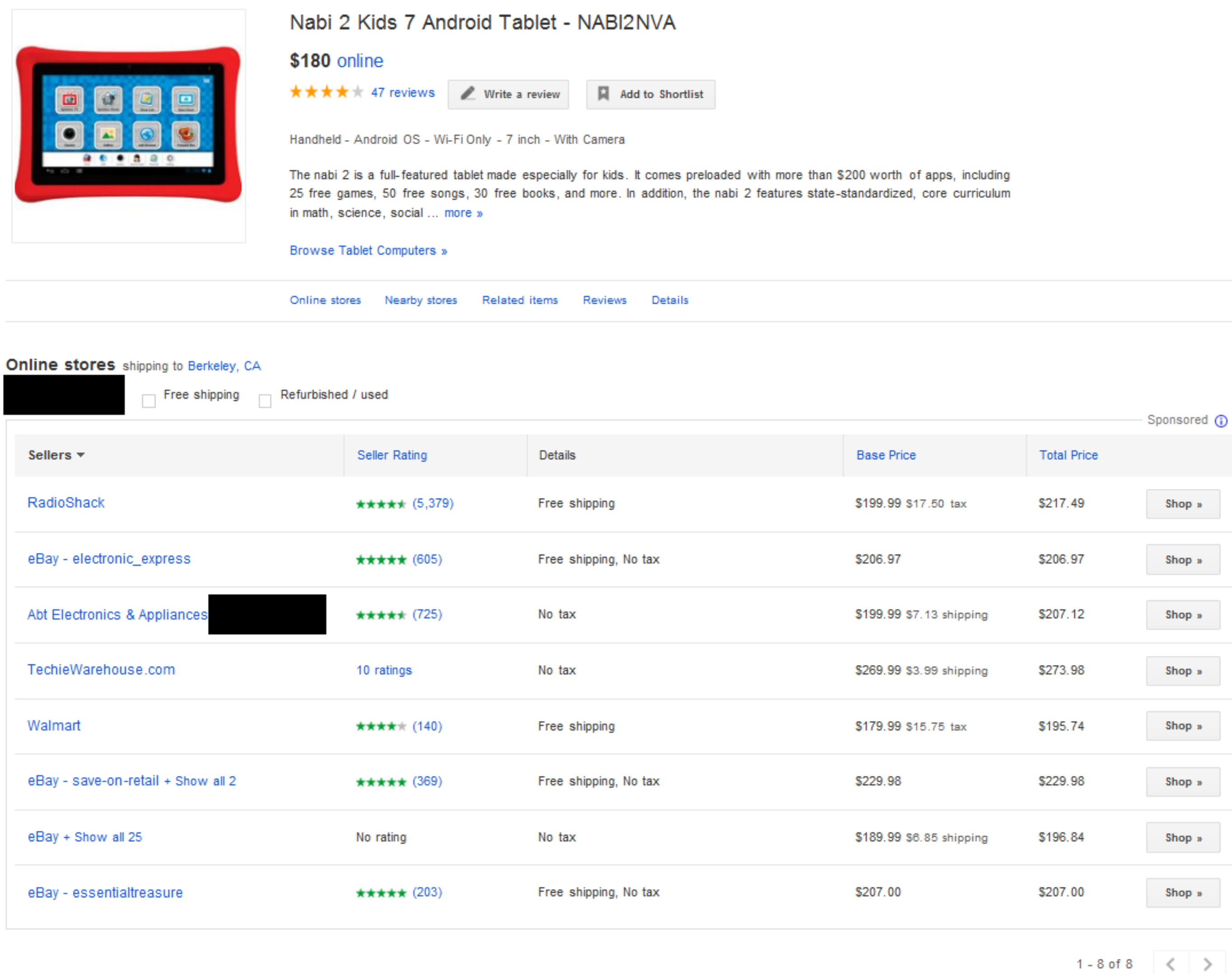
Appendix

A A Typical Shopping Platform

Figure A1 provides an example of how a search result for a particular good is seen by customers in a typical shopping platform. Available information includes the product's name and image, a brief description, the number of reviews, the minimum price online, as well as information about online sellers of the good. The on-screen order of sellers is based on their quality rank and a bid price a seller chooses to pay per click, but the consumer can re-sort sellers by the average review score and the base or total price. Figure A2 provides the list of choices the seller makes on a typical platform: a geographical location of viewers and a language they speak, as well as a bid for the cost per click and the daily budget. Figure A3 provides an example of the ad campaign information available to sellers. It includes the number of clicks, impressions (display of the listing), and conversions (specific actions, such as a purchase, on the seller's website), as well as the click-through rate (clicks divided by impressions), the average cost per click and conversion, and the total cost of the ad.

Figure A1. Shopping Platform Screenshot: A Product Listing



Nabi 2 Kids 7 Android Tablet - NABI2NVA

$180 online

47 reviews Write a review Add to Shortlist

Handheld - Android OS - Wi-Fi Only - 7 inch - With Camera

The nabi 2 is a full-featured tablet made especially for kids. It comes preloaded with more than $200 worth of apps, including 25 free games, 50 free songs, 30 free books, and more. In addition, the nabi 2 features state-standardized, core curriculum in math, science, social ... more »

Browse Tablet Computers »

Online stores Nearby stores Related items Reviews Details

Online stores shipping to Berkeley, CA

[redacted] Free shipping Refurbished / used

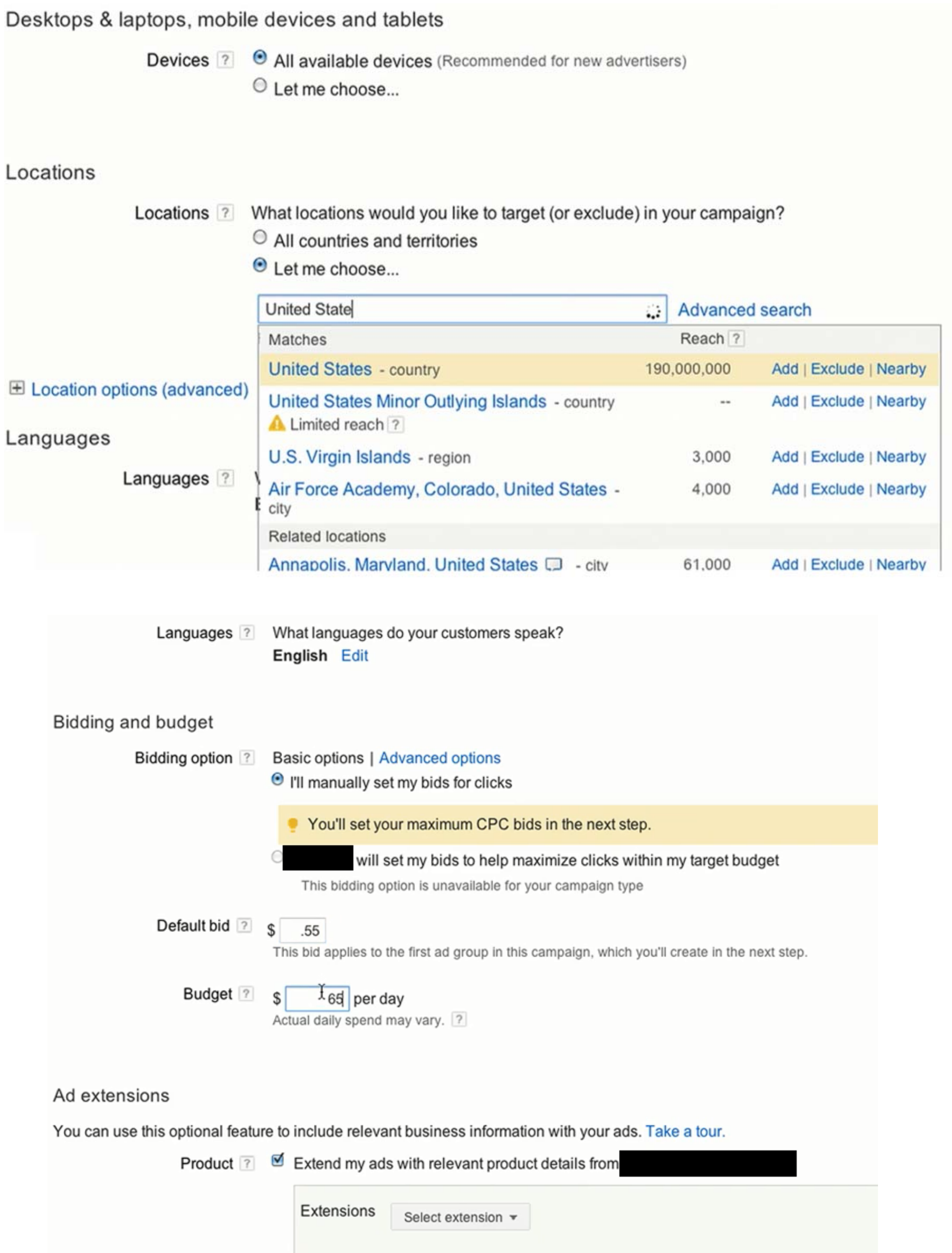
Sponsored

Sellers	Seller Rating	Details	Base Price	Total Price	
RadioShack	(5,379)	Free shipping	$199.99 $17.50 tax	$217.49	Shop »
eBay - electronic_express	(605)	Free shipping, No tax	$206.97	$206.97	Shop »
Abt Electronics & Appliances [redacted]	(725)	No tax	$199.99 $7.13 shipping	$207.12	Shop »
TechieWarehouse.com	10 ratings	No tax	$269.99 $3.99 shipping	$273.98	Shop »
Walmart	(140)	Free shipping	$179.99 $15.75 tax	$195.74	Shop »
eBay - save-on-retail + Show all 2	(369)	Free shipping, No tax	$229.98	$229.98	Shop »
eBay + Show all 25	No rating	No tax	$189.99 $6.85 shipping	$196.84	Shop »
eBay - essentialtreasure	(203)	Free shipping, No tax	$207.00	$207.00	Shop »

1 - 8 of 8

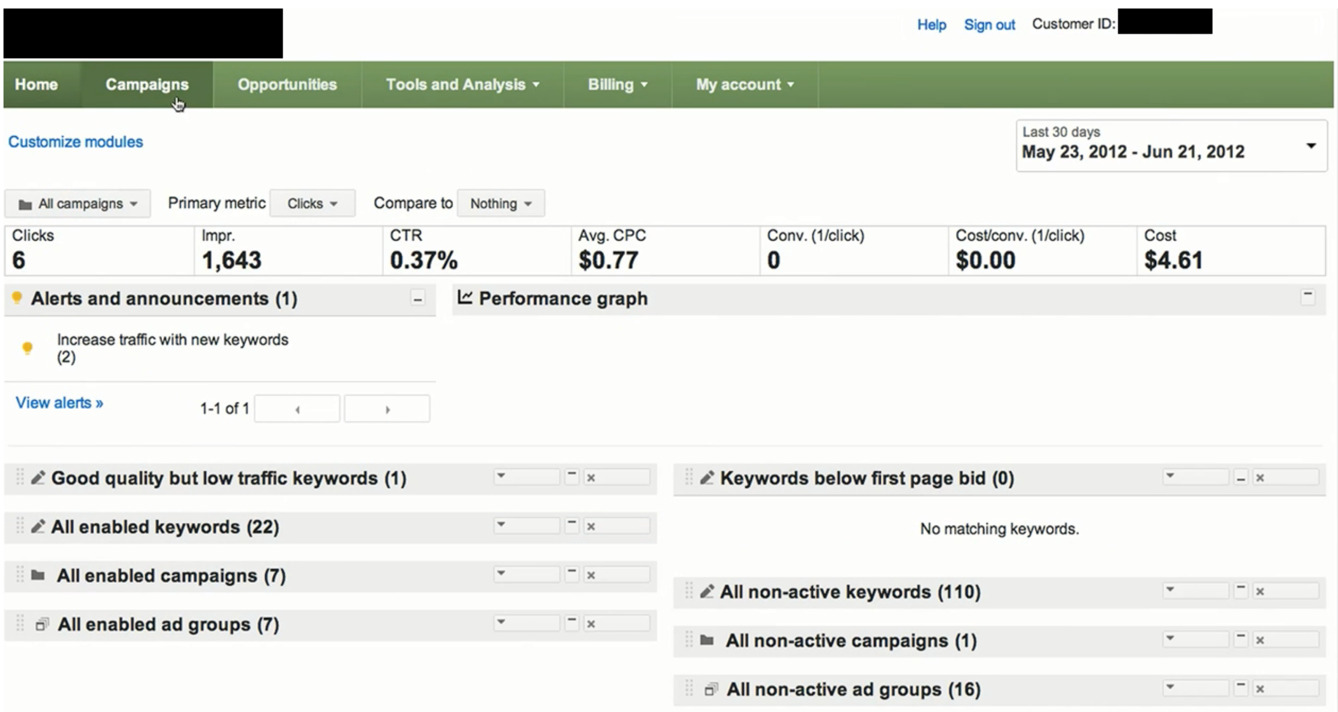
Notes: The screenshot is taken in December 2012 from a typical online shopping platform. Black boxes mask the name of the platform to highlight that it does not necessarily represent the data provider.

Figure A2. Shopping Platform Screenshot: Advertiser Account



Notes: The screenshot is taken in December 2012 from a typical online shopping platform. Black boxes mask the name of the platform to highlight that it does not necessarily represent the data provider.

Figure A3. Shopping Platform Screenshot: Ad Summary



Notes: The screenshot is taken in December 2012 from a typical online shopping platform. Black boxes mask the name of the platform to highlight that it does not necessarily represent the data provider.

B Data Processing and Aggregation

The dataset,[1] as supplied by the data provider, contains a sample of 52,788 goods across 27,315 sellers in the United States and 52,804 goods across 8,757 sellers in the United Kingdom for the period from May 1, 2010, to February 7, 2012. We minimally process the data to deal with omissions, duplications, and inconsistencies. First, we drop prices denominated in a foreign currency, leaving only those in the dollar and sterling for each country, respectively. Second, we drop prices above 500,000 as those are likely to stand for errors and missing values; in fact, most prices are below 5,000 dollars. This leaves us with 52,776 and 52,767 goods and 27,308 and 8,757 sellers in the United States and the United Kingdom, respectively. Finally, in a small number of cases we have more than one daily observation for the same country, seller, and good. If the duplicated observations appear to have the same price, we aggregate them in one data point by summing over clicks. If, instead, prices differ, we take the mode price, sum over clicks, and drop price quotes different from the mode.[2] These transformations affect a tiny share of observations and our assumptions do not affect the results in any meaningful way.

Since the data contain many missing values at the daily frequency (no clicks for a particular quote line on a given day) and to enhance comparison with existing studies, we aggregate the data to the weekly frequency by taking the mode price for a good, seller, and week.[3] To show that this aggregation procedure does not lead to a significant loss in variation, we compute the share of intraweek price variation in total daily variation for each good and seller:

$$\omega_{is} = \frac{\widehat{\mathbb{V}}_t\left[\log p_{ist} - \log p_{ist}^{\text{weekly}}\right]}{\widehat{\mathbb{V}}_t\left[\log p_{ist}\right]}, \tag{B1}$$

where p_{ist} is the daily price, p_{ist}^{weekly} is the mode price within a given week, and $\widehat{\mathbb{V}}$ is the sample variance. In line with our usual approach, we then compute the raw mean over sellers (no weights), $\bar{\omega}_i = \sum_{s\in\mathscr{S}_i} \omega_{is}/S_i$, and the click-weighted mean (within goods), $\bar{\omega}_i^{\text{w}} = \sum_{s\in\mathscr{S}_i} Q_{is}\omega_{is}/Q_i$; the average of $\bar{\omega}_i^{\text{w}}$ with between-good weights $W_i = Q_i/Q$ is also computed. With no weights or within-good weights only, the share of intraweek variation in prices for the median good is zero; with between-good weights, it is around 13 percent in the United States and 11 percent in the United Kingdom (Table B1). Hence, goods that receive a small number of clicks have almost no intraweek variation in prices (and also a lot of missing values when no one clicks on them); the intraweek variation for popular goods is reasonably small and does not seem to create any problems for aggregation.

Table B1. Share of Intraweek Price Variation in Total Daily Variation, percent

	No Weights			Within-Good Weights			Between-Good Weights			
	Mean (1)	Standard Deviation (2)	Median (3)	Mean (4)	Standard Deviation (5)	Median (6)	Mean (7)	Standard Deviation (8)	Median (9)	Number of Goods (10)
United States	5.1	13.0	0.0	3.0	8.9	0.0	14.6	12.1	12.9	52,776
United Kingdom	5.0	15.4	0.0	1.8	8.5	0.0	13.1	12.3	10.6	52,767

Source: Authors' calculations based on proprietary data, provided on condition of nondisclosure.

[1] All tables and figures in the appendix are based on proprietary data, provided on condition of nondisclosure, unless specified otherwise.

[2] When we have more than one mode for duplicated observations, we use the smallest one since we know that smaller prices receive more clicks. We prefer the mode to the mean or the median in order not to generate artificial price quotes, which may spuriously break price spells.

[3] When there are more than one mode, we keep the one with the earliest first occurrence.

C Heterogeneity of Price Rigidity across Products: Tables and Figures

Table C1. Frequency of Price Adjustment and Implied Duration of Spells

	Median Implied Duration, *weeks* (1)	Frequency, *percent* Mean (2)	Standard Deviation (3)	5th Percentile (4)	25th Percentile (5)	Median (6)	75th Percentile (7)	95th Percentile (8)	Number of Goods (9)
Panel A: United States—No Imputation									
Posted Price									
No weights	6.6	17.8	17.4	0.0	4.9	14.0	25.0	52.9	
Within-good weights	5.5	19.7	17.9	0.0	5.3	16.7	28.9	53.8	14,483
Between-good weights	4.7	19.8	11.2	2.8	11.8	19.3	26.4	40.0	
Regular Price: One-Week-Decrease Filter									
No weights	7.3	16.8	16.8	0.0	4.3	12.8	23.4	50.0	
Within-good weights	6.0	18.5	17.2	0.0	4.8	15.4	27.1	50.0	14,458
Between-good weights	5.2	18.1	10.5	2.5	10.5	17.4	24.2	37.0	
Regular Price: One-Week Two-Side Filter									
No weights	10.9	12.3	14.0	0.0	0.4	8.8	17.3	40.0	
Within-good weights	8.7	13.9	14.6	0.0	0.4	10.8	20.0	40.2	16,332
Between-good weights	6.4	15.4	9.5	1.3	8.7	14.5	21.5	32.0	
Regular Price: Two-Week Two-Side Filter									
No weights	12.2	11.7	13.9	0.0	0.0	7.9	16.7	40.0	
Within-good weights	10.0	13.0	14.3	0.0	0.0	9.5	19.4	40.0	16,110
Between-good weights	7.2	13.9	9.1	1.0	7.5	13.0	19.9	29.7	
Panel B: United Kingdom—No Imputation									
Posted Price									
No weights	7.3	20.4	24.1	0.0	0.0	12.8	28.6	80.0	
Within-good weights	7.2	20.7	24.3	0.0	0.0	13.0	30.0	80.0	6,623
Between-good weights	4.5	20.4	13.8	0.0	9.8	20.0	28.3	42.7	
Regular Price: One-Week-Decrease Filter									
No weights	7.7	19.5	23.6	0.0	0.0	12.2	27.7	76.9	
Within-good weights	7.8	19.7	23.7	0.0	0.0	12.0	28.6	77.8	6,601
Between-good weights	4.8	19.1	13.3	0.0	8.3	18.8	26.3	41.2	
Regular Price: One-Week Two-Side Filter									
No weights	12.5	15.2	21.1	0.0	0.0	7.7	20.0	66.7	
Within-good weights	12.5	15.5	21.3	0.0	0.0	7.7	20.1	66.7	7,738
Between-good weights	5.8	16.7	12.6	0.0	6.6	15.8	23.3	37.9	
Regular Price: Two-Week Two-Side Filter									
No weights	13.5	14.7	20.8	0.0	0.0	7.1	20.0	66.7	
Within-good weights	13.5	14.9	21.0	0.0	0.0	7.1	20.0	66.7	7,582
Between-good weights	6.2	15.8	12.2	0.0	6.4	15.0	22.4	36.6	
Panel C: United States—With Imputation									
Posted Price									
No weights	13.4	10.7	13.3	0.0	0.0	7.2	15.2	37.2	
Within-good weights	10.2	12.6	14.2	0.0	0.0	9.3	19.5	40.0	18,515
Between-good weights	5.6	17.1	10.4	1.5	9.4	16.3	23.6	35.9	
Regular Price: One-Week-Decrease Filter									
No weights	14.4	10.2	12.8	0.0	0.0	6.7	14.3	34.2	
Within-good weights	11.1	11.9	13.6	0.0	0.0	8.6	18.1	37.5	18,505
Between-good weights	6.3	15.6	9.7	1.2	8.6	14.7	21.5	32.5	
Regular Price: One-Week Two-Side Filter									
No weights	15.5	9.7	12.4	0.0	0.0	6.3	13.8	33.3	
Within-good weights	12.1	11.2	13.0	0.0	0.0	8.0	16.7	36.0	18,487
Between-good weights	6.9	14.4	9.2	0.9	7.8	13.5	20.2	30.4	
Regular Price: Two-Week Two-Side Filter									
No weights	17.5	9.0	11.9	0.0	0.0	5.6	12.5	32.4	
Within-good weights	13.8	10.3	12.5	0.0	0.0	7.0	15.7	33.3	18,475
Between-good weights	7.9	13.0	8.7	0.6	6.6	11.9	18.4	27.9	

Table C1. Frequency of Price Adjustment and Implied Duration of Spells (*cont.*)

	Median Implied Duration, *weeks* (1)	Frequency, *percent* Mean (2)	Standard Deviation (3)	5th Percentile (4)	25th Percentile (5)	Median (6)	75th Percentile (7)	95th Percentile (8)	Number of Goods (9)
Panel D: United Kingdom—With Imputation									
Posted Price									
No weights	16.5	13.6	20.2	0.0	0.0	5.9	18.2	61.5	
Within-good weights	16.4	14.1	20.6	0.0	0.0	5.9	19.9	63.2	8,991
Between-good weights	5.4	17.9	13.0	0.0	7.2	17.0	27.2	39.1	
Regular Price: One-Week-Decrease Filter									
No weights	17.5	13.0	19.8	0.0	0.0	5.6	17.1	60.0	
Within-good weights	17.8	13.5	20.0	0.0	0.0	5.5	18.5	60.5	8,978
Between-good weights	5.8	16.7	12.5	0.0	6.7	15.8	24.6	37.5	
Regular Price: One-Week Two-Side Filter									
No weights	19.5	12.6	19.4	0.0	0.0	5.0	16.7	60.0	
Within-good weights	19.3	13.0	19.7	0.0	0.0	5.1	17.4	60.0	8,968
Between-good weights	6.3	15.8	12.3	0.0	6.2	14.7	22.4	36.6	
Regular Price: Two-Week Two-Side Filter									
No weights	21.5	12.0	18.9	0.0	0.0	4.5	16.1	58.9	
Within-good weights	21.5	12.3	19.1	0.0	0.0	4.5	16.7	60.0	8,952
Between-good weights	6.8	14.8	11.8	0.0	5.8	13.7	21.2	35.2	

Notes: This table reproduces the frequency of price adjustment and median implied duration from Table 5, adding two additional sale filters and showing moments of the distribution of the frequency across goods.

Table C2. Frequency of Price Increases and Decreases

	Mean (1)	Standard Deviation (2)	5th Percentile (3)	25th Percentile (4)	Median (5)	75th Percentile (6)	95th Percentile (7)	Number of Goods (8)
Panel A: United States								
Posted Price Increases								
No weights	8.3	9.7	0.0	0.0	5.9	12.2	27.3	
Within-good weights	9.2	9.8	0.0	0.0	7.2	14.1	27.8	14,483
Between-good weights	8.9	5.4	0.9	5.4	8.6	12.0	18.7	
Posted Price Decreases								
No weights	9.5	11.0	0.0	0.0	6.5	14.2	31.9	
Within-good weights	10.5	11.2	0.0	0.0	8.3	15.9	32.7	14,483
Between-good weights	10.9	6.9	0.8	5.8	10.1	15.0	22.8	
Regular Price Increases								
No weights	5.7	7.9	0.0	0.0	3.3	8.3	20.0	
Within-good weights	6.4	8.1	0.0	0.0	4.2	9.8	20.0	16,332
Between-good weights	6.8	4.4	0.0	3.7	6.4	9.2	14.3	
Regular Price Decreases								
No weights	6.6	9.1	0.0	0.0	3.7	9.5	23.2	
Within-good weights	7.4	9.4	0.0	0.0	4.8	11.2	25.0	16,332
Between-good weights	8.6	6.1	0.0	4.2	7.7	12.0	19.2	
Panel B: United Kingdom								
Posted Price Increases								
No weights	10.4	14.2	0.0	0.0	5.6	15.0	40.0	
Within-good weights	10.5	14.2	0.0	0.0	5.7	15.1	40.0	6,623
Between-good weights	9.8	7.2	0.0	4.6	9.0	13.1	20.3	
Posted Price Decreases								
No weights	10.0	13.3	0.0	0.0	5.3	14.9	40.0	
Within-good weights	10.2	13.4	0.0	0.0	5.4	15.8	40.0	6,623
Between-good weights	10.6	7.8	0.0	4.2	10.4	15.0	24.0	
Regular Price Increases								
No weights	7.8	12.6	0.0	0.0	2.3	10.8	35.7	
Within-good weights	7.9	12.6	0.0	0.0	2.5	11.1	36.7	7,738
Between-good weights	8.0	6.6	0.0	3.4	7.2	11.9	18.1	
Regular Price Decreases								
No weights	7.4	11.6	0.0	0.0	1.7	10.4	33.3	
Within-good weights	7.6	11.8	0.0	0.0	1.7	11.1	33.3	7,738
Between-good weights	8.7	7.2	0.0	2.7	8.1	12.9	20.8	

Notes: This table shows the distribution of the frequency of price increases and decreases across goods.

Table C3. Cross-Good Heterogeneity of the Size of Price Changes, log points

	Mean (1)	Standard Deviation (2)	5th Percentile (3)	25th Percentile (4)	Median (5)	75th Percentile (6)	95th Percentile (7)	Number of Goods (8)
Panel A: United States								
All Changes								
No weights	0.6	17.6	−21.9	−3.5	0.0	3.9	26.0	
Within-good weights	0.2	18.2	−22.9	−4.5	−0.3	4.0	26.8	17,053
Between-good weights	−2.0	6.6	−10.9	−3.9	−1.6	0.3	5.8	
Absolute Value								
No weights	16.3	17.2	1.0	5.4	11.0	20.4	51.3	
Within-good weights	16.3	17.4	1.0	5.2	10.7	20.5	52.2	17,053
Between-good weights	13.7	9.8	4.2	7.5	11.2	16.7	30.6	
Price Increases								
No weights	17.5	18.3	1.0	5.7	11.8	22.2	55.0	
Within-good weights	17.3	18.6	1.0	5.4	11.3	22.0	56.4	13,795
Between-good weights	13.9	10.7	3.7	7.2	11.2	17.1	33.3	
Price Decreases								
No weights	15.4	17.0	0.9	4.9	10.3	19.3	49.6	
Within-good weights	15.6	17.4	0.9	4.7	10.1	19.7	50.9	14,023
Between-good weights	13.6	10.4	3.6	7.3	10.8	16.4	32.3	
Panel B: United Kingdom								
All Changes								
No weights	0.5	13.2	−15.2	−1.8	0.2	2.6	17.5	
Within-good weights	0.2	13.8	−16.6	−2.4	0.1	2.5	18.2	9,092
Between-good weights	−1.3	6.2	−9.7	−3.4	−0.6	0.7	5.5	
Absolute Value								
No weights	9.5	13.2	0.4	1.7	5.1	11.8	35.2	
Within-good weights	9.7	13.5	0.4	1.7	5.0	11.8	35.9	9,092
Between-good weights	10.1	8.0	1.8	4.6	8.5	14.0	23.6	
Price Increases								
No weights	9.9	13.6	0.4	1.7	5.3	12.3	35.2	
Within-good weights	9.9	13.8	0.4	1.7	5.1	12.1	35.7	6,983
Between-good weights	9.8	8.6	1.4	4.0	8.0	13.3	26.4	
Price Decreases								
No weights	9.4	13.5	0.4	1.6	4.7	11.3	34.8	
Within-good weights	9.6	13.9	0.4	1.5	4.7	11.7	36.3	6,717
Between-good weights	10.4	8.6	1.6	4.9	7.7	14.8	23.2	

Notes: This table reproduces the size of price changes for posted prices from Table 5, adding actual (as opposed to absolute values of) changes and showing moments of the distribution across goods.

Table C4. The Size of *Absolute* Price Changes for Posted and Regular Prices, log points

	Mean (1)	Standard Deviation (2)	5th Percentile (3)	25th Percentile (4)	Median (5)	75th Percentile (6)	95th Percentile (7)	Number of Goods (8)
Panel A: United States								
Posted Price								
No weights	16.3	17.2	1.0	5.4	11.0	20.4	51.3	
Within-good weights	16.3	17.4	1.0	5.2	10.7	20.5	52.2	17,053
Between-good weights	13.7	9.8	4.2	7.5	11.2	16.7	30.6	
Regular Price: One-Week-Decrease Filter								
No weights	16.3	17.2	1.0	5.4	11.0	20.5	51.2	
Within-good weights	16.2	17.4	1.0	5.2	10.7	20.5	52.0	16,983
Between-good weights	13.5	9.7	4.1	7.5	11.0	16.6	30.6	
Regular Price: One-Week Two-Side Filter								
No weights	16.1	17.0	1.0	5.3	10.9	20.2	50.7	
Within-good weights	16.0	17.3	1.0	5.1	10.6	20.3	51.6	16,877
Between-good weights	13.3	9.6	4.0	7.5	10.9	16.6	30.0	
Regular Price: Two-Week Two-Side Filter								
No weights	15.9	17.0	1.0	5.2	10.7	20.0	50.3	
Within-good weights	15.9	17.2	1.0	5.1	10.5	20.1	51.2	16,612
Between-good weights	13.1	9.5	4.0	7.4	10.6	16.1	29.8	
Panel B: United Kingdom								
Posted Price								
No weights	9.5	13.2	0.4	1.7	5.1	11.8	35.2	
Within-good weights	9.7	13.5	0.4	1.7	5.0	11.8	35.9	9,092
Between-good weights	10.1	8.0	1.8	4.6	8.5	14.0	23.6	
Regular Price: One-Week-Decrease Filter								
No weights	9.5	13.1	0.4	1.7	5.1	11.8	34.8	
Within-good weights	9.6	13.4	0.4	1.7	5.0	11.8	35.7	9,044
Between-good weights	10.0	8.0	1.8	4.6	7.7	13.9	23.5	
Regular Price: One-Week Two-Side Filter								
No weights	9.4	13.0	0.4	1.7	5.0	11.6	34.6	
Within-good weights	9.5	13.3	0.4	1.7	4.9	11.7	35.3	8,990
Between-good weights	9.9	8.0	1.8	4.5	7.6	13.7	23.3	
Regular Price: Two-Week Two-Side Filter								
No weights	9.3	12.9	0.4	1.7	5.0	11.5	33.8	
Within-good weights	9.4	13.2	0.4	1.6	4.9	11.5	34.9	8,879
Between-good weights	9.8	8.0	1.8	4.5	7.4	13.6	23.5	

Notes: This table reproduces the absolute size of price changes from Table 5 for different types of sale filters.

Table C5. Synchronization Rate, percent

	Mean (1)	Standard Deviation (2)	25th Percentile (3)	Median (4)	75th Percentile (5)	95th Percentile (6)	Number of Goods/Sellers (7)
Panel A: United States—Posted Prices							
Synchronization across Sellers							
No weights	10.2	18.6	0.0	0.0	13.5	50.0	
Within-good weights	10.6	19.2	0.0	0.0	14.2	48.0	9,937
Between-good weights	15.7	10.0	8.1	15.1	21.6	33.8	
Synchronization across Goods							
No weights	17.2	27.4	0.0	1.6	25.0	100.0	
Within-seller weights	17.6	28.3	0.0	1.2	23.7	100.0	2,344
Between-seller weights	22.5	11.6	12.1	24.9	31.4	31.4	
Panel B: United Kingdom—Posted Prices							
Synchronization across Sellers							
No weights	14.7	24.8	0.0	0.0	20.0	96.3	
Within-good weights	14.8	25.2	0.0	0.0	19.6	96.3	3,867
Between-good weights	17.9	11.1	9.8	17.9	25.7	35.8	
Synchronization across Goods							
No weights	19.7	26.5	0.0	8.2	30.0	83.3	
Within-seller weights	19.3	26.8	0.0	8.3	26.9	85.9	1,258
Between-seller weights	26.1	16.7	12.9	26.0	34.4	57.0	
Panel C: United States—Regular Prices							
Synchronization across Sellers							
No weights	7.8	16.4	0.0	0.0	9.1	33.3	
Within-good weights	8.2	17.0	0.0	0.0	10.0	37.5	10,280
Between-good weights	12.8	8.6	6.4	12.6	18.0	25.7	
Synchronization across Goods							
No weights	14.7	25.7	0.0	0.0	18.2	91.1	
Within-seller weights	15.2	26.7	0.0	0.0	18.5	94.3	2,422
Between-seller weights	18.3	10.3	9.1	20.3	25.8	25.8	
Panel D: United Kingdom—Regular Prices							
Synchronization across Sellers							
No weights	12.1	22.9	0.0	0.0	14.8	56.3	
Within-good weights	12.4	23.4	0.0	0.0	15.2	69.4	4,005
Between-good weights	15.6	10.5	7.8	14.3	23.7	32.6	
Synchronization across Goods							
No weights	16.6	24.7	0.0	5.0	25.0	75.0	
Within-seller weights	16.5	25.0	0.0	4.9	22.3	75.2	1,306
Between-seller weights	22.4	15.3	11.4	21.2	29.5	49.1	

Notes: This table reproduces the synchronization rate from Table 8 and reports moments of the distribution across products.

D Price Rigidity by Product Category: Tables and Figures

Table D1. Median Frequency of Price Adjustment, percent

	Posted Price			Regular Price			
Category	No Weights (1)	Within Weights (2)	Between Weights (3)	No Weights (4)	Within Weights (5)	Between Weights (6)	Number of Goods (7)
Panel A: United States							
Apparel and Accessories	10.3	11.6	10.8	6.6	7.8	8.3	1,101
Arts and Entertainment	10.0	12.5	8.9	5.4	6.7	5.5	949
Baby and Toddler	14.4	15.0	15.1	8.4	10.7	12.3	74
Business and Industrial	9.1	5.2	3.7	4.9	3.3	1.1	14
Cameras and Optics	11.4	12.2	33.3	6.8	7.5	24.9	503
Electronics	14.6	17.4	21.6	9.7	11.1	16.8	3,057
Food, Beverages, and Tobacco	10.3	16.1	14.4	8.8	13.2	13.2	25
Furniture	12.0	15.0	13.2	8.4	10.1	9.7	186
Hardware	13.3	16.6	15.9	8.3	10.4	11.3	879
Health and Beauty	13.5	18.2	17.6	8.3	11.7	13.1	1,787
Home and Garden	12.6	16.3	15.2	8.0	10.5	11.8	2,055
Luggage and Bags	12.3	12.4	12.1	8.5	8.5	9.4	378
Mature	10.0	15.1	19.9	4.9	8.0	13.2	30
Media	20.0	20.0	23.8	14.2	13.1	16.7	1,674
Office Supplies	16.7	18.2	16.7	10.2	12.5	13.2	286
Pet Supplies	12.5	16.4	13.9	7.5	10.0	9.7	500
Services	21.6	22.7	25.5	16.2	17.5	20.5	2
Software	13.5	12.6	24.2	7.1	7.8	20.0	159
Sporting Goods	13.2	16.0	15.6	8.3	11.1	11.6	788
Toys and Games	17.0	20.3	19.9	10.9	14.3	15.4	1,053
Vehicles and Parts	12.5	15.2	19.4	7.1	9.6	13.4	231
Not Classified	*19.3*	*22.2*	*25.9*	*12.7*	*16.6*	*19.1*	*601*
All Goods	***14.0***	***16.7***	***19.3***	***8.8***	***10.8***	***14.5***	***16,332***
Panel B: United Kingdom							
Apparel and Accessories	9.5	9.1	13.0	5.3	4.5	11.1	487
Arts and Entertainment	7.3	6.5	10.1	1.7	1.9	6.2	423
Baby and Toddler	11.7	14.1	15.2	8.1	9.9	12.0	67
Business and Industrial	16.3	9.1	2.5	3.5	1.2	2.3	6
Cameras and Optics	14.3	13.7	20.2	9.7	9.5	16.3	275
Electronics	19.1	19.4	25.2	13.4	13.7	21.3	1,695
Food, Beverages, and Tobacco	0.0	0.0	0.0	0.0	0.0	0.0	16
Furniture	14.3	18.2	26.1	8.0	10.0	22.9	79
Hardware	9.7	9.1	13.3	6.3	5.7	9.5	433
Health and Beauty	8.5	8.0	8.0	4.6	4.5	6.0	1,015
Home and Garden	15.7	16.7	21.8	9.6	10.3	17.4	791
Luggage and Bags	12.5	10.8	15.6	5.9	5.9	8.1	197
Mature	0.0	0.0	0.0	0.0	0.0	0.0	2
Media	20.0	20.0	17.6	14.3	16.7	14.3	547
Office Supplies	16.7	16.7	22.3	9.1	10.0	13.6	72
Pet Supplies	14.3	16.1	13.3	8.3	8.3	11.1	150
Services	19.0	18.4	25.3	6.7	9.5	18.0	5
Software	17.4	19.7	28.3	12.5	12.1	22.6	94
Sporting Goods	3.6	3.7	7.4	0.0	0.0	6.5	627
Toys and Games	12.5	12.5	15.3	7.1	7.2	11.7	553
Vehicles and Parts	8.3	9.1	12.1	1.3	0.9	10.8	62
Not Classified	*9.1*	*9.0*	*11.1*	*3.2*	*2.7*	*9.6*	*142*
All Goods	***12.8***	***13.0***	***20.0***	***7.7***	***7.7***	***15.8***	***7,738***

Notes: This table reproduces the median frequency of price adjustment, reported in Columns (1)–(3) of Table 5, by product category.

Table D2. Median *Absolute* Size of Price Changes, log points

Category	Posted Price: No Weights (1)	Posted Price: Within Weights (2)	Posted Price: Between Weights (3)	Regular Price: No Weights (4)	Regular Price: Within Weights (5)	Regular Price: Between Weights (6)	Number of Goods (7)
Panel A: United States							
Apparel and Accessories	14.0	14.0	13.3	13.9	13.9	13.1	998
Arts and Entertainment	18.4	18.2	15.8	18.4	18.2	15.3	851
Baby and Toddler	16.1	16.2	15.8	15.1	15.1	16.3	73
Business and Industrial	9.9	9.6	9.1	9.8	9.3	7.3	16
Cameras and Optics	13.3	13.4	9.8	13.5	13.5	9.2	414
Electronics	14.7	14.8	13.2	14.5	14.6	12.8	2,983
Food, Beverages, and Tobacco	23.8	24.1	24.3	23.1	23.7	22.7	26
Furniture	13.7	13.4	12.5	13.2	12.8	12.3	169
Hardware	13.8	13.7	11.6	13.7	13.6	11.4	884
Health and Beauty	17.7	17.7	16.3	17.2	17.2	15.5	1,771
Home and Garden	14.5	14.4	12.6	14.3	14.3	12.2	2,053
Luggage and Bags	16.5	16.6	15.9	16.3	16.4	15.7	357
Mature	12.9	13.7	11.3	13.0	13.8	11.4	27
Media	19.9	19.6	16.9	19.7	19.4	16.9	2,459
Office Supplies	18.7	18.9	14.4	18.2	18.5	14.1	303
Pet Supplies	17.9	17.8	15.5	17.6	17.6	15.2	493
Services	6.6	5.8	7.6	6.5	5.6	7.1	2
Software	14.0	14.2	13.1	14.1	14.3	13.0	145
Sporting Goods	11.1	11.3	11.6	10.9	11.1	11.5	875
Toys and Games	19.9	19.9	18.3	19.7	19.8	17.9	1,098
Vehicles and Parts	14.6	14.4	12.0	14.1	13.9	12.7	212
Not Classified	*17.7*	*17.6*	*17.5*	*17.5*	*17.5*	*16.6*	*668*
All Goods	***11.0***	***10.7***	***11.2***	***10.9***	***10.6***	***10.9***	***16,877***
Panel B: United Kingdom							
Apparel and Accessories	9.4	9.7	9.5	9.0	9.2	8.9	519
Arts and Entertainment	6.6	6.7	7.1	6.7	6.8	7.0	410
Baby and Toddler	12.8	13.1	10.0	13.0	13.3	10.1	67
Business and Industrial	7.4	7.3	16.2	7.2	7.2	16.3	6
Cameras and Optics	8.6	8.5	6.8	8.3	8.3	6.7	306
Electronics	8.2	8.3	9.0	8.0	8.2	8.9	2,188
Food, Beverages, and Tobacco	7.6	7.3	14.0	7.6	7.3	14.0	10
Furniture	6.6	6.8	9.2	6.5	6.9	9.2	74
Hardware	8.8	9.0	10.8	8.7	8.9	10.9	442
Health and Beauty	11.0	11.2	11.6	10.8	11.0	12.0	1,040
Home and Garden	8.9	9.1	11.8	8.8	9.0	11.9	994
Luggage and Bags	9.3	9.3	10.3	9.4	9.3	10.0	217
Mature	2.9	2.9	3.8	2.9	2.9	3.8	3
Media	9.3	9.3	10.0	9.3	9.3	10.1	1,015
Office Supplies	7.0	6.8	7.1	6.8	6.7	6.6	118
Pet Supplies	5.8	5.8	8.2	5.8	5.7	4.7	170
Services	16.2	16.6	16.6	15.6	16.1	15.8	5
Software	8.8	9.1	9.5	8.8	9.2	7.7	107
Sporting Goods	10.5	10.6	10.6	10.5	10.5	10.1	512
Toys and Games	16.8	17.1	19.3	16.5	16.8	19.3	570
Vehicles and Parts	6.9	7.0	6.3	6.4	6.4	5.8	60
Not Classified	*15.3*	*15.5*	*17.6*	*15.3*	*15.5*	*15.9*	*157*
All Goods	***5.1***	***5.0***	***8.5***	***5.0***	***4.9***	***7.6***	***8,990***

Notes: This table reproduces the median size of price change, reported in Columns (1)–(3) of Table 5, by product category.

Table D3. Cross-Seller Synchronization Rate for Posted Prices, percent

	No Weights			Within-Good Weights			Between-Good Weights			
Category	Mean (1)	Standard Deviation (2)	Median (3)	Mean (4)	Standard Deviation (5)	Median (6)	Mean (7)	Standard Deviation (8)	Median (9)	Number of Goods (10)
Panel A: United States										
Apparel and Accessories	10.1	20.1	0.0	10.8	21.0	0.0	10.3	10.1	8.4	619
Arts and Entertainment	6.8	15.9	0.0	6.8	15.9	0.0	8.1	8.4	6.7	494
Baby and Toddler	7.4	10.0	4.9	9.4	13.0	7.5	13.7	8.5	11.5	49
Business and Industrial	7.1	8.8	4.9	10.2	13.7	2.0	6.7	8.5	2.0	7
Cameras and Optics	11.5	17.9	5.6	12.3	19.5	4.5	23.3	9.7	25.7	273
Electronics	12.7	18.4	7.4	13.4	19.3	7.4	18.0	8.9	18.2	1,979
Food, Beverages, and Tobacco	16.0	21.1	3.1	14.0	18.7	4.9	12.0	13.3	4.9	13
Furniture	10.2	16.4	6.2	10.8	17.2	5.6	10.6	8.0	10.1	129
Hardware	7.8	17.5	0.0	8.1	18.0	0.0	10.5	8.7	10.0	521
Health and Beauty	6.5	14.6	0.0	6.9	15.4	0.0	9.9	8.8	8.0	1,117
Home and Garden	7.7	14.9	0.0	7.9	15.3	0.0	11.2	8.4	9.4	1,275
Luggage and Bags	7.7	15.2	0.0	7.7	15.7	0.0	10.7	8.4	6.7	192
Mature	6.0	8.5	0.0	5.7	8.6	0.0	10.5	6.8	11.3	23
Media	19.0	26.7	8.3	18.5	26.7	5.7	20.7	12.6	20.1	1,084
Office Supplies	10.0	17.2	0.0	10.0	17.1	0.0	10.7	6.7	8.9	159
Pet Supplies	7.1	13.7	0.0	7.6	14.2	0.0	8.7	7.2	8.4	326
Services	17.4	*n.a.*	17.4	18.3	*n.a.*	18.3	18.3	*n.a.*	18.3	1
Software	9.1	16.8	0.0	9.7	17.5	0.0	15.5	5.3	17.5	95
Sporting Goods	8.8	17.7	0.0	9.0	17.8	0.0	10.9	8.0	10.5	422
Toys and Games	8.5	16.4	0.0	9.2	17.9	0.0	13.4	8.8	13.3	637
Vehicles and Parts	8.1	19.3	0.0	7.9	19.0	0.0	10.4	7.6	14.3	153
Not Classified	*9.5*	*18.9*	*0.0*	*10.5*	*20.3*	*0.0*	*18.0*	*13.1*	*15.9*	*369*
All Goods	***10.2***	***18.6***	***0.0***	***10.6***	***19.2***	***0.0***	***15.7***	***10.0***	***15.1***	***9,937***
Panel B: United Kingdom										
Apparel and Accessories	9.3	19.7	0.0	9.6	20.6	0.0	9.6	9.8	7.0	226
Arts and Entertainment	10.0	21.7	0.0	9.8	21.6	0.0	9.4	8.7	9.9	162
Baby and Toddler	6.8	11.6	0.0	7.0	11.9	0.0	14.6	14.0	12.3	47
Business and Industrial	8.3	14.4	0.0	10.8	18.7	0.0	13.6	19.6	0.0	3
Cameras and Optics	10.0	15.6	0.0	10.5	16.7	0.0	19.6	13.1	14.3	146
Electronics	19.5	25.4	11.7	19.3	25.7	11.3	21.2	10.1	20.9	1,111
Food, Beverages, and Tobacco	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3
Furniture	7.9	11.2	0.0	7.0	9.3	0.0	15.4	5.8	18.8	22
Hardware	9.7	21.1	0.0	9.9	21.4	0.0	11.2	9.0	11.1	171
Health and Beauty	10.8	21.9	0.0	11.6	22.6	0.0	11.4	11.9	5.0	523
Home and Garden	14.6	24.3	3.6	15.1	24.9	1.7	18.3	9.0	17.6	370
Luggage and Bags	12.1	23.1	0.0	10.4	21.6	0.0	9.4	11.5	4.2	67
Mature	0.0	*n.a.*	0.0	0.0	*n.a.*	0.0	0.0	*n.a.*	0.0	1
Media	21.5	32.7	0.0	21.0	33.0	0.0	17.0	14.3	15.4	342
Office Supplies	19.4	29.1	3.2	19.4	30.5	2.8	14.8	11.7	11.7	40
Pet Supplies	2.1	7.4	0.0	3.0	9.6	0.0	12.5	10.0	18.8	31
Services	11.1	19.2	0.0	15.4	26.6	0.0	37.5	22.1	46.2	3
Software	22.9	26.7	16.3	22.0	26.2	15.8	19.5	5.6	17.9	64
Sporting Goods	8.1	20.6	0.0	8.5	21.8	0.0	7.2	10.2	3.3	201
Toys and Games	14.6	28.3	0.0	15.2	29.9	0.0	10.2	13.2	9.7	261
Vehicles and Parts	20.3	37.9	0.0	20.1	37.2	0.0	6.8	12.4	5.7	13
Not Classified	*9.9*	*20.3*	*0.0*	*9.9*	*20.8*	*0.0*	*11.0*	*7.4*	*7.8*	*60*
All Goods	***14.7***	***24.8***	***0.0***	***14.8***	***25.2***	***0.0***	***17.9***	***11.1***	***17.9***	***3,867***

Notes: This table reproduces the cross-seller synchronization rate for posted prices, reported in Columns (1)–(3) of Table 8, by product category.

Table D4. Duration of Product Life, weeks

	Truncated	Halftruncated			Nontruncated				
	Share, percent (1)	Share, percent (2)	Mean (3)	Standard Deviation (4)	Mean (5)	Standard Deviation (6)	Median (7)	Lower Bound (8)	Number of Goods (9)
Panel A: United States									
Apparel and Accessories	0.1	42.1	51.8	22.0	26.3	21.9	24	37.1	2,645
Arts and Entertainment	0.4	48.9	54.0	22.7	26.5	22.9	23	40.2	2,873
Baby and Toddler	10.6	50.6	45.6	24.1	14.7	16.6	9	38.7	160
Business and Industrial	3.0	31.3	44.5	23.7	16.7	22.4	2	27.7	67
Cameras and Optics	7.7	48.6	54.8	26.1	29.3	23.7	26	46.5	978
Electronics	13.7	40.7	50.0	28.2	24.4	22.9	18	44.2	7,606
Food, Beverages, and Tobacco	0.0	59.7	25.5	21.8	22.4	26.5	4	24.2	67
Furniture	8.1	52.4	53.6	25.4	29.4	24.9	30	47.2	334
Hardware	10.1	39.9	52.8	25.8	23.3	23.9	14	42.1	2,831
Health and Beauty	0.3	53.5	53.8	22.5	28.7	22.8	28	42.3	4,425
Home and Garden	8.5	47.7	48.0	25.9	25.4	22.8	21	41.9	5,150
Luggage and Bags	1.3	34.4	42.6	26.2	27.9	22.1	24	33.8	1,077
Mature	16.3	48.8	58.9	23.1	28.4	27.3	28	53.8	43
Media	11.3	31.4	57.3	27.4	25.2	26.3	15	42.9	14,370
Office Supplies	4.1	47.5	49.0	25.8	28.6	23.1	32	41.0	849
Pet Supplies	28.2	44.3	58.1	26.0	33.7	27.5	33	61.3	1,106
Services	11.5	34.6	55.6	31.5	26.3	22.6	28	44.1	26
Software	10.3	39.9	48.0	27.3	22.9	23.5	14	40.1	506
Sporting Goods	2.3	48.8	41.0	27.0	17.5	19.9	9	30.7	2,335
Toys and Games	12.5	46.5	52.9	24.7	26.9	24.1	21	47.2	2,777
Vehicles and Parts	7.0	42.4	50.0	25.2	25.4	23.9	19	40.5	575
Not Classified	*5.5*	*44.5*	*43.9*	*23.9*	*22.5*	*21.2*	*17*	*35.9*	*1,976*
All Goods	***8.5***	***41.5***	***51.7***	***26.2***	***25.3***	***24.1***	***19***	***42.1***	***52,776***
Panel B: United Kingdom									
Apparel and Accessories	0.0	32.1	40.3	24.4	16.3	18.8	7	24.0	2,761
Arts and Entertainment	0.3	32.1	36.7	25.7	13.1	17.9	1	20.9	2,945
Baby and Toddler	4.1	57.4	37.8	26.2	16.3	17.2	9	31.9	169
Business and Industrial	0.0	47.9	27.7	23.8	8.0	10.1	1	17.5	48
Cameras and Optics	5.1	37.8	41.0	24.8	16.4	18.1	10	29.6	978
Electronics	7.4	36.0	42.0	28.5	18.4	21.4	8	32.4	7,693
Food, Beverages, and Tobacco	0.0	50.7	25.6	16.2	13.2	15.8	3	19.5	69
Furniture	0.3	43.5	26.4	21.6	13.5	18.2	5	19.4	338
Hardware	1.4	36.5	41.2	26.6	16.5	20.5	4	26.6	2,770
Health and Beauty	0.0	44.8	39.0	24.1	16.3	19.0	7	26.5	4,425
Home and Garden	1.0	33.8	34.7	26.5	13.2	18.0	3	21.3	5,311
Luggage and Bags	1.4	30.5	30.3	23.6	17.2	18.3	10	22.2	1,037
Mature	0.0	26.7	10.8	19.9	9.4	13.1	2	9.7	30
Media	0.1	18.9	41.6	27.1	14.5	20.0	1	19.8	14,197
Office Supplies	2.5	28.7	31.2	24.4	15.0	17.8	6	21.6	792
Pet Supplies	2.4	34.8	38.8	31.5	15.8	23.4	2	25.7	1,145
Services	8.0	24.0	41.4	26.8	13.8	19.3	2	26.7	50
Software	7.3	34.9	46.2	28.3	17.1	21.3	5	32.8	545
Sporting Goods	0.6	44.2	30.9	21.4	16.3	17.1	10	23.2	2,392
Toys and Games	0.7	31.8	39.1	25.8	19.3	21.9	9	26.1	3,179
Vehicles and Parts	0.8	30.2	32.4	23.1	11.2	15.3	1	18.3	620
Not Classified	*0.3*	*35.3*	*27.6*	*22.4*	*13.2*	*16.8*	*4*	*18.6*	*1,273*
All Goods	***1.7***	***31.5***	***38.3***	***26.3***	***15.5***	***19.7***	***4***	***24.0***	***52,767***

Notes: This table reproduces Table F1 by product category.

Table D5. Average Price Dispersion

Measure	No Weights					Click Weighted					
	CV (1)	VI (2)	IQR (3)	Range (4)	Gap (5)	CV (6)	VI (7)	IQR (8)	Range (9)	Gap (10)	*N* (11)
Panel A: United States											
Apparel and Accessories	15.6	15.3	23.4	27.9	17.8	16.2	16.0	20.4	34.8	15.3	1,599
Arts and Entertainment	18.8	20.3	29.9	34.3	23.4	17.1	19.1	22.2	36.1	19.2	1,718
Baby and Toddler	15.6	17.6	23.6	30.7	19.2	14.8	18.4	17.1	41.3	14.3	88
Business and Industrial	18.5	19.2	29.5	34.4	18.1	19.0	19.0	26.2	39.2	19.2	29
Cameras and Optics	13.2	15.9	21.0	26.4	17.7	12.7	18.4	16.4	45.1	12.3	631
Electronics	20.6	24.3	32.8	40.9	26.0	18.6	26.2	22.3	54.1	18.8	4,583
Food, Beverages, and Tobacco	28.4	31.5	48.1	51.7	36.9	24.7	26.9	35.9	47.0	31.8	35
Furniture	15.2	16.3	22.7	29.7	15.9	15.2	17.0	18.1	37.6	12.7	232
Hardware	20.5	22.6	32.5	38.7	25.2	20.6	23.3	26.5	45.7	21.9	1,475
Health and Beauty	17.1	18.1	26.3	31.9	20.4	19.2	19.7	23.7	43.9	18.0	2,920
Home and Garden	18.7	19.4	28.3	34.5	21.5	18.4	20.1	22.2	44.4	17.0	3,016
Luggage and Bags	17.3	18.0	27.3	31.2	21.8	16.9	18.1	21.1	37.4	17.8	526
Mature	22.0	26.7	35.6	45.1	28.7	18.7	23.3	25.0	45.3	19.3	36
Media	29.6	36.1	50.4	57.0	41.9	31.7	44.3	50.2	76.3	41.1	7,016
Office Supplies	22.8	26.1	36.6	43.9	28.6	24.4	32.6	32.5	58.8	26.5	515
Pet Supplies	21.9	22.9	33.8	40.6	25.1	21.2	22.7	28.4	46.0	20.4	843
Services	10.1	8.6	15.4	17.9	8.6	12.4	11.0	17.0	25.1	8.1	14
Software	18.8	21.3	30.6	35.3	24.6	16.1	19.7	19.1	45.8	16.3	263
Sporting Goods	16.0	16.6	24.5	29.5	19.1	15.5	16.2	18.8	37.3	14.8	1,014
Toys and Games	20.7	23.5	33.5	39.1	27.6	22.3	27.9	33.0	51.8	28.8	1,814
Vehicles and Parts	20.4	21.9	31.5	38.6	23.0	21.3	24.2	28.6	47.5	20.7	328
Not Classified	*20.9*	*22.3*	*33.6*	*38.0*	*26.2*	*21.1*	*22.0*	*27.2*	*43.8*	*22.0*	*1,058*
All Goods	***21.5***	***24.4***	***34.6***	***40.7***	***27.6***	***19.9***	***24.8***	***26.1***	***50.1***	***21.1***	***29,753***
Panel B: United Kingdom											
Apparel and Accessories	15.9	15.1	25.0	27.0	20.4	15.9	14.4	22.0	29.2	19.3	991
Arts and Entertainment	17.7	16.5	27.4	28.7	23.6	15.0	13.6	20.9	26.1	18.8	779
Baby and Toddler	17.5	18.6	26.2	33.0	20.7	17.8	15.4	18.1	38.8	18.9	90
Business and Industrial	26.1	24.2	39.5	42.5	35.8	23.6	21.7	29.7	44.7	29.9	12
Cameras and Optics	17.4	17.6	27.1	30.6	22.7	13.7	13.2	17.0	31.2	15.1	387
Electronics	18.7	20.2	29.8	34.4	24.8	16.6	18.7	19.9	41.9	20.1	3,320
Food, Beverages, and Tobacco	19.9	18.4	30.5	32.9	25.4	17.1	14.2	22.5	33.7	16.8	24
Furniture	19.7	18.8	29.9	33.0	26.5	15.7	14.2	18.4	34.3	15.8	78
Hardware	21.1	21.0	33.1	36.4	27.3	19.6	18.1	26.0	37.8	22.6	771
Health and Beauty	16.5	16.8	26.4	28.6	22.7	21.6	15.1	18.1	46.6	17.5	2,003
Home and Garden	24.9	25.5	39.8	42.6	34.8	21.3	32.9	25.8	59.6	36.9	1,192
Luggage and Bags	19.1	17.2	29.2	30.6	25.6	18.8	15.2	22.9	32.9	22.9	334
Mature	50.7	55.8	90.9	90.9	73.0	53.8	45.6	78.6	90.9	73.0	1
Media	20.3	23.7	34.7	38.1	29.8	21.1	25.8	31.6	44.8	29.4	4,488
Office Supplies	31.6	32.4	50.6	53.7	43.7	31.8	33.3	45.9	59.3	44.9	191
Pet Supplies	34.0	33.5	52.7	55.3	48.4	34.8	32.5	47.8	59.2	44.3	232
Services	14.2	14.7	21.6	26.5	14.4	17.1	18.3	27.1	33.2	13.0	19
Software	12.5	12.2	18.8	22.5	14.9	11.3	13.7	13.0	36.4	9.6	201
Sporting Goods	14.3	13.2	21.7	23.6	18.8	14.0	11.6	16.1	27.2	16.1	957
Toys and Games	20.8	20.9	33.1	35.1	28.6	20.6	20.6	27.5	39.3	27.2	1,158
Vehicles and Parts	22.8	21.9	35.7	38.0	30.0	20.5	18.8	29.8	35.3	25.3	133
Not Classified	*20.7*	*20.6*	*32.2*	*35.1*	*28.7*	*19.5*	*19.0*	*26.2*	*38.4*	*23.4*	*354*
All Goods	***19.4***	***20.4***	***31.3***	***34.3***	***26.7***	***18.6***	***19.8***	***23.1***	***41.8***	***23.0***	***17,715***

Notes: This table reproduces Table 11 by product category.

E Price Rigidity Online versus Offline: Tables and Figures

Table E1. Frequency of Price Changes in Selected Narrow Categories, percent

	Posted Prices			Regular Prices		
	Online			Online		
	No Weights (1)	Between Weights (2)	Offline (3)	No Weights (4)	Between Weights (5)	Offline (6)
Panel A: United States						
Audio Players and Recorders	17.1	23.5	6.2	10.8	19.8	1.8
Bedding	20.0	17.1	10.1	12.5	13.3	1.3
Books	20.0	23.8	1.7	14.2	16.7	1.3
Camera Accessories	7.4	16.4	4.7	4.9	12.4	2.0
Cameras	17.6	34.9	5.2	15.6	30.3	2.7
Camping, Backpacking, and Hiking	13.3	18.0	3.4	7.8	14.5	1.1
Computer Software	12.1	23.8	2.8	7.7	19.1	2.0
Cookware	13.2	17.7	4.8	7.7	10.6	0.7
Costumes	10.8	13.2	7.2	6.1	7.3	0.9
Cycling	15.8	16.5	3.6	10.3	12.5	1.7
Doors and Windows	13.4	8.8	4.3	10.6	5.7	0.8
Gardening	12.5	12.8	2.3	6.8	9.1	1.3
Hair Care	14.3	22.4	5.2	9.7	14.7	1.7
Household Climate Control	11.3	15.7	3.7	7.0	11.1	0.8
Kitchen Appliances	13.4	13.2	5.7	9.3	10.6	0.9
Musical String Instruments	1.9	2.1	2.4	0.7	1.6	1.5
Oral Care	14.4	23.5	1.8	11.3	17.5	1.2
Tableware	11.1	17.6	5.2	6.3	16.1	0.7
Telephony	15.9	23.4	4.7	9.1	22.8	2.7
Vacuums	15.2	32.1	7.1	11.6	25.4	2.0
Vision Care	1.3	5.7	2.9	0.0	5.7	1.4
Watches	12.2	11.8	5.7	7.9	9.0	1.0
Panel B: United Kingdom						
Books	25.9	20.9	6.1	19.9	17.2	4.5
Clothing Accessories	14.6	14.2	2.0	10.6	11.8	1.3
Electrical Appliances	32.9	20.2	7.4	24.6	17.2	5.4
Furniture and Furnishings	30.9	25.8	7.2	25.1	21.3	2.8
Games, Toys, and Hobbies	17.9	16.5	3.7	13.1	13.2	2.4
Garden Plants and Flowers	17.6	18.8	3.2	11.4	15.0	2.7
Garments	15.0	5.6	3.3	12.9	4.3	1.4
Household Textiles	40.2	21.3	5.2	31.8	15.2	2.5
Jewellery, Clocks, and Watches	17.1	15.4	2.5	12.5	11.9	1.5
Kitchenware	24.3	24.8	3.3	18.3	19.7	2.0
Pets	25.4	17.4	2.7	17.6	13.9	2.6
Pharmaceuticals	11.0	7.6	3.4	8.1	5.5	2.8
Recording Media	24.0	22.0	4.5	18.5	18.7	3.5
Repair of Dwelling	19.7	14.4	2.8	15.1	10.6	2.3
Spare Parts and Accessories	14.8	9.7	2.7	9.2	6.8	2.4
Spirits	1.3	1.4	9.4	1.3	1.2	7.5
Sport and Recreation Equipment	9.6	10.2	2.4	7.0	8.4	1.0
Tools and Equipment	18.5	15.7	2.4	14.2	12.4	1.9

Notes: The table compares the frequency of price changes for selected narrow categories in online data used in this paper and in brick-and-mortar stores based on Nakamura and Steinsson (2008) for the U.S. and Kryvtsov and Vincent (2014) for the U.K. Only matched categories are shown.

Table E2. Absolute Size of Price Changes in Selected Narrow Categories, log points

	Posted Prices			Regular Prices		
	Online			Online		
	No Weights (1)	Between Weights (2)	Offline (3)	No Weights (4)	Between Weights (5)	Offline (6)
Panel A: United States						
Audio Players and Recorders	15.1	11.5	9.7	14.5	11.4	12.6
Bedding	12.1	11.1	11.1	12.1	11.2	26.5
Books	20.0	16.9	10.2	19.7	16.9	15.5
Camera Accessories	13.2	11.3	9.0	13.5	11.7	19.4
Cameras	13.6	7.6	7.8	13.5	7.6	10.5
Camping, Backpacking, and Hiking	15.6	14.0	8.4	15.1	13.6	19.4
Computer Software	12.8	9.1	18.2	12.7	9.3	22.7
Cookware	14.1	16.1	8.7	13.2	12.6	32.3
Costumes	21.2	16.7	10.7	20.7	16.4	27.8
Cycling	6.3	8.0	7.2	6.3	8.0	11.1
Doors and Windows	7.8	11.3	8.7	7.5	10.9	29.0
Gardening	11.0	11.8	10.8	11.2	11.6	24.2
Hair Care	20.8	20.3	9.5	20.2	18.6	22.1
Household Climate Control	12.6	10.9	8.0	12.3	10.4	18.1
Kitchen Appliances	12.3	12.6	9.4	12.3	11.6	18.4
Musical String Instruments	16.4	10.8	8.4	16.4	11.3	13.9
Oral Care	23.2	17.2	10.1	19.7	15.2	12.8
Tableware	16.3	13.9	14.5	16.2	14.4	30.8
Telephony	16.5	14.6	13.7	16.3	14.9	22.2
Vacuums	11.7	12.3	8.7	11.6	12.1	13.5
Vision Care	15.4	14.5	7.5	15.3	14.6	18.3
Watches	13.0	11.9	8.6	13.1	11.8	41.9
Panel B: United Kingdom						
Books	9.0	8.9	28.9	9.0	9.0	22.4
Clothing Accessories	8.1	8.1	22.9	7.6	7.7	16.1
Electrical Appliances	8.1	8.3	11.1	8.2	8.3	9.5
Furniture and Furnishings	6.6	6.8	23.0	6.5	6.9	21.2
Games, Toys, and Hobbies	16.8	17.1	19.7	16.5	16.8	17.2
Garden Plants and Flowers	11.6	12.6	23.3	11.9	12.8	19.2
Garments	6.8	6.8	26.4	6.8	6.8	21.7
Household Textiles	8.4	8.6	22.8	8.4	8.5	18.9
Jewellery, Clocks, and Watches	9.8	9.8	19.8	9.2	9.2	16.6
Kitchenware	10.0	10.1	24.1	9.7	9.8	19.1
Pets	5.8	5.8	9.5	5.8	5.7	6.9
Pharmaceuticals	12.3	12.3	18.1	11.9	11.9	11.4
Recording Media	8.2	8.4	24.1	7.8	8.0	19.9
Repair of Dwelling	8.6	9.3	15.2	8.9	9.8	12.0
Spare Parts and Accessories	10.2	10.5	10.9	8.7	8.6	10.1
Spirits	21.4	19.7	10.4	21.4	19.7	5.9
Sport and Recreation Equipment	11.1	11.2	21.9	10.9	11.0	18.8
Tools and Equipment	9.1	9.2	16.0	8.8	9.1	13.2

Notes: The table compares the absolute size of price changes for selected narrow categories in online data used in this paper and in brick-and-mortar stores based on Nakamura and Steinsson (2008) for the U.S. and Kryvtsov and Vincent (2014) for the U.K. Only matched categories are shown.

Table E3. Frequency and Size of Sales in Selected Narrow Categories

	Frequency of Sales, percent			Absolute Size of Sales, log points		
	Online			Online		
	No Weights	Between Weights	Offline	No Weights	Between Weights	Offline
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: United States						
Audio Players and Recorders	1.2	1.9	4.8			
Bedding	1.4	1.5	12.8			
Books	1.2	1.3	0.8			
Camera Accessories	0.4	1.5	3.2			
Cameras	1.1	2.9	4.9			
Camping, Backpacking, and Hiking	1.4	1.5	2.4			
Computer Software	0.5	1.2	1.2			
Cookware	1.2	1.8	6.0			
Costumes	2.4	1.5	8.5			
Cycling	1.1	0.9	3.9			
Doors and Windows	0.5	1.0	5.5			
Gardening	1.0	1.0	1.4			
Hair Care	1.5	2.2	2.7			
Household Climate Control	1.1	1.6	3.6			
Kitchen Appliances	1.1	1.5	7.1			
Musical String Instruments	0.4	0.5	2.7			
Oral Care	0.9	1.1	0.5			
Tableware	1.2	1.7	6.7			
Telephony	1.5	1.6	2.8			
Vacuums	1.0	3.1	8.2			
Vision Care	0.2	0.3	2.0			
Watches	1.1	1.3	8.0			
Panel B: United Kingdom						
Books	0.6	1.3	1.7	8.1	8.1	28.2
Clothing Accessories	0.6	0.4	0.8	0.7	0.7	27.9
Electrical Appliances	0.8	1.0	3.6	11.5	11.5	13.0
Furniture and Furnishings	0.5	1.3	5.3	22.3	22.3	24.6
Games, Toys, and Hobbies	0.9	1.0	1.4	19.5	19.6	22.5
Garden Plants and Flowers	0.7	1.3	0.6	10.8	10.8	25.3
Garments	0.9	0.5	1.9			
Household Textiles	1.1	2.1	3.0			
Jewellery, Clocks, and Watches	0.3	0.7	1.0	22.3	22.3	25.1
Kitchenware	1.0	2.5	1.3	12.8	12.8	26.0
Pets	1.4	0.9	0.3	16.4	16.4	16.5
Pharmaceuticals	0.5	0.9	0.7	2.9	2.9	27.2
Recording Media	0.9	1.5	1.1	10.6	9.9	29.9
Repair of Dwelling	0.5	1.5	0.6	9.4	9.4	21.4
Spare Parts and Accessories	1.0	0.4	0.4			
Spirits	0.0	0.0	3.0			
Sport and Recreation Equipment	0.3	0.5	1.5	20.1	20.1	23.9
Tools and Equipment	0.4	1.0	0.6	8.3	8.3	20.8

Notes: The table compares the frequency and absolute size of sales for selected narrow categories in online data used in this paper and in brick-and-mortar stores based on Nakamura and Steinsson (2008) for the U.S. and Kryvtsov and Vincent (2014) for the U.K. Only matched categories are shown.

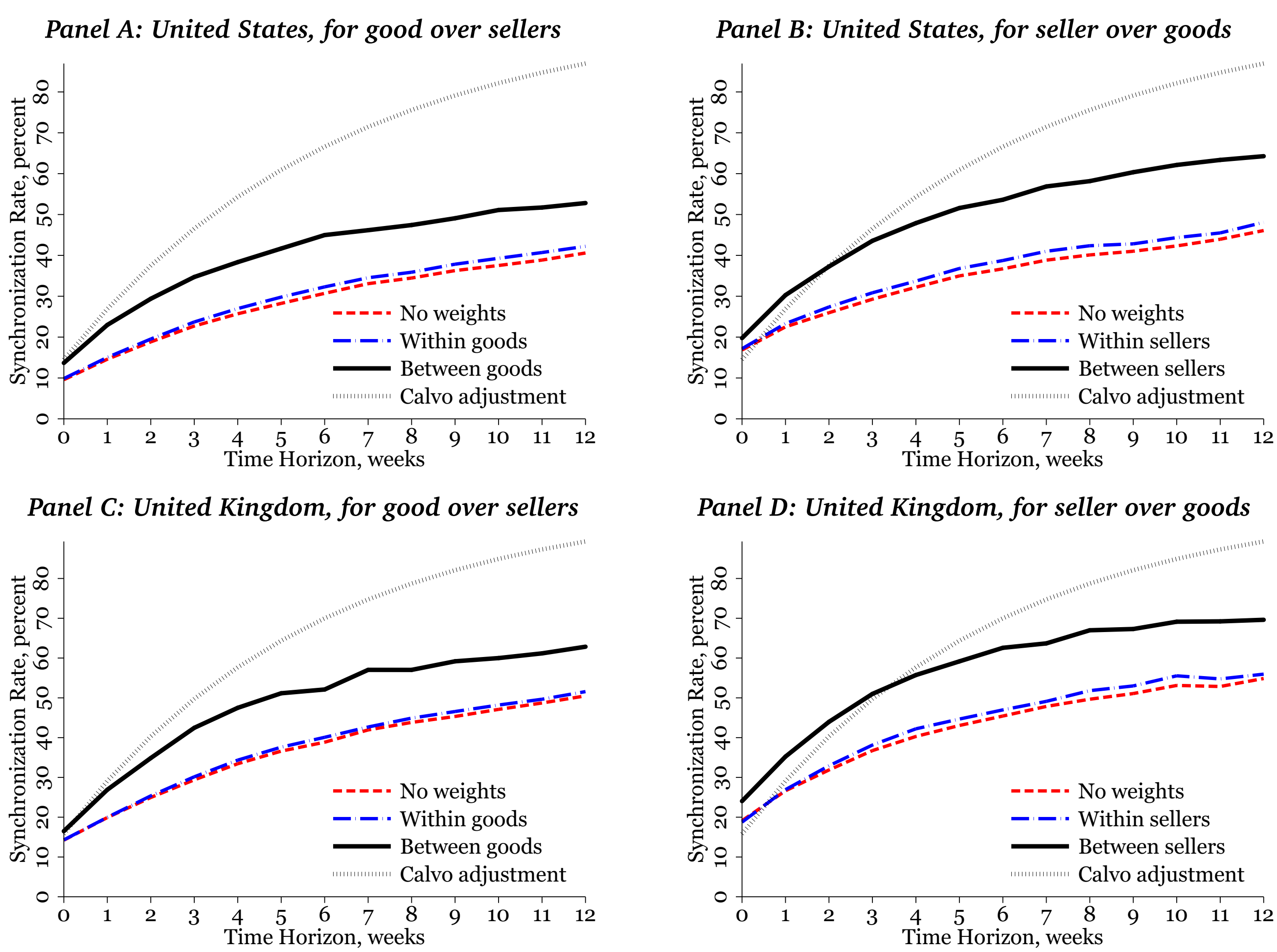
F Additional Results: Selected Tables and Figures

Table F1. Duration of Product Life, weeks

	Truncated	Halftruncated			Nontruncated			Lower Bound		
	Share, percent	Share, percent	Mean	Standard Deviation	Mean	Standard Deviation	Median	Mean	Median	Number of Goods
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Panel A: All Products					
U.S.	8.5	41.5	51.7	26.2	25.3	24.1	19	42.1	42.3	52,776
U.K.	1.7	31.5	38.3	26.3	15.5	19.7	4	24.0	16.2	52,767
					Panel B: Apparel and Accessories with One Seller					
U.S.	0.0	16.0	25.1	23.7	11.0	15.1	2	13.3	4.4	780
U.K.	0.0	17.3	21.5	23.1	7.7	12.5	1	10.1	2.7	1,413
					Panel C: Apparel with One Seller, Excluding Jewelry and Watches					
U.S.	0.0	15.0	16.7	19.4	8.7	12.5	2	9.9	3.2	354
U.K.	0.0	21.6	16.3	18.7	5.5	9.0	1	7.8	2.6	575

Notes: Column (1) reports the share of goods with unobserved entry and exit (truncated from both sides), while Column (2), truncated from either side (but not both). A good entry (exit) is truncated if it enters (exits) within the first (last) five weeks. Columns (3) and (4) report the mean and standard deviation of life duration for halftruncated goods, while Columns (5)–(7), the mean, standard deviation, and median for nontruncated goods. Columns (8) and (9) show the lower bound of the mean and median life duration, respectively (see the text), and Column (10) the total number of goods. To compare, the mean (median) duration in Cavallo, Neiman, and Rigobon (2014) for the U.S. sample is 37 (15) weeks; for H&M and Zara only, the mean and median duration are all in the interval of 10–12 weeks.

Figure F1. Synchronization of *Regular* Price Changes by Time Horizon



Notes: The figure reproduces Figure 2 for regular prices.

Table F2. Frequency and Synchronization of Regular Price Increases and Decreases

	No Weights			Between Weights			
	Mean (1)	Standard Deviation (2)	Median (3)	Mean (4)	Standard Deviation (5)	Median (6)	Number of Goods (7)
			Panel A: United States				
Frequency of							
Price changes	12.3	14.0	8.8	15.4	9.5	14.5	16,332
Price increases	5.7	7.9	3.3	6.8	4.4	6.4	16,332
Price decreases	6.6	9.1	3.7	8.6	6.1	7.7	16,332
Cross-Seller Synchronization of							
Price changes	7.8	16.4	0.0	12.8	8.6	12.6	10,280
Price increases	4.3	12.9	0.0	5.4	5.1	4.5	8,445
Price decreases	4.6	12.9	0.0	8.3	6.5	8.4	8,554
Cross-Good Synchronization of							
Price changes	14.7	25.7	0.0	18.3	10.3	20.3	2,422
Price increases	10.4	22.0	0.0	8.1	4.9	10.7	1,926
Price decreases	9.9	21.2	0.0	11.1	6.4	14.6	1,773
			Panel B: United Kingdom				
Frequency of							
Price changes	15.2	21.1	7.7	16.7	12.6	15.8	7,738
Price increases	7.8	12.6	2.3	8.0	6.6	7.2	7,738
Price decreases	7.4	11.6	1.7	8.7	7.2	8.1	7,738
Cross-Seller Synchronization of							
Price changes	12.1	22.9	0.0	15.6	10.5	14.3	4,005
Price increases	7.2	17.5	0.0	7.4	6.7	7.4	3,200
Price decreases	7.1	17.6	0.0	10.0	8.7	9.6	3,102
Cross-Good Synchronization of							
Price changes	16.6	24.7	5.0	22.4	15.3	21.2	1,306
Price increases	12.3	21.7	1.1	11.4	9.0	12.5	1,071
Price decreases	10.3	18.8	0.0	13.0	8.5	12.9	1,024

Notes: The table reproduces Table 9 for regular prices.

Table F3. Predictors of Regular Price Stickiness

	Frequency of Price Changes, *percent*			Absolute Size of Price Changes, *log points*			Cross-Seller Synchronization Rate, *percent*		
Weights:	No	Within	Between	No	Within	Between	No	Within	Between
Predictors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: United States									
Log number of sellers	6.2***	8.0***	8.0***	−1.1	−1.3	−1.3*	1.6***	1.7***	1.8***
	(0.5)	(0.6)	(0.5)	(0.8)	(0.8)	(0.7)	(0.6)	(0.6)	(0.5)
Concentration, Herfindahl index, (0, 1]	15.4***	20.6***	21.4***	−6.5***	−7.1***	−6.2***	8.5***	10.3***	10.7***
	(2.2)	(2.6)	(2.3)	(1.7)	(1.7)	(1.5)	(2.5)	(2.5)	(2.3)
Log total clicks	−2.9***	−2.3***	−2.3***	0.2	0.3	0.2	−0.6*	−0.3	−0.2
	(0.3)	(0.3)	(0.2)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
Log median price	1.1*	0.4	0.2	−9.0***	−9.2***	−9.0***	1.4**	1.5***	1.6***
	(0.7)	(0.6)	(0.6)	(0.9)	(0.7)	(0.7)	(0.7)	(0.6)	(0.6)
Log median price, squared	−0.1	−0.1	−0.1	0.7***	0.7***	0.7***	−0.1	−0.1	−0.1
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
R^2	0.05	0.06	0.07	0.11	0.11	0.12	0.04	0.04	0.04
N	16,332	16,332	16,332	16,877	16,877	16,877	10,280	10,280	10,280
Panel B: United Kingdom									
Log number of sellers	2.9**	3.9***	4.9***	−1.0	−0.9	−1.2*	2.4	2.4	3.0**
	(1.2)	(1.2)	(1.1)	(0.7)	(0.7)	(0.7)	(1.5)	(1.5)	(1.4)
Concentration, Herfindahl index, (0, 1]	17.8***	20.8***	22.1***	−7.0***	−7.0***	−7.2***	10.0*	11.8**	12.5**
	(3.7)	(3.8)	(3.6)	(1.5)	(1.5)	(1.5)	(5.2)	(5.6)	(5.3)
Log total clicks	−0.9**	−0.8**	−1.1***	0.8***	0.9***	0.9***	−2.3***	−2.1***	−1.8***
	(0.4)	(0.4)	(0.4)	(0.2)	(0.2)	(0.2)	(0.6)	(0.6)	(0.6)
Log median price	3.6***	3.7***	3.4***	−3.5***	−3.9***	−4.1***	2.4*	2.4*	2.6**
	(1.0)	(0.9)	(0.9)	(0.6)	(0.6)	(0.6)	(1.5)	(1.4)	(1.2)
Log median price, squared	−0.4***	−0.4***	−0.4***	0.3***	0.3***	0.3***	−0.1	−0.1	−0.2
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.2)
R^2	0.07	0.07	0.07	0.07	0.08	0.08	0.05	0.05	0.05
N	7,738	7,738	7,738	8,990	8,990	8,990	4,005	4,005	4,005

Notes: The table reproduces Table 10 for regular prices.

Table F4. Predictors of Posted Price Dispersion, not weighted by clicks

	Standard Deviation of Log Price						Net of Seller Fixed Effects					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: United States												
Log number of sellers	0.32					−1.33	−0.30					−1.83**
	(1.90)					(1.16)	(1.65)					(0.85)
Log total clicks	0.39					2.20***	0.14					1.68***
	(0.91)					(0.65)	(0.80)					(0.49)
Log median price	−4.86***					−2.98***	−3.96***					−2.14***
	(0.79)					(0.64)	(0.63)					(0.54)
Frequency of regular price changes		0.09***	0.20***	0.09***	0.19***	0.23***		0.07***	0.17***	0.07***	0.16***	0.18***
		(0.02)	(0.05)	(0.02)	(0.05)	(0.05)		(0.01)	(0.04)	(0.02)	(0.05)	(0.04)
Absolute size of regular price changes		0.50***	0.62***	0.61***	0.66***	0.56***		0.47***	0.58***	0.55***	0.60***	0.53***
		(0.04)	(0.05)	(0.05)	(0.05)	(0.05)		(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Frequency of sales			−0.33***		−0.37***	−0.19**			−0.19**		−0.25***	−0.16**
			(0.10)		(0.10)	(0.08)			(0.08)		(0.08)	(0.06)
Absolute size of sales			0.15***		0.15***	0.13***			0.13***		0.13***	0.12***
			(0.02)		(0.03)	(0.02)			(0.02)		(0.03)	(0.02)
Synchronization of posted price changes				−0.02	−0.05	−0.04				−0.02	−0.03	−0.02
				(0.01)	(0.04)	(0.03)				(0.01)	(0.03)	(0.03)
R^2	0.11	0.18	0.27	0.23	0.31	0.35	0.10	0.20	0.29	0.24	0.33	0.36
N	29,751	12,548	3,458	9,321	3,332	3,332	29,751	12,548	3,458	9,321	3,332	3,332
Panel B: United Kingdom												
Log number of sellers	−6.61***					−5.68***	−3.36***					−2.64**
	(1.64)					(1.62)	(0.98)					(1.27)
Log total clicks	2.54***					3.16***	1.24***					1.87***
	(0.63)					(0.80)	(0.43)					(0.54)
Log median price	−3.98***					−2.38***	−2.56***					−1.56***
	(1.29)					(0.50)	(0.71)					(0.33)
Frequency of regular price changes		0.10***	0.24***	0.09**	0.24***	0.23***		0.06***	0.13***	0.04***	0.11***	0.11***
		(0.03)	(0.07)	(0.04)	(0.07)	(0.06)		(0.01)	(0.03)	(0.02)	(0.03)	(0.03)
Absolute size of regular price changes		0.34***	0.69***	0.38***	0.59***	0.48***		0.33***	0.58***	0.38***	0.50***	0.43***
		(0.06)	(0.16)	(0.08)	(0.14)	(0.14)		(0.05)	(0.15)	(0.07)	(0.11)	(0.09)
Frequency of sales			0.10		−0.14	−0.13			0.22		−0.03	0.03
			(0.35)		(0.10)	(0.09)			(0.32)		(0.06)	(0.06)
Absolute size of sales			0.14**		0.11**	0.11**			0.16**		0.13***	0.13***
			(0.07)		(0.05)	(0.05)			(0.07)		(0.04)	(0.04)
Synchronization of posted price changes				−0.02	−0.11***	−0.09***				−0.01	−0.07***	−0.06**
				(0.02)	(0.03)	(0.03)				(0.02)	(0.03)	(0.02)
R^2	0.07	0.08	0.13	0.10	0.23	0.30	0.04	0.08	0.11	0.13	0.28	0.32
N	17,715	4,836	864	3,441	832	832	17,715	4,836	864	3,441	832	832

Notes: The table reproduces Table 12 without click weighting.

Table F5. Predictors of Posted Price Dispersion, by measure

	Coefficient of Variation, *percent* (1)	Standard Deviation of Log Price *log points* (2)	Value of Information, *log points* (3)	Interquartile Range, *log points* (4)	Range, *log points* (5)	Gap, *log points* (6)
Panel A: United States						
Log number of sellers	-2.66^{***}	-3.24^{***}	-2.57	-2.07^{*}	-2.89	-7.66^{***}
	(0.85)	(1.01)	(1.72)	(1.14)	(2.49)	(1.83)
Log total clicks	4.48^{***}	4.76^{***}	8.49^{***}	5.12^{***}	16.31^{***}	5.26^{***}
	(0.80)	(0.90)	(1.68)	(1.29)	(2.35)	(1.30)
Log median price	-3.87^{***}	-3.94^{***}	-5.71^{***}	-4.18^{***}	-9.97^{***}	-3.73^{***}
	(0.39)	(0.51)	(0.92)	(0.57)	(1.19)	(0.85)
Frequency of regular price changes	0.33^{***}	0.39^{***}	0.52^{***}	0.53^{***}	0.78^{***}	0.53^{***}
	(0.06)	(0.08)	(0.13)	(0.12)	(0.18)	(0.11)
Absolute size of regular price changes	0.23^{***}	0.29^{***}	0.43^{***}	0.47^{***}	0.53^{***}	0.34^{***}
	(0.04)	(0.06)	(0.11)	(0.09)	(0.14)	(0.08)
Frequency of sales	-0.24^{***}	-0.31^{***}	-0.38^{***}	-0.33^{***}	-0.38^{**}	-0.40^{***}
	(0.06)	(0.08)	(0.12)	(0.11)	(0.16)	(0.12)
Absolute size of sales	0.25^{***}	0.29^{***}	0.35^{***}	0.37^{***}	0.54^{***}	0.40^{***}
	(0.03)	(0.04)	(0.06)	(0.06)	(0.07)	(0.05)
Synchronization of posted price changes	-0.03	-0.02	-0.00	-0.02	-0.02	-0.05
	(0.03)	(0.03)	(0.05)	(0.05)	(0.07)	(0.04)
R^2	0.31	0.28	0.24	0.25	0.31	0.21
N	3,349	3,349	3,349	3,349	3,349	3,349
Panel B: United Kingdom						
Log number of sellers	-7.04^{***}	-5.42^{***}	-2.86	-3.32^{*}	-10.79^{***}	-10.87^{***}
	(1.52)	(1.42)	(1.93)	(1.68)	(2.86)	(2.66)
Log total clicks	3.91^{***}	2.92^{***}	4.27^{***}	1.08	14.01^{***}	5.13^{***}
	(0.82)	(0.77)	(1.40)	(1.09)	(2.23)	(1.80)
Log median price	-3.60^{***}	-3.01^{***}	-3.85^{***}	-3.02^{***}	-7.68^{***}	-3.26^{***}
	(0.45)	(0.40)	(0.63)	(0.54)	(0.97)	(0.59)
Frequency of regular price changes	0.15^{**}	0.17^{***}	0.18^{**}	0.21^{***}	0.33^{**}	0.28^{***}
	(0.07)	(0.06)	(0.07)	(0.07)	(0.14)	(0.10)
Absolute size of regular price changes	0.10^{*}	0.11^{*}	0.10	0.13	0.16	0.18^{*}
	(0.06)	(0.06)	(0.09)	(0.08)	(0.13)	(0.10)
Frequency of sales	-0.30^{***}	-0.27^{***}	-0.20	-0.29^{**}	-0.25	-0.30^{**}
	(0.07)	(0.08)	(0.14)	(0.12)	(0.18)	(0.13)
Absolute size of sales	0.25^{*}	0.20^{*}	0.26^{*}	0.16^{**}	0.45^{**}	0.33^{**}
	(0.13)	(0.10)	(0.14)	(0.07)	(0.20)	(0.17)
Synchronization of posted price changes	-0.06^{***}	-0.07^{***}	-0.07^{***}	-0.10^{***}	-0.13^{***}	-0.09^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)
R^2	0.28	0.24	0.15	0.17	0.27	0.18
N	840	840	840	840	840	840

Notes: The table reproduces Column (6) of Table 12 for different measures of price dispersion.

Table F6. Effects of Macroeconomic Shocks on Pricing, not weighted by clicks

	On Impact							Two Weeks Ahead						
	Regular Price						Log	Regular Price						Log
	Frequency of		Absolute Size of		Sales		Number	Frequency of		Absolute Size of		Sales		Number
	Increases	Decreases	Inc.	Dec.	Freq.	Abs. Size	of Clicks	Inc.	Dec.	Inc.	Dec.	Freq.	Abs. Size	of Clicks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Capacity utilization	−0.02	0.17	0.23	0.74	−3.94	0.46	−0.10	−0.02	−0.10	0.28	0.21	−0.44	−0.03	−0.08
	(0.43)	(0.40)	(1.28)	(1.40)	(3.66)	(1.59)	(0.12)	(0.21)	(0.20)	(0.68)	(1.05)	(1.73)	(0.23)	(0.13)
Consumer confidence	−0.03	0.07	−2.96	0.52	−1.48	0.10	0.11	0.22	0.19	−0.41	−0.35	−0.01	0.10	0.05
	(0.49)	(0.48)	(2.76)	(0.99)	(2.14)	(0.14)	(0.12)	(0.20)	(0.21)	(0.52)	(0.74)	(0.88)	(0.08)	(0.11)
CPI, core	−0.99	−1.08	0.40	2.85	5.36	−2.70	0.11	−0.77*	−0.81	0.85	0.22	0.63	−0.81*	0.18
	(0.72)	(0.79)	(2.28)	(1.88)	(4.11)	(2.02)	(0.18)	(0.46)	(0.51)	(1.34)	(1.57)	(1.82)	(0.49)	(0.14)
Employment cost index	0.38	0.28	−5.52	2.90	0.02	−0.36	0.01	0.09	0.01	−2.78*	−3.46	0.36	−0.28	−0.15
	(1.14)	(1.07)	(4.40)	(2.67)	(8.54)	(3.49)	(0.24)	(0.60)	(0.57)	(1.50)	(2.83)	(2.79)	(0.32)	(0.18)
GDP	0.36	0.52	14.70	−16.39	4.25	0.80	−0.24	−0.75	−0.49	6.81	10.50	−1.29	0.49	0.16
	(4.07)	(4.16)	(17.00)	(8.60)	(23.64)	(12.77)	(0.71)	(1.80)	(1.66)	(7.45)	(11.48)	(9.41)	(1.71)	(0.64)
Initial claims	−0.37*	−0.29	−0.28	−1.22	0.90	−0.31	−0.03	−0.22***	−0.24***	0.01	−0.15	−0.20	−0.17*	−0.05
	(0.22)	(0.18)	(0.80)	(1.30)	(1.22)	(0.26)	(0.04)	(0.08)	(0.08)	(0.25)	(0.32)	(0.51)	(0.10)	(0.05)
ISM manufacturing index	−0.03	0.07	−2.75	0.36	−0.80	0.65	0.10	0.04	−0.01	−0.08	−0.01	1.40	−0.05	0.09
	(0.36)	(0.30)	(3.05)	(1.57)	(2.90)	(0.67)	(0.13)	(0.14)	(0.20)	(0.47)	(0.60)	(1.01)	(0.25)	(0.11)
Leading indicators	−0.00	0.15	−0.91	2.38	−1.07	2.02	0.09	0.10	0.11	0.11	0.40	1.78*	0.05	0.09
	(0.50)	(0.55)	(1.34)	(1.21)	(2.68)	(2.46)	(0.11)	(0.22)	(0.23)	(0.62)	(1.07)	(0.93)	(0.27)	(0.14)
New home sales	−0.66	−0.39	−3.07	−6.64	5.83	−0.57	0.07	−0.14	−0.10	−0.27	−0.35	1.72	−0.16	−0.04
	(1.03)	(0.85)	(4.80)	(11.21)	(3.45)	(0.40)	(0.28)	(0.34)	(0.44)	(0.68)	(1.18)	(1.64)	(0.21)	(0.26)
Nonfarm payrolls	0.57	0.82	−0.12	0.09	−5.95	0.36	−0.11	0.25	0.25	−0.22	0.04	−0.07	−0.31	−0.07
	(0.26)	(0.29)	(1.76)	(2.51)	(3.08)	(0.15)	(0.15)	(0.23)	(0.23)	(0.62)	(0.72)	(1.17)	(0.42)	(0.13)
PPI, core	−1.38**	−1.45	−1.05	0.20	−0.13	−0.05	0.01	−0.96***	−0.97***	0.17	−0.11	−0.11	−0.99**	−0.02
	(0.68)	(1.03)	(1.30)	(1.80)	(6.28)	(2.38)	(0.14)	(0.35)	(0.31)	(0.76)	(1.19)	(3.31)	(0.46)	(0.14)
Retail sales	0.53	0.42	−2.01	1.09	5.70	1.19	0.22	0.56	0.63	0.78	1.42	1.46	1.14	0.24
	(0.95)	(1.01)	(2.45)	(1.63)	(4.51)	(1.70)	(0.29)	(0.65)	(0.69)	(0.86)	(1.25)	(2.32)	(1.00)	(0.25)
excluding motor vehicles	−0.02	−0.07	−1.38	0.55	4.13	1.40	0.10	0.16	0.22	0.55	1.12*	2.38*	0.39	0.16
	(0.29)	(0.38)	(1.44)	(0.68)	(3.97)	(1.69)	(0.22)	(0.17)	(0.19)	(0.44)	(0.67)	(1.44)	(0.43)	(0.14)
Unemployment	−0.09	−0.03	−1.46	−2.66	0.65	−0.01	−0.06	−0.17	−0.21	−0.99**	−0.61	−0.21	−0.05	−0.04
	(0.25)	(0.29)	(0.99)	(1.64)	(1.80)	(0.12)	(0.11)	(0.14)	(0.13)	(0.42)	(0.46)	(0.71)	(0.16)	(0.09)
Aggregate shock	***−0.07***	***−0.05***	***−0.17***	***0.35***	***−0.68***	***−0.08***	***0.01***	***0.04***	***0.03***	***0.04***	***−0.12***	***−0.19***	***−0.01***	***−0.02***
	(0.14)	***(0.14)***	***(0.79)***	***(0.95)***	***(1.04)***	***(0.08)***	***(0.05)***	***(0.08)***	***(0.07)***	***(0.21)***	***(0.34)***	***(0.42)***	***(0.08)***	***(0.05)***

Source: Authors' calculations based on Informa Global Markets (IGM) data, combined with proprietary data from the online shopping platform, provided on condition of nondisclosure.
Notes: The table reproduces results in Table 14 without click weighting.