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 change more frequently than offline prices, they nevertheless exhibit relatively long spells of fixed prices. By many metrics, such as large size and low synchronization of price changes, considerable cross-sectional dispersion, and low sensitivity to predictable or unanticipated changes in demand conditions, online prices are as imperfect as offline prices. Our findings suggest a need for more research on the sources of price rigidities and dispersion, as well as on the relative role of menu and search costs in online-pricing frictions. (JEL: E31, L11, L86)

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

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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, according to the *New York Times*, "[i]n the last three months of 2016, Americans spent \$102.7 billion in online sales, which was 8.3% of the overall total of \$1.24 trillion in retail sales."[1] The rise of e-commerce has been truly a global phenomenon, and global e-commerce sales are expected to reach \$4 trillion by 2020 (Statista 2016). While visionaries of the internet age are utterly bold in their predictions, one can already exploit special properties of online retail, such as seemingly low search costs, low costs of monitoring competitors' prices, and low costs of nominal price adjustment (Ellison and Ellison 2005), 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 online shopping platform 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. Similar to the dataset in Gorodnichenko and Talavera (2017), these data pertain to an online-shopping/price-comparison website, a growing gateway for internet commerce. However, in contrast to Gorodnichenko and Talavera (2017) and others who scraped websites to collect their data, we have data directly provided by the platform, which allows us to have the unprecedented quality of information characterizing online markets. Most importantly, this dataset represents a stratified random sample of *all* goods and sellers on the platform. It also expands product coverage tremendously, bringing it significantly closer to that in the CPI and giving us more room to compare online and offline prices.[2] Finally, we have the number of *clicks* for each price listing so that, in contrast to previous works, we can identify and study prices relevant to consumers.

This paper's objective is to document an extensive set of the empirical properties of online prices (such as the frequency and size of price changes, price synchronization across sellers and across goods, cross-store price dispersion, and price responses to

1. "From 'Zombie Malls' to Bonobos: What America's Retail Transformation Looks Like," by J. Taggart and K. Granville. The *New York Times* from 4/15/2017. Available online at https://www.nytimes.com/2017/04/15/business/from-zombie-malls-to-bonobos-americas-retail-transformation.html.

2. Gorodnichenko and Talavera (2017) have longer time series (five years of online price data) and detailed descriptions of goods, but the coverage of goods is limited to electronics, cameras, computers, and software. Note that because Gorodnichenko and Talavera (2017) study cross-country price differentials, they focus on goods sold in multiple countries, which is a relatively small subset of goods sold within a country. Also the platform used in this paper is larger than the platform in Gorodnichenko and Talavera (2017) or any other study. Gorodnichenko and Talavera (2017)—and similar studies—report only a subset of statistics covered in the present paper. Despite differences in the sample of goods, time periods, etc., the results in this paper are broadly similar to the results reported in Gorodnichenko and Talavera (2017).

predictable changes in demand) and to 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. Empirical regularities documented in this paper are compared to the predictions of existing theories of price setting and, thus, provide critical inputs for future theoretical work on the matter.

Our main result is that, despite the power of the internet, online price setting is characterized by considerable frictions. By many metrics, such as the size and synchronization of price changes, price dispersion, or sensitivity to changes in economic conditions, the magnitude of these frictions should be similar to that in offline price setting. However, we also find significant quantitative differences: the frequency of price changes is higher online than offline. These results continue to hold when we compare the properties of online and offline prices for narrowly defined product categories, which ensures that the composition of goods is similar across markets. Jointly, these facts call for more research on the relative importance of menu, information, and search costs—and, more generally, on the price-setting mechanism in online markets.

Specifically, we find that, despite small physical costs of price adjustment and reduced costs of collecting and processing information, 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% in the United States and 5% 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% per week) but the average size of sales (10%–12% or less in the United States and 6% 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, a finding inconsistent with simultaneously low costs of monitoring competitors' prices and low costs of search for better prices. 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, 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% 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). These findings are striking because online stores are uniquely positioned to use dynamic pricing (i.e., 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.[3] 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 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.

3. In 2011 (median year in our sample), the value per head of business-to-consumer (B2C) e-commerce in the United Kingdom was £1,083, making it the leading nation in terms of e-commerce. The growth of U.K. e-commerce has continued since then; in 2015, B2C e-commerce reached £1,760 per head, with about 17% average annual growth in the 2010–2015 period; see Ofcom (2012, 2016).

Although e-commerce has penetrated virtually all sectors of the economy and internet markets attracted enormous attention of economists, analyses of online prices have been fragmented (see Ellison and Ellison 2005 for an early survey). 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 (e.g., Brynjolfsson and Smith 2000), span a short period of time, usually not exceeding a year (e.g., Lünnemann and Wintr 2011), or cover a specific seller (e.g., Einav et al. 2015). In spite of increasing efforts to scrape more and more prices online to broaden data coverage (Cavallo and Rigobon 2012; Cavallo 2013, 2015; Cavallo et al. 2014, 2015), we are aware of just a handful of studies that have information on the quantity margin for internet commerce (e.g., Chu et al. 2008; Baye et al. 2009; Soysal and Zentner 2014; Einav et al. 2015). These studies rely on data from a particular seller and usually have limited coverage of goods. For example, Baye et al. (2009) use data from the Yahoo! Kelkoo price comparison site to estimate the price elasticity of clicks for 18 models of personal digital assistants sold by 19 different retailers between September 2003 and January 2004. Einav et al. (2015) have much broader product coverage; but as they focus on pricing that is specific to eBay, it is hard to generalize their results to other stores. In contrast, the data used in this paper combine a broad coverage of consumer goods with information on the number of clicks each price quote received at a daily frequency for almost two years, a degree of data coverage that has not been within the reach of researchers in the past. These unique properties of our data allow us to provide a comprehensive analysis of the properties of online prices and to move beyond studying particular segments of this market or particular pricing moments. For example, relative to our earlier work (Gorodnichenko and Talavera 2017), we cover price dispersion and the properties of price adjustment (frequency, size, and synchronization of sales and of regular price changes) in much greater detail, study predictors of online prices' properties, and utilize clicks to have a better measure of prices relevant to consumers for a wide spectrum of goods sold online. Thus, apart from presenting new findings, this paper validates the results found in scraped data and multichannel sellers (i.e., sellers with online and offline presence).

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), the costs of updating information (Mankiw and Reis 2002), or sticker costs[4] (Diamond 1993). 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,

4. That is, the inability of firms to change the price for inventories.

affect real variables (Woodford 2003).[5] 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 either that standard macroeconomic models of price rigidities, which emphasize menu costs and search costs, are likely incomplete or that the magnitude of such costs is nontrivial in online markets, too. Since the assumptions of 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. For example, obfuscation emphasized in Ellison and Ellison (2009) and more intensive price experimentation (Baye et al. 2007) may provide building blocks for future theories.[6]

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 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. Concluding remarks are in Section 6.

2. Data

We use proprietary data from a leading online-shopping/price-comparison platform[7] 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 *goods* 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. The platform—and our dataset—cover virtually all product categories available on 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 (e.g., scanner data) and therefore allows us to compare price setting in online and

5. 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, the indexation of price contracts, or "rule-of-thumb" behavior give rise to intrinsic inflation persistence; see Fuhrer (2006, 2010).

6. Other prominent theoretical models that provide possible explanations for price variation include Bakos (1997), Baye and Morgan (2001), and Hong and Shum (2006). De los Santos et al. (2012) test consumer search models using online browsing data.

7. Examples of major shopping platforms and price comparison websites include Google Shopping, Nextag, and Pricegrabber. Online Appendix A describes how a typical shopping platform operates.

brick-and-mortar stores. However, we cannot match individual products online and offline, as UPC codes are masked within narrow categories. For example, we know that product *i* is a particular cell phone, but we do not know its brand or model. 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. Despite the large number of sellers on the platform overall, typically there are a limited number of sellers offering a particular product, thus making it easy to search for the best price. 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. Shopping/price-comparison platforms routinely use clicks as a proxy for transactions they generate for a seller's listing, and the service charge for using the platform is typically per-click. The rate of conversion from clicks to purchases is about 2%–3% (CPC Strategy 2014), and generally clicks are correlated with sales at the aggregate level. Large stores (which sell more than 100 goods in our sample) receive the lion's share of clicks. Thus, using clicks as weights downplays the role of small sellers.

Note that because the sample is stratified by *goods* rather than *stores*, one should bear in mind that even "small" stores in our data can sell many goods that were not sampled. For example, if the sample of goods is 1% of the population, a store selling 10,000 goods will be represented by only 100 randomly drawn goods. Hence, a low number of goods per store should not be interpreted as suggesting that the stores in the sample are small or that the sample is populated nearly exclusively by marketplace sellers typical for eBay and other shopping platforms. While the sampling is not appropriate for measuring the absolute size of stores, it does preserve the ranking of stores by size and market shares.

Unfortunately, we do not have information on actual sales, local taxes, shipping costs, detailed description of goods, names of sellers, sellers' costs/bids/budgets, and ratings of goods and sellers. 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-ad 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.[8] 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 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 online platform'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 shopping platform explicitly recommends that its sellers remove ads with a click-through rate smaller than 1% 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).

Our platform and similar platforms are used by consumers intensively as these platforms offer easy price comparison and shopping experience. For example, a study by the European Commission (2014) reports that 74% of all shoppers in the European Union use internet comparison tools (price comparison websites are the most popular ones: 73% of comparison tool users) to compare prices (69% of users) and find the cheapest price (68% of users). Forty-eight percent of users check a price comparison website before making an online purchase, and 35% of users report that the use of a comparison tool results in a purchase. While there is no such study for the United States, scattered reports paint a similar picture. For example, Statista (2015), a consultant firm, reports that 16% of U.S. consumers in 2014 used a price comparison website to make their most recent purchase, thus making price comparison websites the most popular location for making e-commerce purchases.

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

8. Gorodnichenko and Talavera (2017) document that prices reported on a price comparison website (similar to the one used in this paper) are highly correlated with the corresponding prices quoted by online stores (correlation is approximately 0.98). Likewise, Cavallo (2017) reports a high consistency of offline and online prices for multichannel sellers with presence on the internet and in conventional markets.

TABLE 1. Data Coverage

Category	*United States* Number of Goods (1)	Number of Sellers (2)	*United Kingdom* Number of Goods (3)	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***

(e.g., 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 online 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 a corresponding capital letter (e.g., $\bar{p}_{is} = \sum_t p_{ist}/T$ 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.[9] We find that a relatively small number of products and sellers 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:

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

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 baseline click-weighted 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. We relegate all relevant results obtained using within-good weights $\bar{f}^{\mathrm{w}}$ to Online Appendix C.

Price Distribution and Clicks. 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

9. Details on data aggregation from daily to a weekly frequency is relegated to Online Appendix B.

TABLE 2. Distribution of Prices, local currency

	Mean Log Price		Mean Price, percentile					
	Mean	SD	5	25	50	75	95	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: United States								
No weights	3.37	1.53	4	11	25	71	474	52,776
Click weighted	4.15	1.51	7	22	61	192	852	
Panel B: United Kingdom								
No weights	3.13	1.56	3	8	19	57	381	52,767
Click weighted	3.82	1.44	5	17	48	134	473	

Note: 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.

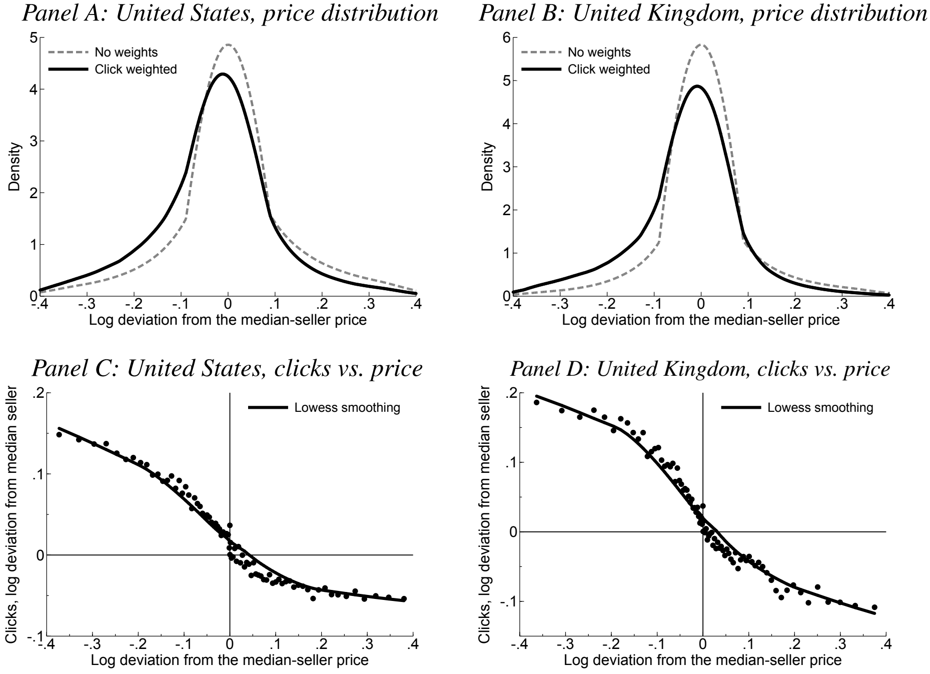

FIGURE 1. Prices and Clicks: In the top two panels, the dashed line shows the distribution of the log price deviation from the median across sellers, and the solid line shows the between-good click-weighted distribution of that deviation. In the bottom two panels, the dots represent data points averaged within bins based on percentiles of the log-deviation of price. The Lowess smoothing is calculated with a 0.05 bandwidth.

cost \$11 or less; products that cost \$100 or more represent around 20% 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, $\widetilde{p}_{it}$:

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

Panels A and B of Figure 1 plot 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%; that is, sellers with a price substantially below the median product price receive a larger number of clicks.

To show the relationship between prices and clicks, Panels C and D of Figure 1 plot clicks against prices, measured as log-deviation from the median seller for a good on a given date. To enhance visibility, we show the scatterplot for bins based on the percentiles of the price measure, and then pass a Lowess smoother to allow for nonlinearities in the clicks–price relationship. The figure paints a clear picture that sellers with a price significantly below the median obtain more clicks. The curve is flatter in the region of a positive price deviation, supporting the notion that the clicks are especially sensitive to prices when prices are in the lower end of the price distribution.

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. Price adjustment for online markets may also employ algorithmic approaches ("dynamic pricing") to avoid costs associated with collecting and processing information as well as costs related to making collective decisions (e.g., "meeting" costs). In a similar spirit, consumers can compare prices across retailers without leaving their desks (smaller search costs). As a result, we should observe a slightly 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 et al. (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 (i.e., prices we observe in the data) and regular prices (i.e., prices that exclude sales).

In contrast to scanner data, our dataset does not have sales flags and therefore we use filters as in Nakamura and Steinsson (2008), Eichenbaum et al. (2011), and Kehoe and Midrigan (2015) to identify temporary price changes.[10] 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, using a standard procedure in the literature.

Consider the following price series: {\$2, n.a., \$2, n.a., \$1, \$2}, where "n.a." denotes missing values. In the "no imputation" case, we assume that "n.a." breaks a price series so that we have only one series of consecutive observations, {\$1, \$2}. In this case, there is one "regular" price change from \$1 to \$2 because \$1 is preceded by "n.a." and not by \$2. In the "imputation" case, we replace "n.a." with an actual price if the prices before and after "n.a." are equal to each other. We also identify an episode as a sale if the first *observable* price before "n.a." and the last observable price after "n.a." are the same. That is, in our example, we replace the first "n.a." with a \$2 price and we drop the second "n.a." from the identification of sales. The imputed series of *regular* prices thus becomes {\$2, \$2, \$2, n.a., n.a. \$2}; the imputed series of sale flags is {0, n.a., 0, n.a., 1, 0}; and the imputed series of regular price *changes* is {n.a., 0, 0, n.a., n.a., 0}, where the first "n.a." is due to spell truncation.[11] We report statistics for the two assumptions separately and present additional results for alternative imputation procedures in Online Appendix Table G.2. We find that reasonable modifications to our imputation procedure do not alter our conclusions.

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%, 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% depending on a computation technique. The median size of sales is 10.5%–11.9% with equal weights and 4.4%–5.3% with between-good weights. These sizes are smaller than the size of sales in regular stores (about 20%–30%). Using our

10. We use both $\vee$- and $\wedge$-shaped filters to account not only for temporary price cuts but also for temporary price increases (e.g., due to stockout).

11. In this example, our "imputation" filter applies to one missing value between two observed prices. In practice, our filters are applied up to five missing values between any two observed prices. This procedure is valid because we compute the frequency of price changes and then use it to infer the implied duration of price spells, instead of computing duration directly. Hence, we make no additional assumptions on unobserved prices. We do not use imputation as our baseline frequency statistic or for any other measure reported in this paper. Online Appendix Table G.1 shows that imputing an arbitrarily large number of missing values between two observed prices has little effect on the frequency of price changes. To assess the extent of imputation, Online Appendix Figure G.1 reports the distribution over goods of the share of imputed price changes. On average, 27.3% of price changes in the U.S. sample are imputed.

TABLE 3. Frequency and Size of Sales

	One-Week Filter				Two-Week Filter				
	Mean Freq. (1)	Std. Dev. (2)	Med. Freq. (3)	Med. Size (4)	Mean Freq. (5)	Std. Dev. (6)	Med. Freq. (7)	Med. Size (8)	N (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
Click weighted	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
Click weighted	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
Click weighted	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
Click weighted	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 (%), 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 United States and Kryvtsov and Vincent (2014) for the United Kingdom; the mean frequency is converted to the weekly rate.

"imputation" procedure for missing values tends to generate a higher frequency and size of sales. The magnitudes are similar for the United Kingdom, although there is some variation across countries for disaggregate categories of goods, which likely reflects idiosyncratic factors affecting specific markets in the two countries.

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.[12] 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).[13] We find (Online Appendix Table G.3) that the synchronization of sales across sellers is below 2% in each country. The synchronization of sales across goods within a seller is

12. 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 $(A-1)/(B-1)$; that is, the statistic is calculated only *conditional* on having at least one sale. See Section 3.4 for more details.

13. Guimaraes and Sheedy (2011) propose a model of sales that are strategic substitutes. Alternatively, Anderson et al. (2017) 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).

less than 3% in the United States and 4% in the United Kingdom. Because the degree of synchronization is similar to the frequency of sales, we conclude that the 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.[14] 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:

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

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

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 as

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

The first two rows in each panel of Table 4 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 12 weeks when no weights 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 20%–65%.

14. 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 et al. (2011), price changes smaller than 0.1% are not counted as price changes. We exclude quote lines with fewer than five observations. Following Nakamura and Steinsson (2008), we compute the frequency of price changes and then infer the implied duration of spells, to avoid bias due to spell truncation.

TABLE 4. Frequency and Size of Price Changes

	No Imputation		With Imputation		
	No Weights (1)	Click Weighted (2)	No Weights (3)	Click Weighted (4)	Offline Stores (5)
Panel A: United States					
Posted Price					
Median frequency, %	14.0	19.3	8.2	15.7	4.7
Implied duration, weeks	6.6	4.7	11.6	5.8	20.8
Median absolute size, log points	11.0	11.2			10.7
Regular Price					
Median frequency, %	8.8	14.5	7.0	12.9	2.1
Implied duration, weeks	10.9	6.4	13.9	7.3	47.1
Median absolute size, log points	10.9	10.9			8.5
Panel B: United Kingdom					
Posted Price					
Median frequency, %	12.8	20.0	7.7	16.3	4.6
Implied duration, weeks	7.3	4.5	12.5	5.6	21.2
Median absolute size, log points	5.1	8.5			11.1
Regular Price					
Median frequency, %	7.7	15.8	6.7	14.3	3.2
Implied duration, weeks	12.5	5.8	14.5	6.5	30.7
Median absolute size, log points	5.0	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. Column (2) reports click-weighted results using our default weighting method. Columns (3)–(4) 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 (5) shows the corresponding statistics from Nakamura and Steinsson (2008) for the United States and Kryvtsov and Vincent (2014) for the United Kingdom, converted to a weekly frequency. Regular prices are identified using a one-week filter for sales.

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 (Online Appendix Table G.4). Despite significant heterogeneity in the frequency of price changes across products (Online Appendix D), our aggregate statistics are not driven by any particular categories (Online Appendix E).

Price spells for online stores appear significantly shorter than for brick-and-mortar stores (by up to a half 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. These magnitudes are similar to the results reported in earlier papers (Lünnemann and Wintr 2011; Boivin et al. 2012; Gorodnichenko and Talavera 2017) for specific segments of e-commerce.[15] We find the same pattern when we compare

15. The frequency of price adjustment in our data is higher than the frequency of price adjustment for multichannel stores (Cavallo 2017). The adjustment of online prices for this type of stores is likely "slowed

the properties of online and offline prices *within narrowly defined product categories* (see Online Appendix F). Therefore, our findings are not driven by differences in the composition of goods in e-commerce and conventional retailers.[16] Because large online stores receive a large share of clicks (Online Appendix Figure G.2), our results with between-good weights (our baseline) are similar to the results we obtain for the sample restricted to large stores (Online Appendix Table G.5). However, when we focus on very large stores (100+ products), we find smaller shares of stores that do not change their prices at all (Online Appendix Figure G.3). We also find that the hazard of price adjustment is decreasing in the duration of price spells (Online Appendix Figure G.4).

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

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

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

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

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 4 reports the absolute size of price change. In the United States, online sellers change their prices on average by 11%, which is somewhat larger than the estimates reported in earlier studies. This magnitude is remarkably stable and close to that for brick-and-mortar stores. Again, we find similar results when we compare the size of price changes for online and offline prices for goods within narrowly defined product categories. 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 changes is smaller (approximately 5%), but it approaches the U.S.

down" by the stickiness of offline prices and the apparent desire of these stores to maintain consistency of online and offline prices.

16. Ideally, one would like to match specific goods sold online to exactly the same goods sold offline, thereby completely eliminating potential differences in the composition. Unfortunately, we cannot do this because we do not have names or detailed descriptions of the goods in our dataset, and available offline-price datasets with broad coverage (e.g., BLS micro-level price data) do not have detailed descriptions of goods.

statistic when between-good weights are applied (8.5%). Price decreases are slightly smaller than price increases (Online Appendix Table G.6). We also find that very large stores (100+ products) are less likely than small stores to have large price changes (Online Appendix Figure G.5).

3.3. Do Prices Change Mostly during Product Replacement?

Nakamura and Steinsson (2012) emphasize that product replacement 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 ("product replacement bias"). In the context of online prices, (Cavallo et al. 2014, henceforth, CNR) scraped price data from selected online retailers (Apple, H&M, IKEA, and Zara) and documented three facts related to the product replacement bias: (1) most products do not change their prices throughout the lifetime (77% 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 an average product to have at least one price change).

To assess the importance of product replacement 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.[17] In the United States, 11.9% of goods have a constant price within their life span (column 1 of Table 5)—this is significantly lower than 77% in CNR. Moreover, goods with no price change account for only 1% 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% and the corresponding share of clicks to 26% (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%, 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 5) goods with and without price changes along four dimensions: (1) the average number of clicks for a price quote; (2) the *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,

17. Our data do not provide direct information about when a good is introduced or discontinued. We approximate entry and exit of goods with the dates when goods appear for the first and last time. We also drop products that enter or exit within the first or last five weeks of our data to avoid truncation bias in product-life duration. We find similar results when we exclude goods with truncated entry/exit (Online Appendix Table G.7).

TABLE 5. Price Adjustment and Product Replacement

	All Products		Apparel, One Seller		—excl. Jewelry and Watches	
	Const. Price (1)	Price Change (2)	Const. Price (3)	Price Change (4)	Const. Price (5)	Price Change (6)
Panel A: United States						
Share of goods, %	11.9	88.1	31.0	69.0	42.4	57.6
Share of clicks, %	1.3	98.7	25.7	74.3	30.8	69.2
Av. number of clicks per quote	1.5	1.7	1.5	1.4	1.7	1.7
Av. number of price quotes	9.1	12.2	8.6	10.7	7.7	10.6
Av. 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	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, %	17.0	83.0	29.5	70.5	34.1	65.9
Share of clicks, %	3.3	96.7	25.5	74.5	34.3	65.7
Av. number of clicks per quote	1.8	1.7	1.4	1.3	1.6	1.4
Av. number of price quotes	8.7	10.8	8.0	9.6	8.3	8.9
Av. 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	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 et al. (2014) is 23% for the entire U.S. sample (21% for H&M and 3% for Zara).

and 5 sellers as opposed to 36 weeks, 9 quotes, and 1 seller for goods with no price changes. The U.K. data look remarkably similar in this regard. Hence, goods with no price changes have a shorter 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). We find that the frequency of price adjustment is similar across goods with different product lives (Online Appendix Table G.8).

3.4. Synchronization

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 $B > 1$. Note that this statistic is calculated for a given good and period *conditional* on having at least one price change. 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 the 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.[18] 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 a weekly frequency, but may be able to do so at lower frequencies. Measuring synchronization over horizons longer than one week, however, is more 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.[19] 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.[20]

18. 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 $\bar{q}_{it} = \sum_{s\in\mathscr{S}_{it}} q_{ist}/S_{it}$.

19. 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 $\{t, t+1, t+2\}$.

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

TABLE 6. Synchronization Rate, %

	Synchronization across Sellers				Synchronization across Goods			
	Mean (1)	SD (2)	Med. (3)	Over 3 Months (4)	Mean (5)	SD (6)	Med. (7)	Over 3 Months (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
Click weighted	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
Click weighted	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
Click weighted	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
Click weighted	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 a 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 a one-week, two-side filter.

To put the measured synchronization rates into perspective, we report the 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 under Calvo pricing, yet the measured synchronization rate is not zero because some price changes just coincide in time. Because the Calvo assumption of a fixed hazard of price adjustment may be at odds with the data, we also construct cumulative synchronization rates using empirical hazard functions and maintaining the assumption of price adjustment independence across goods/sellers.

Synchronization across Sellers. Bhaskar (2002), among others, emphasizes that nominal shocks should have limited real effects if price changes are synchronized. In a limiting case, if price adjustment is perfectly synchronized, the real effects of nominal shocks can last at most as long as the duration of price spells. Our evidence suggests that the synchronization of price changes across sellers is remarkably low in both countries (see columns 1–4 of Table 6). The average synchronization rate for posted prices (no weights) is about 10% in the United States and 15% in the United Kingdom; more than half of products in each country have zero synchronization. The average rate is even smaller for regular prices (no weights): 8% and 12% in each country, respectively; hence, sales are more synchronized than regular price changes. Although the synchronization rate is higher when aggregated using between-good weights—in the United States the median is 15% for posted prices and 13% for

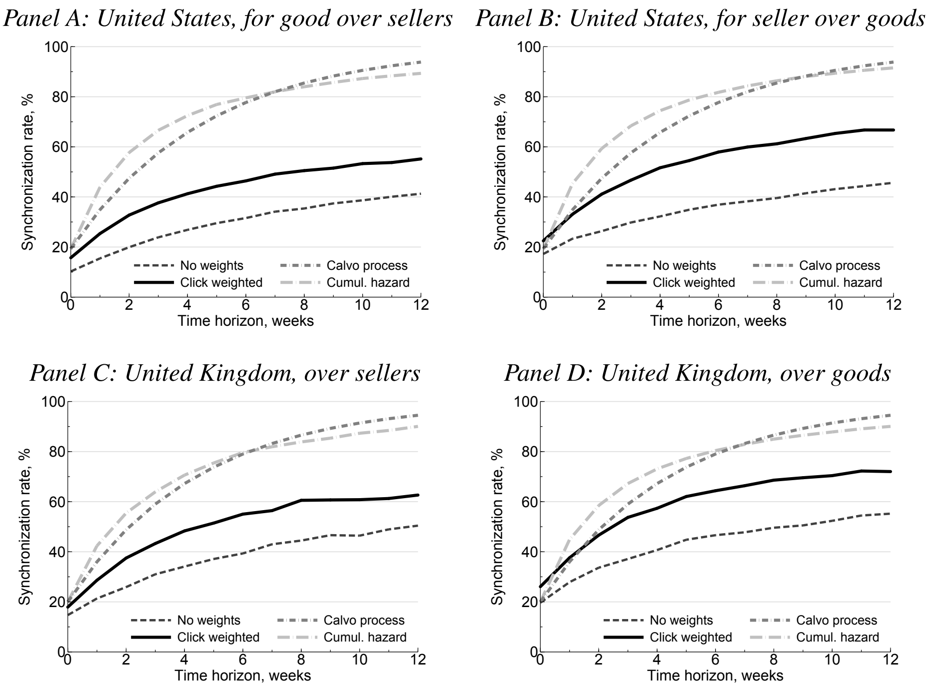

FIGURE 2. Synchronization Rate for Posted Prices by Time Horizon: Panels A and C report the upper bound synchronization *across sellers* at a week-h horizon, while Panels B and D report synchronization *across goods*. The dashed line shows the raw average and the solid line shows the click-weighted measure. The "dash-dot" line shows the synchronization rate under the assumption of a fixed probability of price adjustment, as in Calvo (1983), based on the between-good click-weighted median frequency. The "long dash–dot" line shows the cumulative hazard rate starting from the empirical Calvo rate at $h = 0$. Empirical hazard rates are reported in Online Appendix Figure G.4.

regular prices, and in the United Kingdom the values are 18% and 14%, respectively—it is still significantly lower than one could have expected. Alternative measures of synchronization yield the same conclusion.[21]

Can this result be explained by the timing of price responses? For example, although the cost of monitoring competitors' prices in online markets is low, online sellers might still need some time to collect and analyze information, as well as to make decisions about price changes. Yet, even at a three-month horizon, no more than 60% of competitors adjust their prices (see column 4 of Table 6). Moreover, the curve representing the synchronization rate over time (Panels A and C of Figure 2) lies below the curve for Calvo pricing and is significantly flatter than it.

21. In Online Appendix Table G.9, we report the coefficient of variation of the fraction of price changes over time. If price setting is Calvo, this alternative measure equals zero, regardless of the Calvo rate. However, unlike our baseline measure, it is not bounded between 0 and 1, and cannot be used to measure the time required by sellers to synchronize prices.

The synchronization rates across time also lie below the corresponding cumulative hazard function, which accounts for empirical heterogeneity in the probability of a price change across spells of different duration.[22] This pattern suggests significant heterogeneity in price responses 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. This result also holds for regular prices (Online Appendix Figure G.6). In short, price changes in online markets are rather staggered over time, which corresponds to 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 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 6). In the United States, the average synchronization rate is 17%, without weights, and 23% when between-seller weights are applied (15% and 18% for regular prices). In the United Kingdom, the synchronization rates are slightly higher: 20% (unweighted) and 26% (weighted) for posted prices (17% and 22%, respectively, for regular prices). The unweighted median rates are all below 10% (and very close to zero in the U.S. data). At a three-month horizon (see column 8 of Table 6 and Panels B and D of Figure 2), the share of goods with price changes is still below 60% (75% with between-seller weights)—not much higher than a corresponding measure of cross-seller price synchronization.[23]

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 much evidence for either claim in the online-market data: (*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

22. The fact that the cumulative hazard function lies above the Calvo curve means that the probability of a price change falls with the duration of price spells, as captured by the decreasing hazard rates depicted in Online Appendix Figure G.4.

23. 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 the category-level rates to the store level. Irrespective of whether we use a narrow or broad definition of categories, we continue to find low synchronization rates, which are similar to our benchmark measure.

differences in the frequency of price adjustment (i.e., whenever price increases are more frequent than decreases, they are also more likely to be synchronized). These conclusions also hold for regular prices (see Online Appendix Tables G.10 and G.11).

3.5. Predictors of Price Stickiness

Market and good characteristics could be related to the heterogeneity of price stickiness across products. We focus on five 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; (4) the median product price; and (5) the share of prices that end at 95 to 99 cents or pence ("price points").[24] 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 fourth statistic can be a proxy for the intensity of consumer search: the absolute return to search is higher for more expensive products.[25] Finally, the last statistic measures the degree of inattention to exact prices when consumers face a choice between multiple sellers (Knotek II 2011). Because price points are separated, price adjustment for goods with strong prevalence can become less frequent.

Because the time-dimension of our data is relatively short, we measure pricing moments—the frequency, size, and cross-seller synchronization of price changes—and potential predictors at the good level (i.e., we exploit cross-sectional variation in goods' characteristics). For example, the good-level frequency of price changes is calculated as follows. For each store selling a given good, we calculate the price-line frequency of price changes. Then we aggregate it to the good level using the mean frequency (with and without click weighting) across stores, to use as a left-hand side variable. In this regression analysis, we control for category fixed effects and cluster standard errors at the narrow-category level.

Results in Table 7 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), which is consistent with the notion that more competition should yield more flexible prices. Market concentration measured by the Herfindahl index, however, is associated with more flexible prices. This result suggests that markets with three or four big players have more price competition than markets with mostly small players. This finding is also in line with Ellison et al. (2016) arguing that managers of small firms

24. All variables are in logs except for the share of price points and the Herfindahl index (each variable is between zero and one). The Herfindahl index is computed at the good level as $H_i = \sum_{s \in \mathscr{S}_i} (Q_{is}/Q_i)^2$, 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.

25. 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.

TABLE 7. Predictors of Posted-Price Stickiness

	Frequency of Price Changes, %		Absolute Size of Price Changes, *log points*		Cross-Seller Synchronization Rate, %	
Weights:	N	Y	N	Y	N	Y
Predictors	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: United States						
Log number of sellers	8.7***	10.2***	−0.5	−0.9	2.4***	2.7***
	(0.6)	(0.6)	(0.8)	(0.7)	(0.7)	(0.6)
Herfindahl index, $(0,1]$	18.1***	23.8***	−5.1***	−5.5***	10.4***	13.2***
	(2.6)	(2.7)	(1.8)	(1.5)	(3.0)	(2.9)
Log total clicks	−5.0***	−3.9***	−0.2	−0.1	−0.9***	−0.6*
	(0.4)	(0.3)	(0.3)	(0.3)	(0.4)	(0.3)
Log median price	2.0**	1.0	−10.0***	−9.9***	2.0**	2.1***
	(0.9)	(0.8)	(0.9)	(0.7)	(0.9)	(0.7)
Log median price, squared	−0.2**	−0.2**	0.8***	0.8***	−0.1	−0.2*
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Share of price points	−6.9***	−7.4***	7.3***	6.6***	−1.3	−0.8
	(1.6)	(1.3)	(1.3)	(1.2)	(1.2)	(1.1)
R^2	0.09	0.10	0.12	0.13	0.05	0.05
N	14,483	14,483	17,053	17,053	9,937	9,937
Panel B: United Kingdom						
Log number of sellers	4.3***	6.4***	−0.8	−1.1**	3.0**	3.5***
	(1.2)	(1.2)	(0.5)	(0.5)	(1.3)	(1.3)
Herfindahl index, $(0,1]$	18.5***	23.2***	−5.4***	−5.7***	10.0*	12.4**
	(4.3)	(4.3)	(1.2)	(1.3)	(5.1)	(5.3)
Log total clicks	−2.5***	−2.3***	0.4**	0.5***	−2.3***	−2.0***
	(0.4)	(0.4)	(0.2)	(0.2)	(0.6)	(0.5)
Log median price	5.7***	5.3***	−4.1***	−4.9***	3.8**	3.9***
	(1.3)	(1.1)	(0.5)	(0.5)	(1.6)	(1.4)
Log median price, squared	−0.7***	−0.6***	0.4***	0.4***	−0.3	−0.3*
	(0.2)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)
Share of price points	−19.6***	−16.5***	11.8***	11.0***	−14.1***	−10.8***
	(1.6)	(1.3)	(1.1)	(1.0)	(2.0)	(1.6)
R^2	0.12	0.12	0.11	0.12	0.07	0.06
N	6,623	6,623	9,092	9,092	3,867	3,867

Notes: The table presents estimates of the regression of the frequency (columns 1–2), size (columns 3–4), and cross-seller synchronization (columns 5–6) of price changes on the given set of variables. The "N" columns use the unweighted measures of price stickiness, raw median price across sellers, and assign equal weights to each observation in the regression. The "Y" columns use the within-good click-weighted measures of price stickiness, weighted median price across sellers, and further weight observations by the number of clicks obtained by each good (baseline weights). Concentration is measured with the Herfindahl index, normalized to be between zero and one. Price points are prices that end at 95 to 99 cents (pence). 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% significance level, respectively.

are less likely to monitor competitors' prices than managers of large firms. Market size, measured by the number of clicks, is associated with more (rather than less) price stickiness. Price flexibility increases in the median price for low- and moderate-price goods (approximately 75% of goods in our sample). Such a pattern is consistent with the view that increased returns to search should make prices more flexible. However, very expensive products on the platform tend to have stickier prices. Finally, the bigger is the share of price points, the stickier are prices, suggesting that bounded rationality may play some role in price rigidity. We conclude that properties of online markets such as product demand, a product price, and the intensity of competition across sellers have strong association with the degree of price stickiness. The conclusions are largely the same for regular prices (Online Appendix Table G.12) and for the frequency of sales (Online Appendix Table G.13).

3.6. Relation to Theoretical Models

Our results paint a mixed picture for standard macroeconomic models of pricing. On the one hand, online prices indeed change more frequently than offline prices, which is consistent with reduced costs of nominal price adjustment in e-commerce. Moreover, when we focus on prices relevant to consumers, the frequency of price adjustment for online prices increases further. On the other hand, many properties of online prices are hard to reconcile with lower "menu" costs. The size of price changes is similar for offline and online prices. Synchronization rates are low across goods within a seller and across sellers within a good. These findings present a challenge for popular modelling approaches. For example, low synchronization rates across goods within a seller are inconsistent with current pricing models for multiproduct firms, as these models emphasize simultaneous price changes within a firm. An increase in the frequency of price changes, combined with a stable size of price changes, is inconsistent with basic "menu" cost models, which yield a negative relationship between the frequency and the size of price changes. And yet, standard predictors of price stickiness account for some variation in price stickiness across goods, so that conventional models appear to provide useful insights about frictions affecting online price setting. In the next section, we explore additional moments of the data to shed more light on the nature of these frictions.

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 (2015) 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 recently (Clark and Vincent 2014; Kaplan and Menzio 2015; Sheremirov 2015). Yet, previous literature calls for more research on price dispersion in online markets, as data for large shopping platforms whose product coverage and pricing are similar to that in brick-and-mortar stores (i.e., prices are set by sellers rather than through auctions) are in limited access.[26]

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.[27] 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

We use the coefficient of variation (CV) and standard deviation of log prices at a weekly frequency as our preferred measures of price dispersion 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.[28] Once we compute a corresponding measure of price dispersion across sellers for each good and week, we aggregate it to the good level by taking appropriate time averages. We then compute the cross-good raw average of this measure (no weights) and the click-weighted average. As the share of identified weekly sales is small (within the 1.3%–1.7% range; see Table 3) and half of the products in the dataset do not have sales at all, the dispersion of regular prices is

26. Dispersion of online prices has been studied for specific markets such as books (e.g., Chevalier and Goolsbee 2003), CDs (e.g., Brynjolfsson and Smith 2000), consumer electronics (e.g., Baye et al. 2004), prepaid phone cards (e.g., Ong and Zhong 2011), travel (e.g., Clemons et al. 2002), or business-to-business supplies (e.g., Ghose and Yao 2011). While analyses of these markets are informative, these markets are unusual in many respects (e.g., Einav et al. 2015 study bidding and price behavior in eBay auctions), and hence generalization is not straightforward. To the best of our knowledge, there is no other study with a large coverage of sellers *and* goods in the e-commerce sector. However, online prices have been studied in the context of cross-border price dispersion and exchange-rate pass-through (e.g., Boivin et al. 2012; Gorodnichenko and Talavera 2017).

27. Because shopping platforms also work as price comparison websites, there is pressure to post only competitive prices. Otherwise, listings with noncompetitive prices receive a low on-screen rank (i.e., such listings are less likely to appear on the first page of a search result) and reduced quality rank, which raises the bid price for the on-screen rank in the future. Therefore, sellers with noncompetitive prices are penalized indirectly. Such a practice to rank listings and to price on-screen bids should lead to even smaller price dispersion.

28. Earlier literature often relied on relative price variability (Van Hoomissen 1988; Lach and Tsiddon 1992) or the dispersion of price *changes* (Midrigan 2011). With the access to offline scanner data, many studies, however, turned their attention to price dispersion as a better measure of market imperfections (Kaplan and Menzio 2015; Sheremirov 2015). We follow this approach. We relegate our results for alternative measures of dispersion (Baye et al. 2004, 2010) to Online Appendix (Table G.14).

TABLE 8. Average Dispersion of Posted Prices across Sellers

	United States				*United Kingdom*			
	CV	std(log p)	std(ε)	N	CV	std(log p)	std(ε)	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No weights	21.5	23.6	21.2	29,753	19.4	21.3	16.5	17,715
Click weighted	19.9	20.3	17.5		18.6	18.6	14.9	

Notes: Columns (1)–(3) and (5)–(7) report the average dispersion of posted prices measured with the CV (in %), std(log p), and std(ε) in the United States and the United Kingdom, respectively, where ε is a residual from the regression of log p on good and seller fixed effects. Columns (4) and (8) report the number of goods in the two samples. The CV is computed as the ratio of the standard deviation to the mean.

almost the same as dispersion of posted prices. To save space, we focus on results for posted prices and relegate results for regular prices to the online appendix.

In the United States, the CV is 22% and does not change materially when within- or between-good weights are applied (20% with between-good weights; column 1 of Table 8). This is similar to estimates in Kaplan and Menzio (2015) and larger than in Sheremirov (2015)—two recent studies of price dispersion across brick-and-mortar stores.[29] The standard deviation of log prices is similar to the CV (column 2 of Table 8). In the United Kingdom, the amount of price dispersion is roughly the same as in the United States: the CV is 19% (regardless of the weights used; see column 5 of Table 8).

The average gap between the two lowest prices is 28 log points, while the range is 41 log points (Online Appendix Table G.14). Together with the fact that, on average, the value of information is less than the gap—two alternative measures of price dispersion presented in the online appendix—this suggests that there is more mass in the left tail of price distribution than in the right tail. Note that such a high degree of price dispersion cannot be explained by small fringe sellers, as price dispersion remains very high even when we restrict our attention to large sellers with more than a hundred products listed on the platform. 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 a seller's optimal strategy is to offer a low price for the former and the reservation price for the latter (Morgan et al. 2006; Baye and Morgan 2009). Alternatively, if consumers face ex ante different information sets à la Varian (1980) (i.e., 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

29. Kaplan and Menzio (2015), using the Nielsen household panel for the period between 2004 and 2009, report a CV at the UPC level of 19%. Sheremirov (2015) uses the IRI scanner data for the 2001–2011 period and documents the average standard deviation of log prices at 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.

customers), while every other firm will charge the monopoly price since the other firms face demand from uninformed customers only.

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 sellers' 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. 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 the dispersion for the residuals, which gives us price dispersion net of sellers' heterogeneity in shipping costs, return policies, etc.[30] In other words, since the terms of sale are unlikely to change much in a relatively short period (e.g., Nakamura and Steinsson 2008 document that shipping costs typically change once in a few years), 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% of variation in price dispersion across goods in the United States and about 40% in the United Kingdom (columns 3 and 7 of Table 8), which is approximately double of the corresponding contribution for offline grocery stores (Kaplan et al. 2016). 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. Again, restricting the sample to large stores or excluding eBay-like sellers does not alter the results materially. 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 the inability of online markets to eliminate arbitrage opportunities. Studying how price dispersion varies over the product life can

30. Controlling for time dummies does not affect the results.

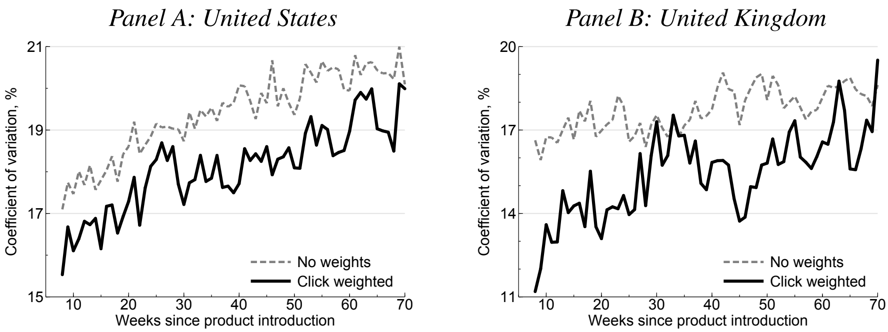

FIGURE 3. Cross-Seller Dispersion of Posted Prices over Product Life: The figure plots the raw and click-weighted means (over goods) of the coefficient of variation for posted prices against the time passed since the product introduction. Goods introduced during the first seven weeks are cut off to account for truncated observations, and only goods with duration of life of more than a year are considered. To construct this figure, we drop one outlier, a product in "Media," which would cause an idiosyncratic spike in the U.S. click-weighted CV at week 44.

also inform us about the nature of price rigidities. For example, Cavallo et al. (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. Our measure of price dispersion over the product life is constructed as follows. Suppose there are only two products, product 1 and product 2. If product 1 is present during, say, weeks $\{5,6,7\}$, and product 2 is present during weeks $\{7,8,9,10\}$, we relabel the time variable as $\{1,2,3\}$ for product 1 and $\{1,2,3,4\}$ for product 2 so that time is measured in weeks after product entry rather than in calendar weeks. Using cross-sectional price dispersion for each product and week, we compute an aggregate measure of price dispersion over different stages of product life. In this analysis, 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. 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.

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 of the introduction, from 15% to 20%. In the United Kingdom, a corresponding increase in dispersion is even bigger, from 11% to 19%. 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 life, and heterogeneity in product lives cannot explain cross-sectional dispersion of prices. We find similar results when

TABLE 9. Spatial vs. Temporal Price Dispersion

	United States				*United Kingdom*			
	No weights		Click weighted		No weights		Click weighted	
	<5%	>95%	<5%	>95%	<5%	>95%	<5%	>95%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1st quartile	43.0	16.3	23.1	10.4	42.4	18.1	19.9	9.7
2nd quartile	46.1	4.4	26.3	0.5	47.3	5.0	24.2	0.5
3rd quartile	43.6	5.7	31.7	0.6	45.3	6.4	32.1	0.7
4th quartile	60.1	6.5	53.0	1.7	61.6	6.4	52.8	1.6
Av. SD of time in each quartile	0.305		0.254		0.309		0.248	

Notes: For each price line (a time-series of prices for a good-seller), we compute the share of the period spent in each quartile of the cross-seller price distribution. This exercise is similar to Figure 4 in Lach (2002). The table reports the share of price lines that almost never (less than 5% of the time) or almost always (more than 95% of the time) fall into a given quartile. The bottom line shows the average (across price lines) standard deviation of the fractions of time spent in each quartile. Under perfectly temporal dispersion, this measure is 0, whereas under perfectly spatial dispersion, it is approximately 0.43.

we use dispersion net of seller fixed effects (Online Appendix Figure G.7). This result is consistent with low synchronization of prices across sellers.[31]

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 (2015) shows that, for reasonable parameterizations, popular menu-cost models make a similar prediction. When a firm responds 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 of 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 (see Baye et al. 2010 for an overview of the literature.) Varian (1980) argues that over time consumers should learn whether a firm charges a high price or a low price, thereby eliminating spatial price dispersion. Consistent with this prediction, Lach (2002) presents evidence of temporal price dispersion for brick-and-mortar stores in Israel. 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. Indeed, the conventional meaning of "spatial" hardly applies to online stores.

31. For example, price dispersion rises over time if there is no price synchronization and idiosyncratic shocks to price changes are not perfectly correlated, $\Delta \log p_{st} = \varepsilon_{st}$ with $\mathbb{C}\mathrm{orr}(\varepsilon_{it}, \varepsilon_{jt}) \neq 1$. If, instead, all firms followed a common benchmark price (mean or min price in the previous period, $\bar{p}_{t-1}$) and shocks were common, $\Delta \log p_{st} = -\mu(p_{s,t-1} - \bar{p}_{t-1}) + \varepsilon_t$, price dispersion would fall over time.

Following Lach (2002), we first establish whether seller j's price for good i (price line ij) is in a particular quartile of the price distribution across all sellers of good i on corresponding date t. Then we calculate the fraction of time that price line ij spends in a given quartile. Finally, we compute the average (unweighted and click-weighted) fractions across goods. If price dispersion is temporal, the fractions for a given price line should be close to 0.25; that is, a price moves along the cross-seller price distribution of good i and over time may appear in any part of the distribution with an equal probability. If price dispersion is spatial, then price line ij spends a disproportionate fraction of time in one of the quartiles (in an extreme case, all of the time; i.e., the fraction for one quartile is one and the fractions for other quartiles are zeros). Regardless of whether we use observed prices (p_{ist}) or prices net of seller fixed effects (ε_{ist}), we find strong support for spatial price dispersion (Table 9): about one-third of price lines spend more than 95% of the time within one quartile of the cross-seller price distribution (column 2). The case is especially strong for the 1st quartile: in the United States, 16.3% of price lines are almost always in the 1st quartile (10.4% when click weighted; column 4). Furthermore, between 43% and 60% of price lines (column 1) spend almost no time in a particular quartile in the U.S. data. For example, 43% of price lines never appear in the first quartile (the cheapest) and 60% of price lines never appear in the fourth quartile (the most expensive). The magnitudes are comparable for the United Kingdom (columns 5–8). We plot the distribution of these fractions over price lines ij in Online Appendix Figure G.8.

To provide an additional summary statistic of how price lines are distributed over time, we report the average (across price lines) standard deviation of the fractions of time spent in each quartile. To see why this metric is useful, consider two cases. Under perfectly temporal dispersion, each store has an equal probability to be at any quartile in any week. Then the fractions of time spent at quartiles Q1, Q2, Q3, and Q4 are all 0.25, and the standard deviation is 0. Under perfectly spatial dispersion, one-fourth of the sample is always in quartile Q1, one-fourth of the sample is always in quartile Q2, and so on. The standard deviation of the fractions for a price line is $\sqrt{3}/4$.[32] Hence, by checking whether the average standard deviation is closer to 0 or to 0.43, we can evaluate the relative importance of spatial vs. temporal dispersion. The last row in Table 9 shows that the standard deviation for the United States and the United Kingdom is approximately 0.3 (around 0.25 when weighted), which is closer to spatial price dispersion. Thus, both approaches point to potentially significant segmentation of the market.

Spatial price dispersion for a given good does not necessarily entail that stores set consistently low or high prices for *all* goods. As argued by Kaplan et al. (2016), a given store may charge relatively low prices for one set of goods and relatively high prices for another set of goods, so that the price of a typical purchase bundle is similar to the prices of this bundle in other stores. Unfortunately, our data do not have information on purchased baskets of goods, and thus we cannot test this theory directly. However,

32. The standard deviation is computed as $\sqrt{0.25\times(1-0.25)^2+0.75\times(0-0.25)^2}=\sqrt{3}/4\approx 0.43$.

we conjecture that this explanation of the observed price dispersion can offer only a partial account. Indeed, it is common for offline shoppers to buy multiple items conditional on visiting a store. As a result, customers choose a store and then choose what goods to buy. For online shopping, customers choose an item they would like to purchase and then choose a store that offers the best price. As a result, online sellers have weaker incentives to price specific goods high or low while keeping the prices of a basket constant.

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.[33] Second, prices may be different because they are set at different times and frequencies (Nakamura et al. 2011) and hence in response to different demand and supply conditions. This is the channel emphasized in models with sticky prices. Third, sellers can price discriminate among consumers (Guimaraes and Sheedy 2011, Coibion et al. 2015, Kaplan and Menzio 2015, Sheremirov 2015). 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 10) and relegate results for other measures and weighting schemes to Online Appendix (Tables G.15 and G.16).

We tend to find that a larger number of sellers and a smaller market size (measured by the number of clicks) are associated with smaller price dispersion.[34] The absolute magnitudes of the estimated coefficients on these two variables are similar to each other. One may interpret this result as suggesting that price dispersion is 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 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. Predictably, products with the prevalence of price points tend to have smaller price dispersion than products for which price points are not important.

In models of price stickiness (e.g., 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

33. Search costs affect not only the price distribution but also the distribution of clicks across sellers (Koulayev 2014).

34. Our results do not support the finding of Stavins (2001) that price dispersion increases with competition, which was documented for the airline market.

TABLE 10. 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	0.58					−3.49***	−0.05					−3.79***
	(1.73)					(1.01)	(1.47)					(0.82)
Log total clicks	0.03					4.98***	−0.23					4.34***
	(0.84)					(0.91)	(0.75)					(0.81)
Log median price	−4.85***					−3.85***	−4.01***					−3.10***
	(0.54)					(0.48)	(0.47)					(0.41)
Share of price points	−3.45					−6.96***	−2.20					−4.89***
	(2.91)					(1.75)	(2.48)					(1.50)
Frequency of regular price changes		0.16***	0.26***	0.17***	0.27***	0.37***		0.14***	0.23***	0.15***	0.23***	0.33***
		(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***	−0.30***			−0.35***		−0.43***	−0.26***
			(0.12)		(0.11)	(0.07)			(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)	(0.03)
Synchronization of posted price changes				−0.02	−0.06	−0.01				−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	0.29	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	−5.55***					−5.40***	−2.78***					−2.77***
	(1.39)					(1.42)	(0.95)					(0.88)
Log total clicks	1.76***					2.92***	0.64					1.61***
	(0.57)					(0.77)	(0.41)					(0.58)
Log median price	−4.20***					−3.00***	−2.74***					−2.29***
	(0.74)					(0.40)	(0.45)					(0.34)
Share of price points	−4.58***					−1.28	−0.60					3.30***
	(1.21)					(1.82)	(0.98)					(1.20)
Frequency of regular price changes		0.05	0.04	0.06	0.10**	0.16**		0.04**	−0.02	0.03	0.03	0.07*
		(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	0.10		0.05***	−0.06	0.05***	0.02	0.06
		(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**	0.21**			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***	−0.03*
				(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	0.26
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. Price points are prices that end at 95 to 99 cents (pence). Variables and observations are weighted by clicks when possible; unweighted results are relegated to the online 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% significance level, respectively.

in models with menu costs the relationship between the frequency of price changes and price dispersion is more nuanced, Sheremirov (2015) 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, cross-sectional price dispersion should disappear in these models. In line with this prediction, we find that the synchronization of price changes 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.[35] 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 of sales 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 observed price dispersion in online market.

35. For example, Sheremirov (2015) 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.

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

4.4. Relation to Theoretical Models

We document considerable dispersion of online prices for precisely defined goods, with differences in terms of trade across sellers being a relatively small source of the dispersion. Two findings are particularly challenging for models emphasizing search frictions. First, price dispersion is increasing over the product cycle, whereas search models tend to predict decreasing price dispersion. Second, this class of models tends to give rise to temporal price dispersion, with sellers moving up and down in the price distribution as a result of their mixed strategies. Conventional Calvo and "menu" cost models also predict temporal price dispersion, as the stochastic timing of price adjustment and random shocks put sellers' prices in different parts of the price distribution. In contrast, we show that price dispersion is closer to being spatial; that is, sellers charge consistently low or consistently high prices relative to their competitors. However, standard models of pricing do have teeth: the estimated relationships between price dispersion and frictions emphasized by standard models suggest that these workhorse models can account for some variation in the data. In the next section, we focus on the dynamics of price adjustment in response to fluctuations in demand, so that we can have a better understanding of which models have best fit.

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.).[36] 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 et al. 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.

36. For example, Deck and Wilson (2003) study theoretical properties of three "automated algorithms" responding to competitors' prices: undercutting, low-price matching, and trigger pricing. Although we do not have information on whether these algorithms were used by the sellers on the platform, our results provide indirect evidence that their usage was, at best, limited. Undercutting and trigger algorithms imply large synchronization of price changes, overall, and a response to price decreases stronger than to price increases, in particular. Low-price matching implies small price dispersion. These implications do not match empirical facts documented in Sections 3.4 and 4.

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 policymakers' 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.

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 4 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, $\bar{p}_t^{\mathrm{w}} = \sum_{s \in \mathscr{S}_t} (q_{st}/Q_t) p_{st}$, and the log of the total number of clicks, $\log Q_t = \log \sum_{s \in \mathscr{S}_t} q_{st}$.[37] In each country and each year, the number of clicks goes up and the average price goes down during the holiday sales. This finding is consistent with Warner and Barsky (1995), who find that brick-and-mortar stores choose to time 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 5 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 11 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

37. We find similar results when we consider alternative measures of prices (median, minimum, etc.).

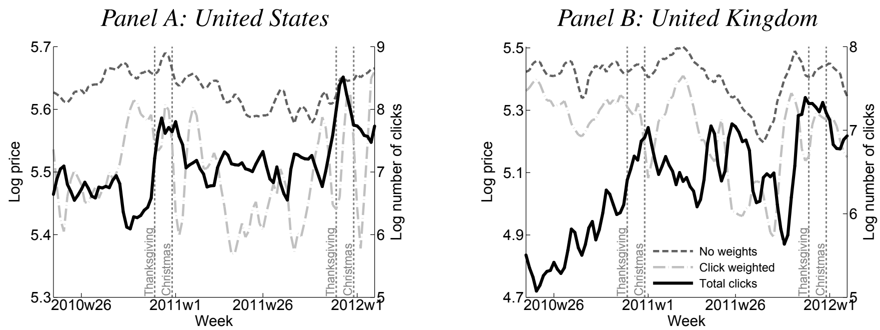

FIGURE 4. Average Price and Total Clicks for a Representative Good (headphones): The dashed line is the average unweighted price across all sellers, the lighter dash-dot line shows the click-weighted average, and the solid line shows the log number of total clicks. Each time-series is a centered three-week moving average.

TABLE 11. Intraweek Variation in Prices and Clicks

	United States				United Kingdom			
	Click Share, %	Log Deviation from Weekly Median, *log points*: Total Clicks	Mean Price	Weighted Mean Price	Click Share, %	Log Deviation from Weekly Median, *log points*: Total Clicks	Mean Price	Weighted Mean Price
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(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 of the sample are dropped. The sample period is between Monday, May 3, 2010, and Sunday, February 5, 2012.

shopping activity on the platform is the lowest. In contrast, the shopping activity in brick-and-mortar stores is the highest on weekends (BLS 2014; Koustas 2014), indicating potential complementarity of online and offline shopping (people shop online during the workweek, while shopping offline on the weekend). 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 log points 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

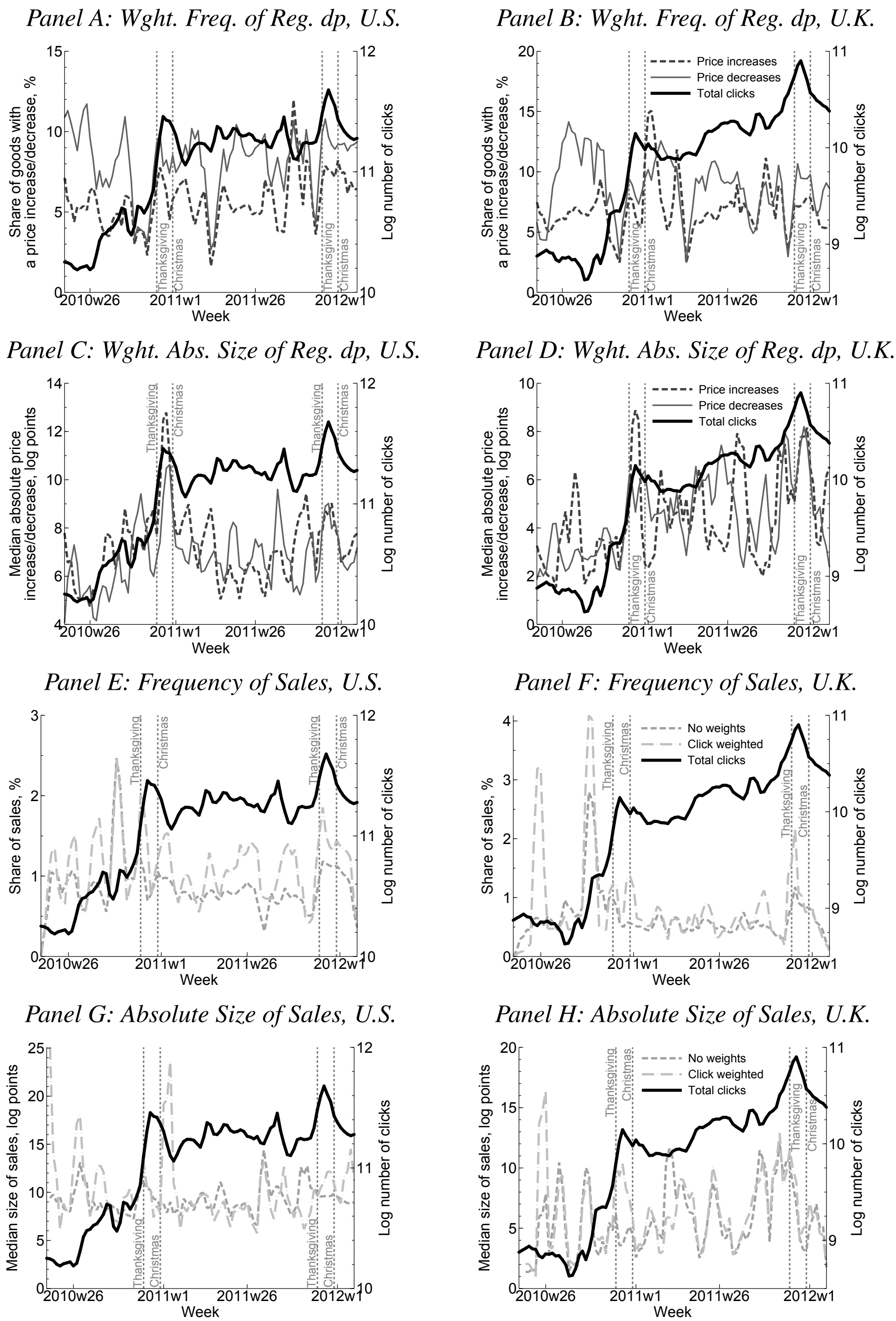

FIGURE 5. Price Adjustment during Holiday Sales: centered three-week moving average

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

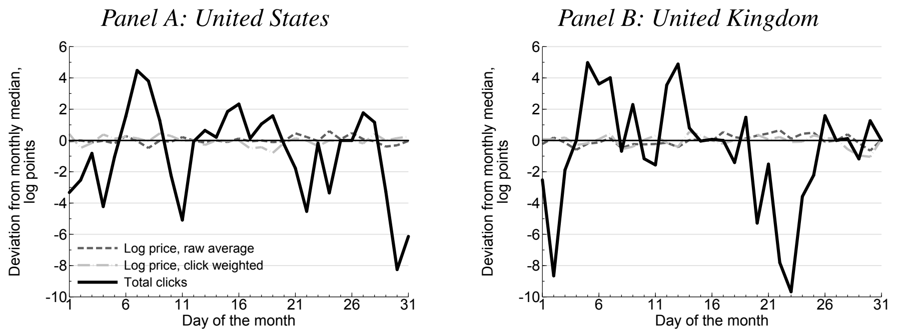

FIGURE 6. Intramonth Variation in Prices and Clicks: The dashed line shows the median (over months) deviation of the raw mean log price on a given day from the median day of the same month, the lighter dash-dot line shows the same deviation for the between-good, click-weighted mean, and the solid line shows the deviation for the total number of clicks. The sample period is between May 1, 2010, and January 31, 2012.

log points 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 6 shows that the intramonth variation of the number of clicks also significantly exceeds that of the average price, a fact that also holds *within product categories*. 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. Consistent with Olafsson and Pagel (2016), 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.

Relation to Theoretical Models. Similar to offline prices, online prices appear to react to changes in demand (proxied with clicks) at low frequencies. At the same time, we document that online prices are insensitive to variation in demand at higher frequencies. Specifically, online prices do not appear to respond to considerable intraweek or intramonth variation in demand. Given that this variation in demand is predictable, standard models emphasizing the state-dependent nature of price adjustment should have difficulties explaining differential sensitivity of prices to low- and high-frequency variation in demand. Similarly, while search models can explain greater flexibility and lower prices in times of peak demand (e.g., Christmas), it is not clear why firms in this setting would choose not to respond to predictable spikes in demand at high frequencies (e.g., Mondays). Our results may lend some support to models emphasizing the role of customer capital in price setting, as changing prices based on the time of the day or the day of the week may negatively affect the seller's reputation and erode its customer base. We leave exploration of this channel to future research.

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 employ dynamic pricing and 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 indeed change *more frequently* 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 changes, large cross-sectional dispersion, and low sensitivity to predictable fluctuations in demand, quantitatively similar to offline prices. Hence, consistent with Blinder (1994), Rotemberg (2011), and others, the cost of price change may stem not only from physical costs of changing price tags or information costs but also from psychological costs of alienating consumers by breaking implicit price contracts. Our results also point to a potentially nontrivial size of search costs (e.g., due to obfuscation, as in Ellison and Ellison 2009), despite the convenience and efficiency of ever-improving search engines.

References

Alvarez, Fernando and Francesco Lippi (2014). "Price Setting with Menu Cost for Multiproduct Firms." *Econometrica*, 82(1), 89–135.

Anderson, Eric, Benjamin A. Malin, Emi Nakamura, Duncan Simester, and Jón Steinsson (2017). "Informational Rigidities and the Stickiness of Temporary Sales." *Journal of Monetary Economics*, 90, 64–83.

Bakos, J. Yannis (1997). "Reducing Buyer Search Costs: Implications for Electronic Marketplaces." *Management Science*, 43(12), 1676–1692.

Baye, Michael R., J. Rupert J. Gatti, Paul Kattuman, and John Morgan (2007). "A Dashboard for Online Pricing." *California Management Review*, 50(1), 202–216.

Baye, Michael R., J. Rupert J. Gatti, Paul Kattuman, and John Morgan (2009). "Clicks, Discontinuities, and Firm Demand Online." *Journal of Economics & Management Strategy*, 18(4), 935–975.

Baye, Michael R. and John Morgan (2001). "Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets." *American Economic Review*, 91(3), 454–474.

Baye, Michael R. and John Morgan (2009). "Brand and Price Advertising in Online Markets." *Management Science*, 55(7), 1139–1151.

Baye, Michael R., John Morgan, and Patrick Scholten (2004). "Price Dispersion in the Small and in the Large: Evidence from an Internet Price Comparison Site." *Journal of Industrial Economics*, 52(4), 463–496.

Baye, Michael R., John Morgan, and Patrick Scholten (2010). "Information, Search, and Price Dispersion." In *Economics and Information Systems*, *Handbooks in Information Systems*, vol. 1, edited by Terrence Hendershott, pp. 323–376. Elsevier.

Benabou, Roland (1988). "Search, Price Setting and Inflation." *Review of Economic Studies*, 55(3), 353–376.

Benabou, Roland (1992). "Inflation and Efficiency in Search Markets." *Review of Economic Studies*, 59(2), 299–329.

Bhaskar, V. (2002). "On Endogenously Staggered Prices." *Review of Economic Studies*, 69(1), 97–116.

Bilotkach, Volodymyr, Yuriy Gorodnichenko, and Oleksandr Talavera (2010). "Are Airlines' Price-Setting Strategies Different?" *Journal of Air Transport Management*, 16(1), 1–6.

Bilotkach, Volodymyr, Yuriy Gorodnichenko, and Oleksandr Talavera (2012). "Sensitivity of Prices to Demand Shocks: A Natural Experiment in the San Francisco Bay Area." *Transportation Research Part A: Policy and Practice*, 46(7), 1137–1151.

Bils, Mark and Peter J. Klenow (2004). "Some Evidence on the Importance of Sticky Prices." *Journal of Political Economy*, 112(5), 947–985.

Blinder, Alan S. (1994). "On Sticky Prices: Academic Theories Meet the Real World." In *Monetary Policy*, edited by N. Gregory Mankiw, pp. 117–154. University of Chicago Press.

BLS (2014). "American Time Use Survey—2013 Results." News release.

Boivin, Jean, Robert Clark, and Nicolas Vincent (2012). "Virtual Borders." *Journal of International Economics*, 86(2), 327–335.

Brynjolfsson, Erik and Michael D. Smith (2000). "Frictionless Commerce? A Comparison of Internet and Conventional Retailers." *Management Science*, 46(4), 563–585.

Calvo, Guillermo A. (1983). "Staggered Prices in a Utility-Maximizing Framework." *Journal of Monetary Economics*, 12(3), 383–398.

Cavallo, Alberto F. (2013). "Online and Official Price Indexes: Measuring Argentina's Inflation." *Journal of Monetary Economics*, 60(2), 152–165.

Cavallo, Alberto F. (2015). "Scraped Data and Sticky Prices." *Review of Economics and Statistics*, Forthcoming.

Cavallo, Alberto F. (2017). "Are Online and Offline Prices Similar? Evidence from Large Multi-Channel Retailers." *American Economic Review*, 107(1), 283–303.

Cavallo, Alberto F., Brent Neiman, and Roberto Rigobon (2014). "Currency Unions, Product Introductions, and the Real Exchange Rate." *Quarterly Journal of Economics*, 129(2), 529–595.

Cavallo, Alberto F., Brent Neiman, and Roberto Rigobon (2015). "The Price Impact of Joining a Currency Union: Evidence from Latvia." *IMF Economic Review*, 63(2), 281–297.

Cavallo, Alberto F. and Roberto Rigobon (2012). "The Distribution of the Size of Price Changes." NBER Working Paper No. 16760.

Chevalier, Judith and Austan Goolsbee (2003). "Measuring Prices and Price Competition Online: Amazon.com and BarnesandNoble.com." *Quantitative Marketing and Economics*, 1(2), 203–222.

Chu, Junhong, Pradeep Chintagunta, and Javier Cebollada (2008). "Research Note—A Comparison of Within-Household Price Sensitivity Across Online and Offline Channels." *Marketing Science*, 27(2), 283–299.

Clark, Robert and Nicolas Vincent (2014). "Booms, Busts, and Price Dispersion." *Economics Letters*, 124(3), 399–401.

Clemons, Eric K., Il-Horn Hann, and Lorin M. Hitt (2002). "Price Dispersion and Differentiation in Online Travel: An Empirical Investigation." *Management Science*, 48(4), 534–549.

Coibion, Olivier, Yuriy Gorodnichenko, and Gee Hee Hong (2015). "The Cyclicality of Sales, Regular and Effective Prices: Business Cycle and Policy Implications." *American Economic Review*, 105(3), 993–1029.

CPC Strategy (2014). "The Comparison Shopping Report Q2 2014." Available at http://www.cpcstrategy.com/comparison-shopping/the-comparison-shopping-report-q2-2014/.

De los Santos, Babur, Ali Hortaçsu, and Matthijs R. Wildenbeest (2012). "Testing Models of Consumer Search Using Data on Web Browsing and Purchasing Behavior." *American Economic Review*, 102(6), 2955–2980.

Deck, Cary A. and Bart J. Wilson (2003). "Automated Pricing Rules in Electronic Posted Offer Markets." *Economic Inquiry*, 41(2), 208–223.

Diamond, Peter A. (1993). "Search, Sticky Prices, and Inflation." *Review of Economic Studies*, 60(1), 53–68.

Eichenbaum, Martin, Nir Jaimovich, and Sergio Rebelo (2011). "Reference Prices, Costs, and Nominal Rigidities." *American Economic Review*, 101(1), 234–262.

Einav, Liran, Theresa Kuchler, Jonathan Levin, and Neel Sundaresan (2015). "Assessing Sale Strategies in Online Markets Using Matched Listings." *American Economic Journal: Microeconomics*, 7(2), 215–247.

Ellison, Glenn and Sara Fisher Ellison (2005). "Lessons About Markets from the Internet." *Journal of Economic Perspectives*, 19(2), 139–158.

Ellison, Glenn and Sara Fisher Ellison (2009). "Search, Obfuscation, and Price Elasticities on the Internet." *Econometrica*, 77(2), 427–452.

Ellison, Sara Fisher, Christopher M. Snyder, and Hongkai Zhang (2016). "Costs of Managerial Attention and Activity as a Source of Sticky Prices: Structural Estimates from an Online Market." CESifo Working Paper No. 6285.

European Commission (2014). "Study on the Coverage, Functioning and Consumer Use of Comparison Tools and Third-Party Verification Schemes for Such Tools." Available at https://ec.europa.eu/futurium/en/content/study-coverage-functioning-and-consumer-use-comparison-tools-and-third-party-verification.

Fuhrer, Jeffrey C. (2006). "Intrinsic and Inherited Inflation Persistence." *International Journal of Central Banking*, 2(3), 49–86.

Fuhrer, Jeffrey C. (2010). "Inflation Persistence." In *Handbook of Monetary Economics*, vol. 3, edited by Benjamin M. Friedman and Michael Woodford, pp. 423–486. Elsevier.

Ghose, Anindya and Yuliang Yao (2011). "Using Transaction Prices to Re-Examine Price Dispersion in Electronic Markets." *Information Systems Research*, 22(2), 269–288.

Golosov, Mikhail and Robert E. Lucas, Jr. (2007). "Menu Costs and Phillips Curves." *Journal of Political Economy*, 115(2), 171–199.

Gorodnichenko, Yuriy and Oleksandr Talavera (2017). "Price Setting in Online Markets: Basic Facts, International Comparisons, and Cross-Border Integration." *American Economic Review*, 107(1), 249–282.

Guimaraes, Bernardo and Kevin D. Sheedy (2011). "Sales and Monetary Policy." *American Economic Review*, 101(2), 844–876.

Head, Allen, Lucy Qian Liu, Guido Menzio, and Randall Wright (2012). "Sticky Prices: A New Monetarist Approach." *Journal of the European Economic Association*, 10(5), 939–973.

Hong, Han and Matthew Shum (2006). "Using Price Distributions To Estimate Search Costs." *RAND Journal of Economics*, 37(2), 257–275.

Kaplan, Greg and Guido Menzio (2015). "The Morphology of Price Dispersion." *International Economic Review*, 56(4), 1165–1206.

Kaplan, Greg, Guido Menzio, Leena Rudanko, and Nicholas Trachter (2016). "Relative Price Dispersion: Evidence and Theory." NBER Working Paper No. 21931.

Kehoe, Patrick and Virgiliu Midrigan (2015). "Prices Are Sticky After All." *Journal of Monetary Economics*, 75(C), 35–53.

Klenow, Peter J. and Oleksiy Kryvtsov (2008). "State-Dependent or Time-Dependent Pricing: Does It Matter for Recent U.S. Inflation?" *Quarterly Journal of Economics*, 123(3), 863–904.

Klenow, Peter J. and Benjamin A. Malin (2010). "Microeconomic Evidence on Price-Setting." In *Handbook of Monetary Economics*, vol. 3, edited by Benjamin M. Friedman and Michael Woodford, pp. 231–284. Elsevier.

Knotek II, Edward S. (2011). "Convenient Prices and Price Rigidity: Cross-Sectional Evidence." *Review of Economics and Statistics*, 93(3), 1076–1086.

Koulayev, Sergei (2014). "Search for Differentiated Products: Identification and Estimation." *RAND Journal of Economics*, 45(3), 553–575.

Koustas, Dmitri K. (2014). "Measuring the Consumption of the Unemployed Using High-Frequency Data." Unpublished manuscript.

Kryvtsov, Oleksiy and Nicolas Vincent (2014). "On the Importance of Sales for Aggregate Price Flexibility." Bank of Canada Working Paper No. 14-45.

Lach, Saul (2002). "Existence and Persistence of Price Dispersion: An Empirical Analysis." *Review of Economics and Statistics*, 84(3), 433–444.

Lach, Saul and Daniel Tsiddon (1992). "The Behavior of Prices and Inflation: An Empirical Analysis of Disaggregated Price Data." *Journal of Political Economy*, 100(2), 349–389.

Lünnemann, Patrick and Ladislav Wintr (2011). "Price Stickiness in the US and Europe Revisited: Evidence from Internet Prices." *Oxford Bulletin of Economics and Statistics*, 73(5), 593–621.

Mankiw, N. Gregory (1985). "Small Menu Costs and Large Business Cycles: A Macroeconomic Model of Monopoly." *Quarterly Journal of Economics*, 100(2), 529–537.

Mankiw, N. Gregory and Ricardo Reis (2002). "Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve." *Quarterly Journal of Economics*, 117(4), 1295–1328.

Midrigan, Virgiliu (2011). "Menu Costs, Multiproduct Firms, and Aggregate Fluctuations." *Econometrica*, 79(4), 1139–1180.

Morgan, John, Henrik Orzen, and Martin Sefton (2006). "An Experimental Study of Price Dispersion." *Games and Economic Behavior*, 54(1), 134–158.

Nakamura, Alice O., Emi Nakamura, and Leonard I. Nakamura (2011). "Price Dynamics, Retail Chains and Inflation Measurement." *Journal of Econometrics*, 161(1), 47–55.

Nakamura, Emi and Jón Steinsson (2008). "Five Facts about Prices: A Reevaluation of Menu Cost Models." *Quarterly Journal of Economics*, 123(4), 1415–1464.

Nakamura, Emi and Jón Steinsson (2012). "Lost in Transit: Product Replacement Bias and Pricing to Market." *American Economic Review*, 102(7), 3277–3316.

Ofcom (2012). "International Communications Market Report 2012."
Available at http://stakeholders.ofcom.org.uk/binaries/research/cmr/cmr12/icmr/ICMR-2012.pdf.

Ofcom (2016). "International Communications Market Report 2016."
Available at https://www.ofcom.org.uk/__data/assets/pdf_file/0026/95642/ICMR-Full.pdf.

Olafsson, Arna and Michaela Pagel (2016). "The Liquid Hand-to-Mouth: Evidence from a Personal Finance Management Software." Working paper.
Available at http://arnaolafsson.weebly.com/uploads/2/3/7/5/23754531/paydayliquidity.pdf.

Olivei, Giovanni and Silvana Tenreyro (2007). "The Timing of Monetary Policy Shocks." *American Economic Review*, 97(3), 636–663.

Ong, David and Zemin Zhong (2011). "Paying More To Top Up: An Online Field Experiment on Price Dispersion." Unpublished manuscript.

Rotemberg, Julio J. (2011). "Fair Pricing." *Journal of the European Economic Association*, 9(5), 952–981.

Sheremirov, Viacheslav (2015). "Price Dispersion and Inflation: New Facts and Theoretical Implications." Federal Reserve Bank of Boston Working Paper No. 15-10.

Sheshinski, Eytan and Yoram Weiss (1977). "Inflation and Costs of Price Adjustment." *Review of Economic Studies*, 44(2), 287–303.

Soysal, Gonca and Alejandro Zentner (2014). "Measuring E-Commerce Concentration Effects When Product Popularity is Channel-Specific." Available at https://ssrn.com/abstract=2424840.

Statista (2015). "On Which Website or App Did You Make Your Most Recent Purchase?" Available at https://www.statista.com/statistics/376255/recent-online-shopping-destinations-usa/.

Statista (2016). "Retail E-commerce Sales Worldwide from 2014 to 2020." Available at https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/.

Stavins, Joanna (2001). "Price Discrimination in the Airline Market: The Effect of Market Concentration." *Review of Economics and Statistics*, 83(1), 200–202.

Stigler, George J. (1961). "The Economics of Information." *Journal of Political Economy*, 69(3), 213–225.

Taylor, John B. (1980). "Aggregate Dynamics and Staggered Contracts." *Journal of Political Economy*, 88(1), 1–23.

Van Hoomissen, Theresa (1988). "Price Dispersion and Inflation: Evidence from Israel." *Journal of Political Economy*, 96(6), 1303–1314.

Varian, Hal R. (1980). "A Model of Sales." *American Economic Review*, 70(4), 651–659.

Warner, Elizabeth J. and Robert B. Barsky (1995). "The Timing and Magnitude of Retail Store Markdowns: Evidence from Weekends and Holidays." *Quarterly Journal of Economics*, 110(2), 321–352.

Woodford, Michael (2003). *Interest and Prices*. Princeton University Press.

ONLINE APPENDIX FOR PRICE SETTING IN ONLINE MARKETS: DOES IT CLICK?

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Appendix A: Online Shopping Platforms with an Example

E-commerce is an extraordinarily dynamic market. To provide a sense of where price comparison websites stand relative to one another, we use reports compiled by CPC Strategy, an e-commerce consultancy and market research firm (Figure A.1). Despite the fact that the market leader has a 2–3 times higher traffic and revenue than its competitors, there is less discrepancy among other players. The cost of sale on paid platforms averaged around 20% during our sample period, while the conversion rate varied between 1% and 3%. The budgets vary based on scales of sellers, ranging from about $10 thousand per month for a small business to about $4 million for a giant seller.[1]

As an example, we provide some more detailed statistics for Google Shopping, one of the leading platforms. The platform provides two bidding strategies: (*i*) a seller can manually set bids for a click (e.g., 20 cents per click); or (*ii*) use the platform's clicks-maximizing algorithm. CPC Strategy (2017) reports that in 2016 the average cost per click was about 42 cents, ranging from 20 cents for cosmetic products to $1.61 for luggage-and-travel products (Table A.1).

Both the daily budget and bidding strategy are essential for an efficient listing campaign. When a customer searches for a given product, offers with the highest bids are shown first. When a seller manually chooses a very low price per click, their products may appear on the last page of the search result, providing virtually no visibility.

Our data come from an online platform-aggregator where sellers advertise their product. In order to be listed, each seller has to provide (1) a product data feed, (2) a budget, and (3) a bidding strategy. The data feed contains detailed product information: namely, product name, description, price, availability, product category, as well as shipping and tax expenses. Sellers can regularly update their inventory/product data to maintain high accuracy. Sellers also allocate their daily budgets, as well as provide information about target customers (e.g., currency, time zone, country of sale).

Figures A.2 and A.3 provide an example of how a search result for a particular good is seen by customers on 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 that a seller chooses to pay per click, but consumers can re-sort sellers by the average review score and the (base or total) price. Figure A.4 provides the list of choices that sellers make 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 a daily budget. Figure A.5 provides an example of an 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.

1. For details, see http://www.wordstream.com/blog/ws/2015/05/21/how-much-does-adwords-cost.

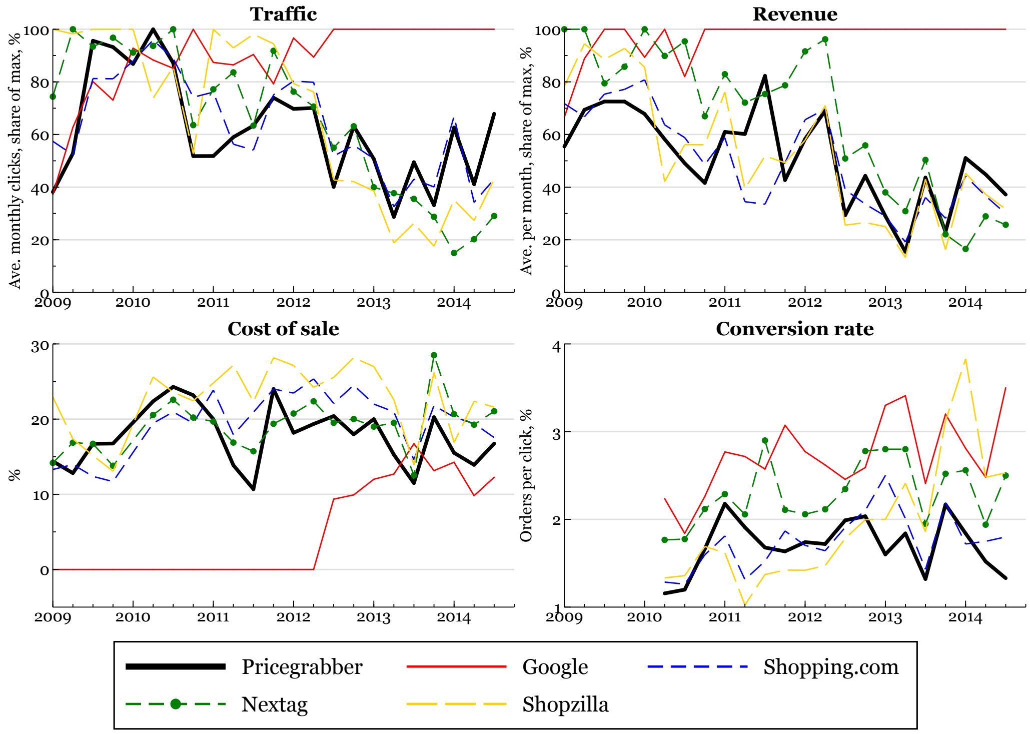


FIGURE A.1. Price Comparison Websites. *Source:* CPC Strategy reports

TABLE A.1. An Example of Online Shopping Platform: Google Shopping, U.S. 2016 Data

Product Category	Click-through Rate, % (1)	Click-to-Sale Conversion Rate, % (2)	Average Order Value, $ (3)	Return on Ad Spending, % (4)	Cost per Click, $ (5)
Apparel	0.78	3.67	40.61	565	0.26
Appliances	1.43	1.62	230.78	567	0.66
Art Supplies	1.62	1.66	78.45	412	0.32
Automotive	1.41	1.50	169.95	750	0.34
Babies and Kids	0.89	1.42	188.13	707	0.38
Beauty and Cosmetics	1.05	2.79	47.80	289	0.46
Books, Music, and Gifts	1.37	2.22	68.42	483	0.31
Cosmetics	1.90	2.49	30.75	383	0.20
Electronics	1.49	1.95	79.10	381	0.41
Food and Grocery	1.47	1.43	179.80	619	0.42
Footwear	1.17	2.18	119.04	627	0.41
Health and Fitness	1.36	2.44	111.11	446	0.61
Home	1.98	3.76	49.44	226	0.82
Home and Furniture	0.89	1.51	233.55	614	0.57
Luggage and Travel	0.91	1.08	549.70	369	1.61
Medical	1.35	1.75	277.51	693	0.70
Office	1.10	2.31	151.21	376	0.93
Outdoor	1.60	2.91	113.61	911	0.36
Pet Supplies	1.29	6.35	36.50	440	0.53
Sports and Outdoors	1.49	1.97	135.71	623	0.43
Tools	1.23	1.15	277.91	827	0.39
Toys	1.03	0.75	240.12	349	0.51
Watches and Jewelry	0.85	0.61	1,190.31	993	0.73
Other	*1.55*	*3.13*	*69.66*	*396*	*0.55*
All Goods	***1.20***	***2.46***	***91.70***	***542***	***0.42***

Source: CPC Strategy (2017).

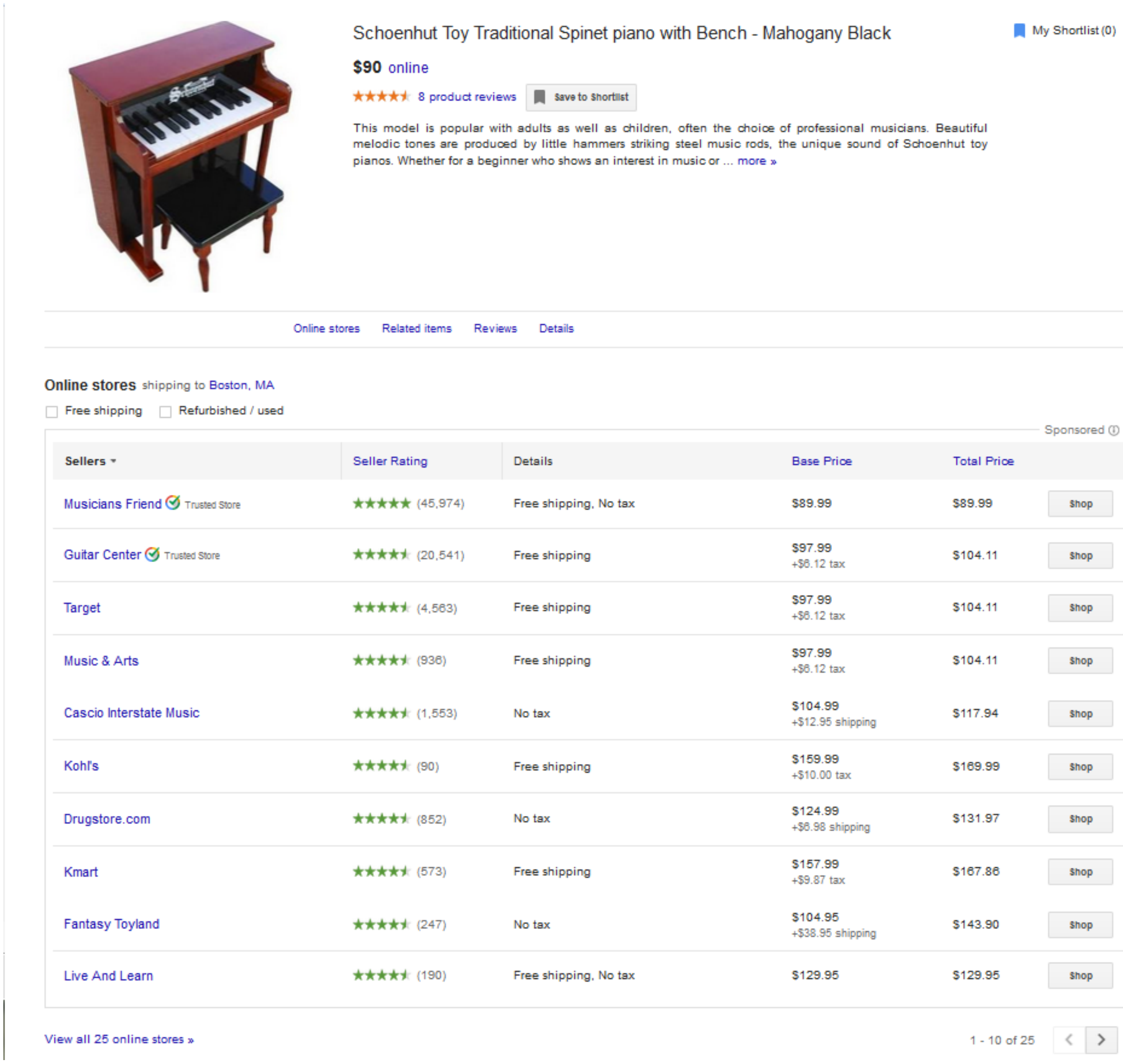


FIGURE A.2. Shopping Platform Screenshot: A Product Listing, U.S. The screenshot was taken in June 2015 from a typical online shopping platform operating in the United States.

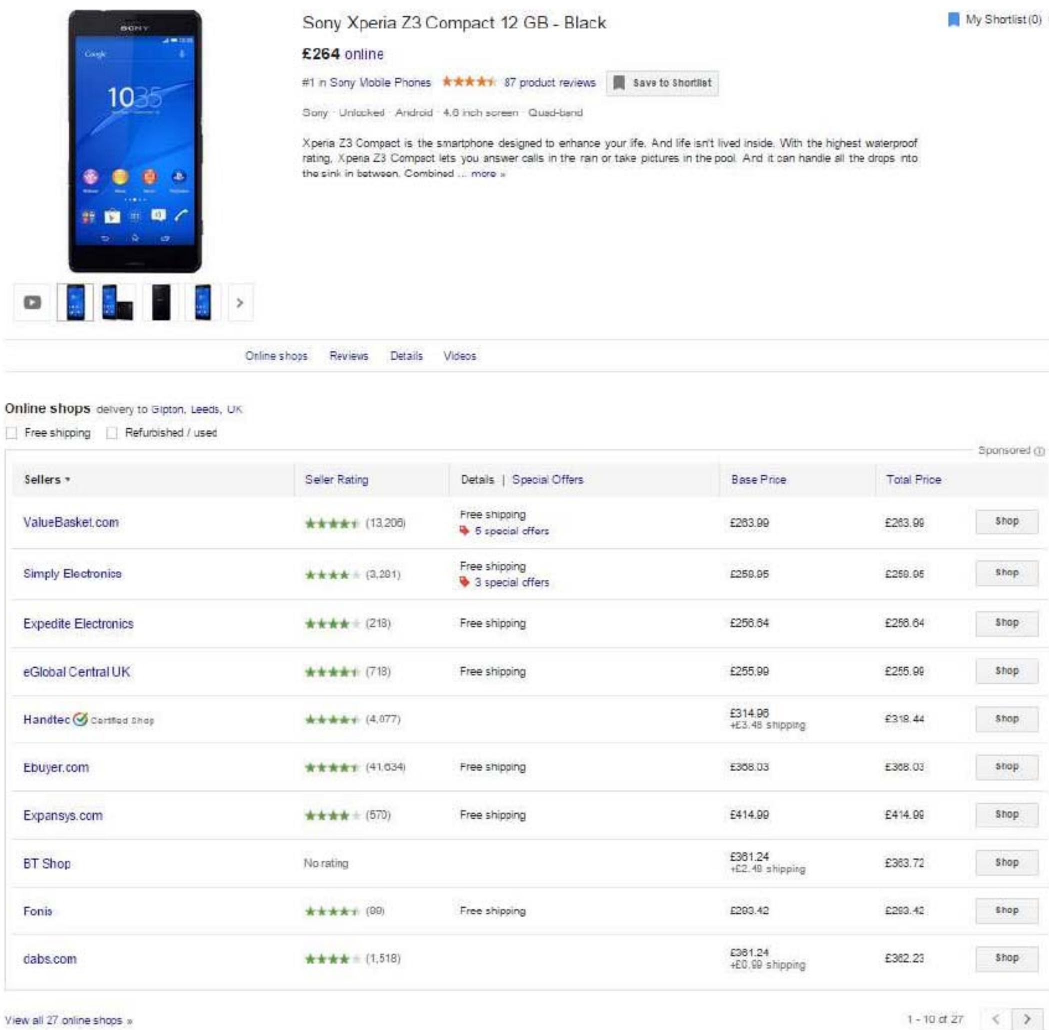


FIGURE A.3. Shopping Platform Screenshot: A Product Listing, U.K. The screenshot was taken in June 2015 from a typical online shopping platform operating in the United Kingdom.

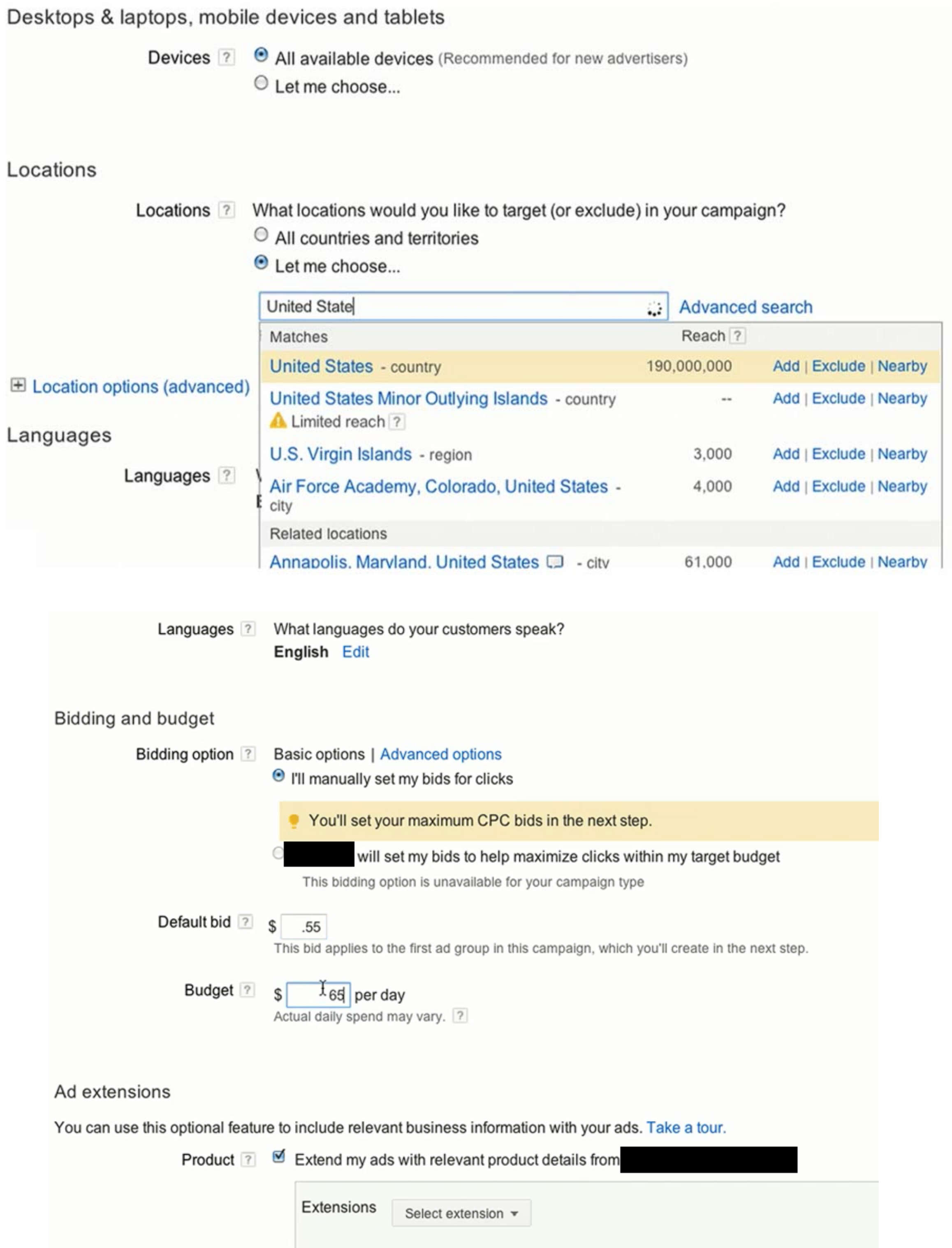


FIGURE A.4. Shopping Platform Screenshot: Advertiser Account. The screenshot was taken in December 2012 from a typical online shopping platform. Black boxes mask the name of the platform to emphasize that it does not necessarily represent the data provider.

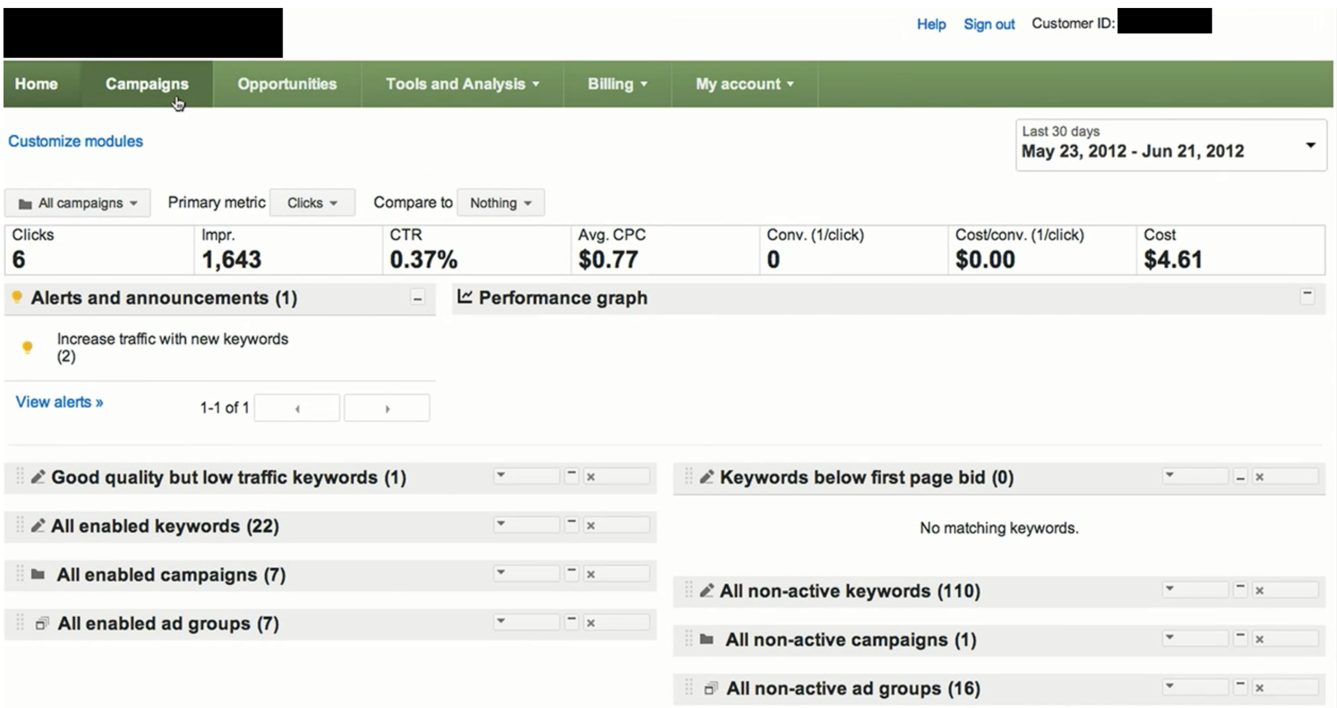


FIGURE A.5. Shopping Platform Screenshot: Ad Summary. The screenshot was taken in December 2012 from a typical online shopping platform. Black boxes mask the name of the platform to emphasize that it does not necessarily represent the data provider.

Appendix B: Data Processing and Aggregation

The dataset, 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 pound 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. 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 only a tiny share of observations and our assumptions do not affect the results in any meaningful way.

Since the data contain many missing daily observations (likely due to no clicks for a particular price line on a given day), and to enhance comparison with existing studies, we aggregate the data to a 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:

$$\omega_{is} = \frac{\widehat{\mathbb{V}}_t\left[\log p_{ist} - \log p_{ist}^{\text{weekly}}\right]}{\widehat{\mathbb{V}}_t\left[\log p_{ist}\right]}, \tag{B.1}$$

where p_{ist} is the daily price, p_{ist}^{weekly} is the mode price within a given week, and $\widehat{\mathbb{V}}$ is sample variance. In line with our usual approach, we then compute the raw mean over sellers (no weights), $\bar{\omega}_i = \sum_{s\in\mathscr{S}_i} \omega_{is}/S_i$, the click-weighted mean (within goods), $\bar{\omega}_i^{\text{w}} = \sum_{s\in\mathscr{S}_i} Q_{is}\omega_{is}/Q_i$, and the average of $\bar{\omega}_i^{\text{w}}$ with between-good weights $W_i = Q_i/Q$. With no weights or with 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% in the United States and 11% in the United Kingdom (Table B.1). 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 B.2 shows that intraday price changes are relatively rare on this platform during the sample period.

2. When we have more than one mode for duplicated observations, we use the smallest one, since lower 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 is more than one mode, we keep the one with the earliest first occurrence.

TABLE B.1. Share of Intraweek Price Variation in Total Daily Variation, %

	No Weights			Within-Good Weights			Between-Good Weights			
	Mean	SD	Med.	Mean	SD	Med.	Mean	SD	Med.	*N*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(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

TABLE B.2. High-Frequency Price Changes: Intraday and Adjacent Days

	United States		*United Kingdom*	
	Obs.	%	Obs.	%
	(1)	(2)	(3)	(4)
No price changes	3,798,599	96.50	1,264,830	96.93
Price changes	137,794	3.50	40,031	3.07
Price changes on adjacent days	112,122	2.85	37,480	2.87
Price changes within a day	25,672	0.65	2,551	0.20
1	22,898	0.58	2,256	0.17
2	1,723	0.04	175	0.01
3	444	0.01	56	0.00
>3	607	0.02	64	0.00
Total	3,936,393	100.00	1,304,861	100.00

Note: “Price changes” indicates the sum of those on adjacent days and within a day, and “Price changes within a day” is the sum of rows “1”, “2”, “3” and “>3.”

Appendix C: Within-Good Weights

TABLE C.1. Distribution of Prices, local currency

	Mean Log Price		Mean Price, percentile					
	Mean	SD	5	25	50	75	95	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(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 (baseline)	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 (baseline)	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. See Table 2 in the paper.

TABLE C.2. Frequency and Size of Sales

	One-Week Filter				Two-Week Filter				
	Mean Freq.	Std. Dev.	Med. Freq.	Med. Size	Mean Freq.	Std. Dev.	Med. Freq.	Med. Size	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(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 (%), 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 a one-week, two-side sale filter (see the paper). Columns (5)–(8) report the same statistics for a two-week sale filter. Column (9) reports the number of goods. The statistics for offline stores are from Nakamura and Steinsson (2008) for the United States and Kryvtsov and Vincent (2014) for the United Kingdom; the mean frequency is converted to weekly rates. See Table 3 in the paper.

TABLE C.3. 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, %	14.0	16.7	19.3	8.2	9.8	15.7	4.7
Implied duration, weeks	6.6	5.5	4.7	11.6	9.7	5.8	20.8
Med. abs. size, log points	11.0	10.7	11.2				10.7
Regular Price							
Median frequency, %	8.8	10.8	14.5	7.0	8.3	12.9	2.1
Implied duration, weeks	10.9	8.7	6.4	13.9	11.6	7.3	47.1
Med. abs. size, log points	10.9	10.6	10.9				8.5
Panel B: United Kingdom							
Posted Price							
Median frequency, %	12.8	13.0	20.0	7.7	7.7	16.3	4.6
Implied duration, weeks	7.3	7.2	4.5	12.5	12.5	5.6	21.2
Med. abs. size, log points	5.1	5.0	8.5				11.1
Regular Price							
Median frequency, %	7.7	7.7	15.8	6.7	6.7	14.3	3.2
Implied duration, weeks	12.5	12.5	5.8	14.5	14.5	6.5	30.7
Med. abs. 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 United States and Kryvtsov and Vincent (2014) for the United Kingdom, converted to a weekly frequency. Regular prices are identified using a one-week filter for sales. See Table 4 in the paper.

TABLE C.4. Synchronization Rate, %

	Synchronization across Sellers				Synchronization across Goods			
	Mean (1)	SD (2)	Med. (3)	3 Months (4)	Mean (5)	SD (6)	Med. (7)	3 Months (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 rate *for a good across sellers*. Column (4) reports the upper bound of synchronization at a three-month horizon. Columns (5)–(8) report the same measures for the weekly synchronization rate *for a seller across goods*. Regular prices are identified based on a one-week, two-side filter. See Table 6 in the paper.

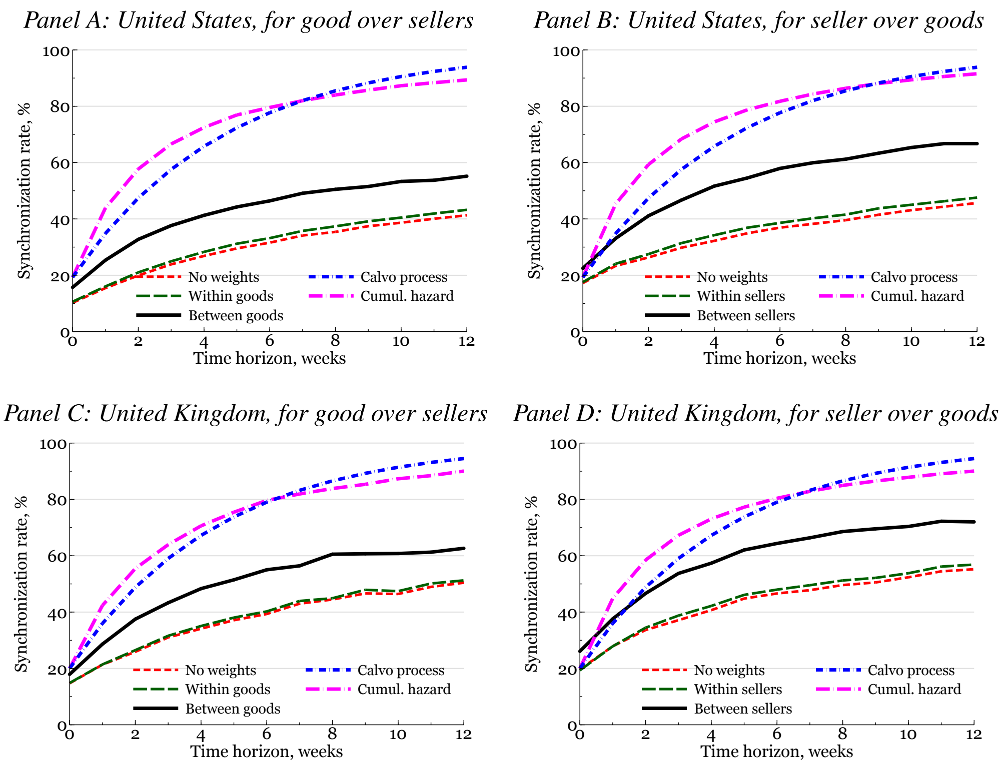


FIGURE C.1. Synchronization Rate for Posted Prices by Time Horizon: Panels A and C report the upper bound synchronization *across sellers* at a week-h horizon, while Panels B and D report synchronization *across goods*. The red dashed line aggregates using the raw average, the green long-dash line uses within-good/seller click weights, and the black solid line uses between weights. The blue dash-dot line shows synchronization under the assumption of a fixed probability of price adjustment, as in Calvo (1983), based on a between-good click-weighted median frequency. The magenta long dash–dot line shows the cumulative hazard rate starting from the Calvo rate at $h = 0$. See Figure 2 in the paper.

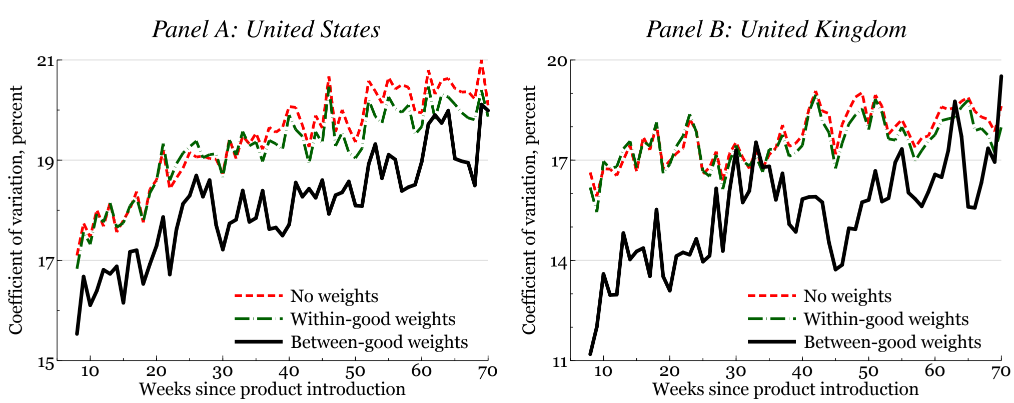


FIGURE C.2. Cross-Seller Dispersion of Posted Prices over Product Life: The figure plots the raw and click-weighted mean over goods of the CV for posted prices against the time passed since product introduction. Goods introduced during the first seven weeks are cut off to account for truncated observations, and only goods with duration of life of more than a year are considered. See Figure 3 in the paper.

TABLE C.5. Predictors of Posted-Price Stickiness

	Frequency of Price Changes, %			Absolute Size of Price Changes, *log points*			Cross-Seller Synchronization Rate, %		
Weights:	No	W	B	No	W	B	No	W	B
Predictors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: United States									
Log number of sellers	8.7***	10.4***	10.2***	−0.5	−0.7	−0.9	2.4***	2.5***	2.7***
	(0.6)	(0.7)	(0.6)	(0.8)	(0.8)	(0.7)	(0.7)	(0.7)	(0.6)
Herfindahl index, (0, 1]	18.1***	23.3***	23.8***	−5.1***	−5.8***	−5.5***	10.4***	12.5***	13.2***
	(2.6)	(3.0)	(2.7)	(1.8)	(1.8)	(1.5)	(3.0)	(3.2)	(2.9)
Log total clicks	−5.0***	−4.1***	−3.9***	−0.2	−0.2	−0.1	−0.9***	−0.7*	−0.6*
	(0.4)	(0.3)	(0.3)	(0.3)	(0.4)	(0.3)	(0.4)	(0.4)	(0.3)
Log median price	2.0**	1.2	1.0	−10.0***	−10.1***	−9.9***	2.0**	2.0***	2.1***
	(0.9)	(0.8)	(0.8)	(0.9)	(0.7)	(0.7)	(0.9)	(0.7)	(0.7)
Log median price, squared	−0.2**	−0.2**	−0.2**	0.8***	0.8***	0.8***	−0.1	−0.1	−0.2*
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Share of price points	−6.9***	−7.8***	−7.4***	7.3***	7.3***	6.6***	−1.3	−1.1	−0.8
	(1.6)	(1.3)	(1.3)	(1.3)	(1.2)	(1.2)	(1.2)	(1.1)	(1.1)
R^2	0.09	0.09	0.10	0.12	0.12	0.13	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	4.3***	5.7***	6.4***	−0.8	−0.9	−1.1**	3.0**	3.0**	3.5***
	(1.2)	(1.3)	(1.2)	(0.5)	(0.5)	(0.5)	(1.3)	(1.3)	(1.3)
Herfindahl index, (0, 1]	18.5***	22.7***	23.2***	−5.4***	−5.6***	−5.7***	10.0*	12.3**	12.4**
	(4.3)	(4.6)	(4.3)	(1.2)	(1.2)	(1.3)	(5.1)	(5.4)	(5.3)
Log total clicks	−2.5***	−2.4***	−2.3***	0.4**	0.5***	0.5***	−2.3***	−2.3***	−2.0***
	(0.4)	(0.4)	(0.4)	(0.2)	(0.2)	(0.2)	(0.6)	(0.6)	(0.5)
Log median price	5.7***	5.9***	5.3***	−4.1***	−4.5***	−4.9***	3.8**	3.7**	3.9***
	(1.3)	(1.1)	(1.1)	(0.5)	(0.5)	(0.5)	(1.6)	(1.6)	(1.4)
Log median price, squared	−0.7***	−0.7***	−0.6***	0.4***	0.4***	0.4***	−0.3	−0.3	−0.3*
	(0.2)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.2)
Share of price points	−19.6***	−17.6***	−16.5***	11.8***	11.1***	11.0***	−14.1***	−11.8***	−10.8***
	(1.6)	(1.4)	(1.3)	(1.1)	(1.1)	(1.0)	(2.0)	(1.8)	(1.6)
R^2	0.12	0.12	0.12	0.11	0.11	0.12	0.07	0.06	0.06
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. Price points are prices that end at 95 to 99 cents (pence). 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% significance level, respectively. See Table 7 in the paper.

Appendix D: Heterogeneity across Products

TABLE D.1. Frequency of Price Adjustment and Implied Duration of Spells

	Median Duration, *weeks*	Frequency, %		Percentile						
		Mean	SD	5	25	50	75	95	*N*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(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	11.6	11.9	13.7	0.0	2.5	8.2	16.1	38.9	
Within-good weights	9.7	13.3	14.2	0.0	2.6	9.8	19.2	40.0	14,483
Between-good weights	5.8	16.6	10.4	1.6	8.9	15.7	23.2	35.8	
Regular Price: One-Week-Decrease Filter									
No weights	12.7	11.2	13.1	0.0	2.3	7.5	15.0	36.7	
Within-good weights	10.6	12.4	13.6	0.0	2.4	9.0	17.9	38.2	14,458
Between-good weights	6.6	15.1	9.7	1.2	8.0	14.1	20.9	31.9	
Regular Price: One-Week Two-Side Filter									
No weights	13.9	10.5	12.7	0.0	2.0	7.0	14.3	34.5	
Within-good weights	11.6	11.6	13.1	0.0	2.1	8.3	16.7	36.4	14,425
Between-good weights	7.3	14.0	9.2	1.0	7.2	12.9	19.7	29.7	
Regular Price: Two-Week Two-Side Filter									
No weights	15.5	9.7	12.2	0.0	1.5	6.3	12.9	33.3	
Within-good weights	13.4	10.7	12.6	0.0	1.6	7.2	15.1	34.0	14,385
Between-good weights	8.3	12.6	8.6	0.7	6.2	11.4	17.9	27.3	

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

	Median Duration, *weeks*	Frequency, %								
				Percentile						
		Mean	SD	5	25	50	75	95	*N*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel D: United Kingdom—With Imputation									
Posted Price									
No weights	12.5	15.9	21.8	0.0	0.0	7.7	20.8	70.4	
Within-good weights	12.5	16.1	21.9	0.0	0.0	7.7	21.4	71.4	6,623
Between-good weights	5.6	17.5	12.9	0.0	6.8	16.3	26.9	38.7	
Regular Price: One-Week-Decrease Filter									
No weights	13.5	15.2	21.3	0.0	0.0	7.1	20.0	68.8	
Within-good weights	13.7	15.3	21.4	0.0	0.0	7.0	20.0	69.2	6,601
Between-good weights	6.0	16.4	12.5	0.0	6.3	15.3	24.1	37.2	
Regular Price: One-Week Two-Side Filter									
No weights	14.5	14.7	21.0	0.0	0.0	6.7	18.8	66.7	
Within-good weights	14.5	14.7	21.0	0.0	0.0	6.7	19.1	66.7	6,587
Between-good weights	6.5	15.5	12.2	0.0	5.8	14.3	21.9	36.0	
Regular Price: Two-Week Two-Side Filter									
No weights	15.5	14.0	20.4	0.0	0.0	6.3	17.6	64.7	
Within-good weights	15.9	14.0	20.5	0.0	0.0	6.1	17.6	66.7	6,560
Between-good weights	7.0	14.5	11.8	0.0	5.5	13.3	20.9	34.9	

Note: This table reproduces the frequency of price adjustment and median implied duration from Table 4, adding two additional sale filters and showing moments of the distribution of the frequency across goods.

TABLE D.2. Frequency of Price Increases and Decreases

	Mean	SD	Percentile 5	25	50	75	95	*N*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(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	

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

TABLE D.3. Cross-Good Heterogeneity of the Size of Price Changes, log points

	Mean (1)	SD (2)	Percentile 5 (3)	25 (4)	50 (5)	75 (6)	95 (7)	*N* (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	

Note: This table reproduces the size of price changes for posted prices from Table 4, adding actual (as opposed to absolute values of) changes and showing moments of the distribution across goods.

TABLE D.4. The Size of *Absolute* Price Changes for Posted and Regular Prices, log points

	Mean	SD	Percentile					N
			5	25	50	75	95	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(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	

Note: This table reproduces the absolute size of price changes from Table 4 for different types of sale filters.

TABLE D.5. Synchronization Rate, %

	Mean	SD	Percentile				*N*
			25	50	75	95	
	(1)	(2)	(3)	(4)	(5)	(6)	(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 6 and reports moments of the distribution across products.

Appendix E: Heterogeneity across Product Categories

TABLE E.1. Median Frequency of Price Adjustment, %

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	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***

Note: This table reproduces the median frequency of price adjustment, reported in columns (1)–(2) of Table 4, by product category.

TABLE E.2. 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***

Note: This table reproduces the median size of price change, reported in columns (1)–(2) of Table 4, by product category.

TABLE E.3. Cross-Seller Synchronization Rate for Posted Prices, %

Category	No Weights			Within-Good Weights			Between-Good Weights			
	Mean (1)	SD (2)	Med. (3)	Mean (4)	SD (5)	Med. (6)	Mean (7)	SD (8)	Med. (9)	*N* (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, Bev., 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, Bev., 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***

Note: This table reproduces the cross-seller synchronization rate for posted prices, reported in columns (1)–(3) of Table 6, by product category.

TABLE E.4. Duration of Product Life, weeks

	Truncated	Halftruncated			Nontruncated				
	Share, %	Share, %	Mean	SD	Mean	SD	Med.	Lower Bound	*N*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(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, Bev., 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, Bev., 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: 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) report the mean, standard deviation, and median for nontruncated goods. Column (8) shows the lower bound of the mean life duration (see the paper), and column (9) shows the total number of goods. To compare, the mean (median) duration in Cavallo et al. (2014) for the U.S. sample is 37 (15) weeks; for H&M and Zara only, the mean and median duration are around 10–12 weeks.

TABLE E.5. Average Price Dispersion

Measure	No Weights CV (1)	No Weights VI (2)	No Weights IQR (3)	No Weights Range (4)	No Weights Gap (5)	Click Weighted CV (6)	Click Weighted VI (7)	Click Weighted IQR (8)	Click Weighted Range (9)	Click Weighted 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, Bev., 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, Bev., 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: Columns (1)–(5) report the unweighted average price dispersion for posted prices measured with the CV, value of information (VI), interquartile range (IQR), range, and gap, respectively. Columns (6)–(10) report the click-weighted values and column (11) reports the number of goods. The CV is computed as the ratio of the standard deviation to the mean. The VI is the log difference between the average and minimum price. (It 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). The IQR is computed as the log difference between the 75th and 25th percentile; the range as the log difference between the highest and lowest price; and the gap as the log difference between the two lowest prices. See Table 8 in the paper.

Appendix F: Comparison with Brick-and-Mortar Stores

TABLE F.1. Frequency of Price Changes in Selected Narrow Categories, %

	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 United States and Kryvtsov and Vincent (2014) for the United Kingdom. Only matched categories are shown.

TABLE F.2. Median 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 United States and Kryvtsov and Vincent (2014) for the United Kingdom. Only matched categories are shown.

TABLE F.3. Frequency and Size of Sales in Selected Narrow Categories

	Frequency of Sales, %			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 United States and Kryvtsov and Vincent (2014) for the United Kingdom. Only matched categories are shown.

Appendix G: Miscellaneous Supporting Results

TABLE G.1. Frequency and Size of Price Changes: A Longer Imputation Period

	No Imputation			Complete 90-Week Imputation		
	No Weights (1)	Within Weights (2)	Between Weights (3)	No Weights (4)	Within Weights (5)	Between Weights (6)
Panel A: United States						
Posted Price						
Median frequency, %	14.0	16.7	19.3	7.1	8.4	14.9
Implied duration, weeks	6.6	5.5	4.7	13.6	11.4	6.2
Median absolute size, log points	11.0	10.7	11.2			
Regular Price						
Median frequency, %	8.8	10.8	14.5	6.0	7.1	12.1
Implied duration, weeks	10.9	8.7	6.4	16.1	13.5	7.8
Median absolute size, log points	10.9	10.6	10.9			
Panel B: United Kingdom						
Posted Price						
Median frequency, %	12.8	13.0	20.0	6.9	6.7	15.7
Implied duration, weeks	7.3	7.2	4.5	14.0	14.5	5.8
Median absolute size, log points	5.1	5.0	8.5			
Regular Price						
Median frequency, %	7.7	7.7	15.8	5.9	5.8	13.6
Implied duration, weeks	12.5	12.5	5.8	16.5	16.8	6.9
Median absolute size, log points	5.0	4.9	7.6			

Note: This table reproduces the results of Table 4 in the paper for the case when we allow for full imputation of missing prices (up to the entire sample period) in columns (4)–(6).

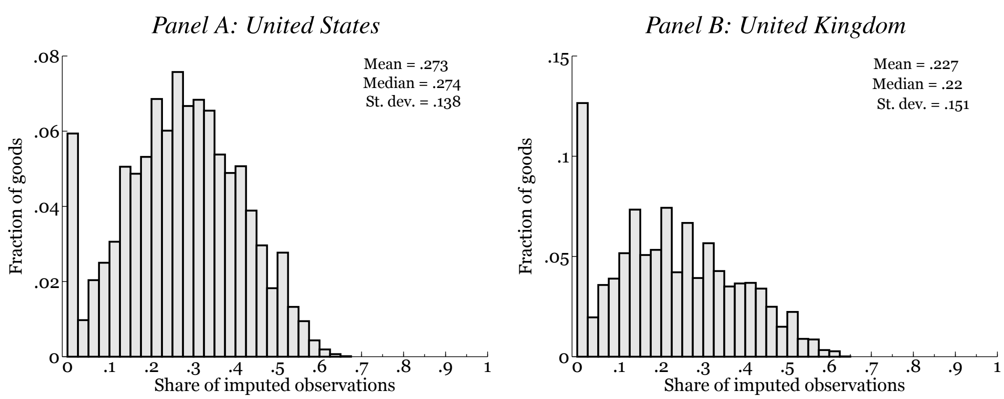


FIGURE G.1. Fraction of Imputed Missing Prices: Distribution over Goods. The figure produces a histogram of the share of imputed missing prices over goods. The imputation procedure is based on the baseline filter described in Section 3.1.

TABLE G.2. Frequency of Regular Price Changes: Alternative Imputation Schemes

	No Weights (1)	Click Weighted (2)
Panel A: United States		
Sales break regular price spell (contiguous observations only)	12.3	16.2
Sales don't break regular price spell (no missing price imputation)	8.8	14.5
Carry forward the last observed price if missing and no change later (missing-price imputation)	7.0	12.9
Carry forward the last observed price for missing AND sales	6.3	12.4
Panel B: United Kingdom		
Sales break regular price spell (contiguous observations only)	11.1	17.8
Sales don't break regular price spell (no missing price imputation)	7.7	15.8
Carry forward the last observed price if missing and no change later (missing-price imputation)	6.7	14.3
Carry forward the last observed price for missing AND sales	6.3	13.7

Notes: This table computes the frequency of *regular* price changes for the case when we allow carrying forward the last price for missing prices and sales episodes. Rows 2 and 3 correspond to our baseline results in Table 4 in the paper.

TABLE G.3. Synchronization of Sales

	Across Sellers of the Same Good			Across Goods by the Same Seller		
	Mean (1)	SD (2)	Med. (3)	Mean (4)	SD (5)	Med. (6)
Panel A: United States						
No Imputation						
No weights	0.8	5.2	0.0	2.1	9.6	0.0
Within weights	1.0	6.3	0.0	2.4	11.4	0.0
Between 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 weights	1.2	7.0	0.0	2.6	11.0	0.0
Between 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 weights	1.1	7.3	0.0	2.9	12.7	0.0
Between 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 weights	0.8	5.7	0.0	3.7	14.7	0.0
Between 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.

TABLE G.4. Frequency of Price Increases and Decreases

	Mean (1)	SD (2)	Med. (3)
Panel A: United States			
Posted Price Increases			
No weights	8.3	9.7	5.9
Within-good weights	9.2	9.8	7.2
Between-good weights	8.9	5.4	8.6
Posted Price Decreases			
No weights	9.5	11.0	6.5
Within-good weights	10.5	11.2	8.3
Between-good weights	10.9	6.9	10.1
Regular Price Increases			
No weights	5.7	7.9	3.3
Within-good weights	6.4	8.1	4.2
Between-good weights	6.8	4.4	6.4
Regular Price Decreases			
No weights	6.6	9.1	3.7
Within-good weights	7.4	9.4	4.8
Between-good weights	8.6	6.1	7.7
Panel B: United Kingdom			
Posted Price Increases			
No weights	10.4	14.2	5.6
Within-good weights	10.5	14.2	5.7
Between-good weights	9.8	7.2	9.0
Posted Price Decreases			
No weights	10.0	13.3	5.3
Within-good weights	10.2	13.4	5.4
Between-good weights	10.6	7.8	10.4
Regular Price Increases			
No weights	7.8	12.6	2.3
Within-good weights	7.9	12.6	2.5
Between-good weights	8.0	6.6	7.2
Regular Price Decreases			
No weights	7.4	11.6	1.7
Within-good weights	7.6	11.8	1.7
Between-good weights	8.7	7.2	8.1

Note: This table shows the frequency of price increases and decreases.

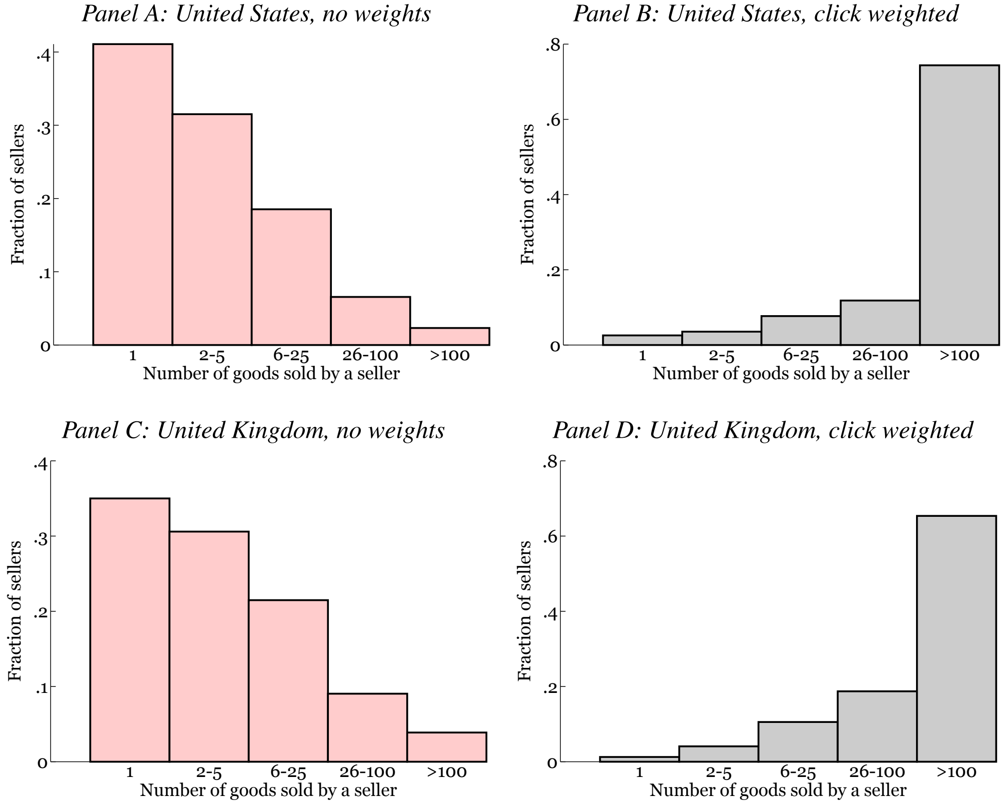


FIGURE G.2. Distribution of Sellers by Number of Goods Listed: The figure shows that although a majority of the platform's sellers have only a small number of goods listed, our click-weighted results come mostly from large sellers that advertise hundreds of goods on the platform.

TABLE G.5. Frequency and Size of Price Changes by Seller Size

	All Sellers (1)	Number of Goods by Seller: 10 or fewer (2)	11–100 (3)	More than 100 (4)
Panel A: United States				
Posted Price				
Median frequency, %	19.3	5.3	5.8	21.1
Implied duration, weeks	4.7	18.5	16.8	4.2
Median absolute size, log points	11.2	14.2	7.7	11.2
Regular Price				
Median frequency, %	14.5	3.2	4.3	16.1
Implied duration, weeks	6.4	30.5	22.8	5.7
Median absolute size, log points	10.9	12.6	7.4	11.0
Panel B: United Kingdom				
Posted Price				
Median frequency, %	20.0	5.3	7.8	25.6
Implied duration, weeks	4.5	18.4	12.4	3.4
Median absolute size, log points	8.5	8.6	6.1	8.6
Regular Price				
Median frequency, %	15.8	4.1	7.1	20.0
Implied duration, weeks	5.8	23.9	13.5	4.5
Median absolute size, log points	7.6	8.6	6.0	7.1

Notes: The table reproduces Table 4 by seller size. The results confirm that our findings are overall representative for large sellers. This pattern also holds *within* categories.

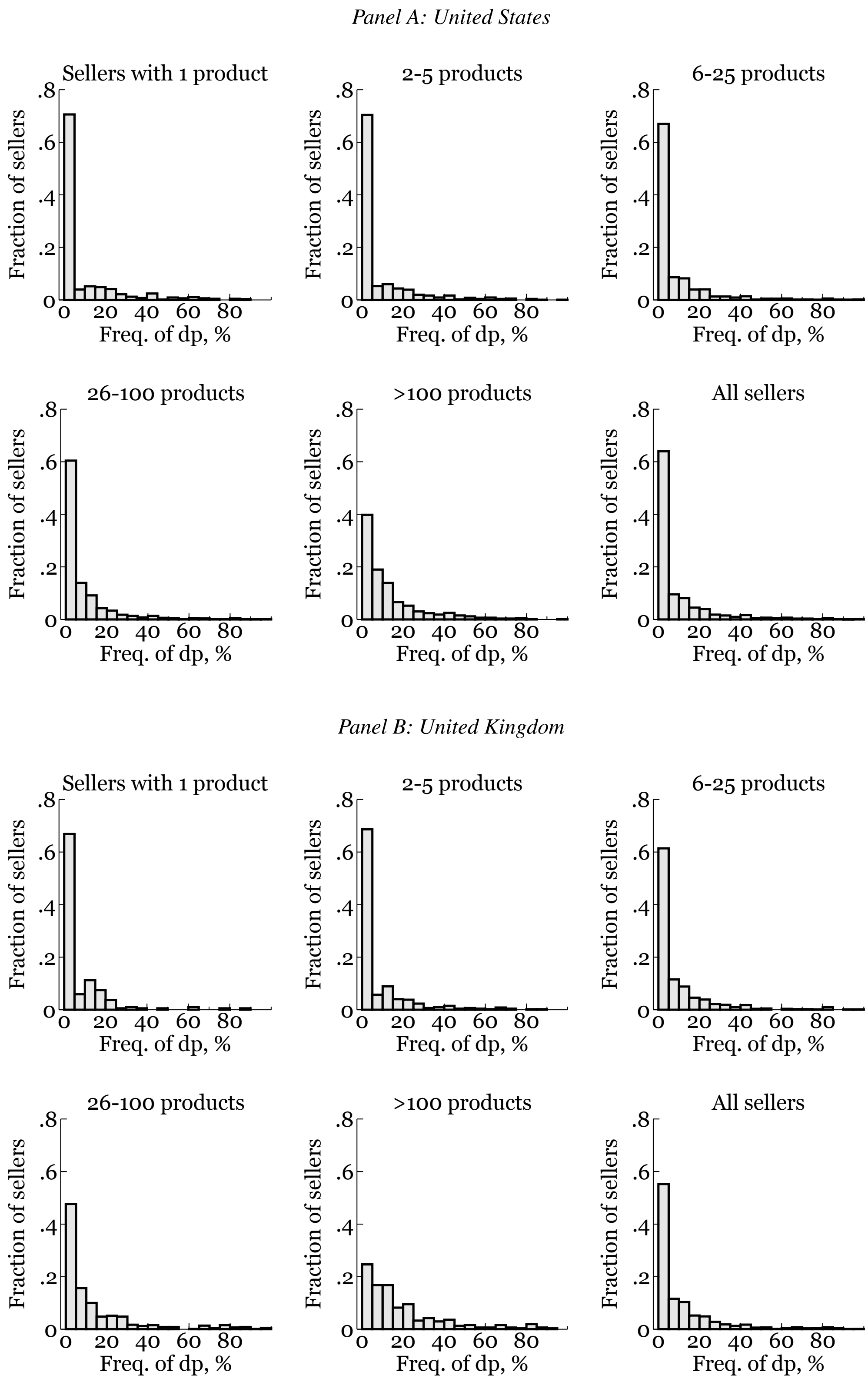


FIGURE G.3. Distribution of Frequency of Posted Price Changes over Sellers

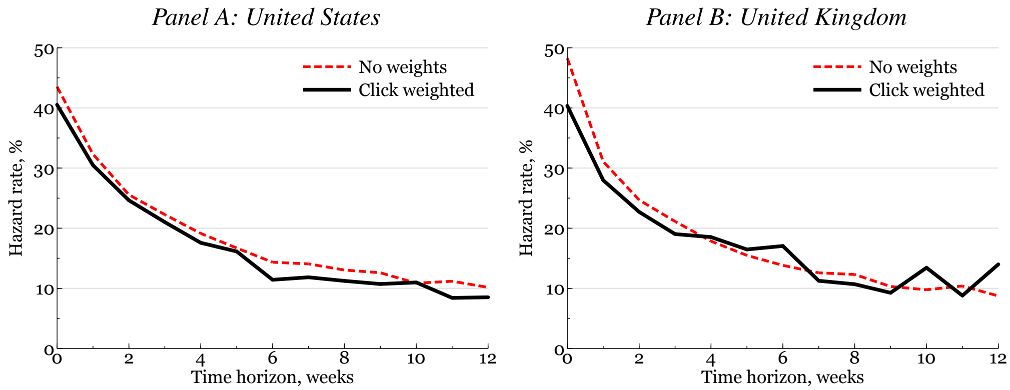


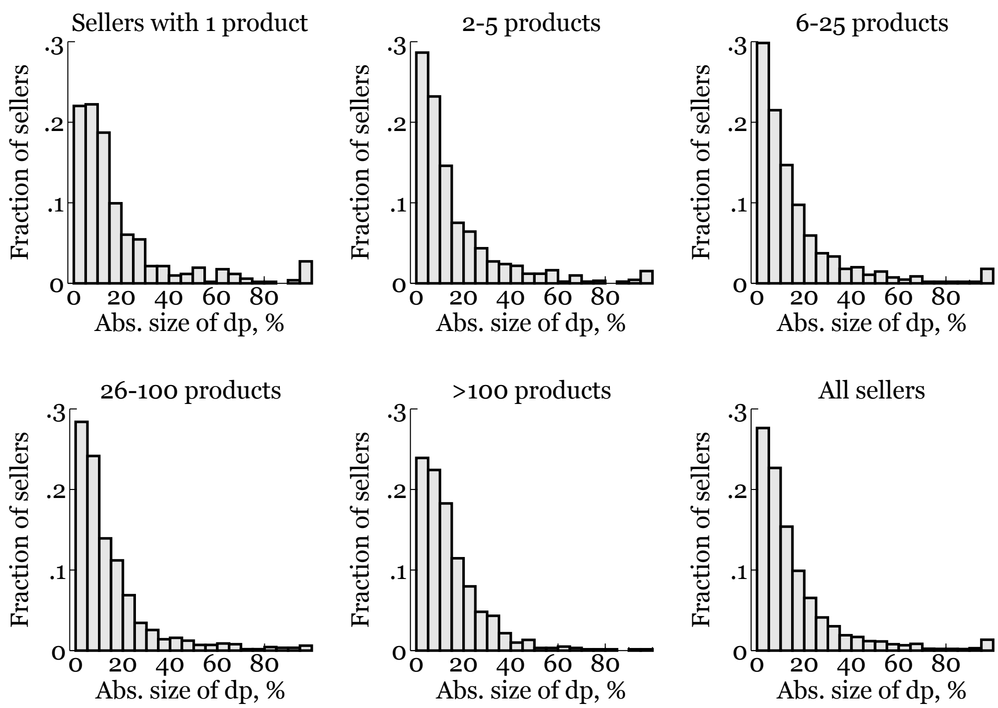
FIGURE G.4. Hazard Function: The figure plots the raw and click-weighted hazard rates.

TABLE G.6. The Absolute Size of Price Increases vs. Price Decreases, log points

	Mean (1)	SD (2)	Med. (3)
Panel A: United States			
All Price Changes			
No weights	16.3	17.2	11.0
Within-good weights	16.3	17.4	10.7
Between-good weights	13.7	9.8	11.2
Price Increases			
No weights	17.5	18.3	11.8
Within-good weights	17.3	18.6	11.3
Between-good weights	13.9	10.7	11.2
Price Decreases			
No weights	15.4	17.0	10.3
Within-good weights	15.6	17.4	10.1
Between-good weights	13.6	10.4	10.8
Panel B: United Kingdom			
All Price Changes			
No weights	9.5	13.2	5.1
Within-good weights	9.7	13.5	5.0
Between-good weights	10.1	8.0	8.5
Price Increases			
No weights	9.9	13.6	5.3
Within-good weights	9.9	13.8	5.1
Between-good weights	9.8	8.6	8.0
Price Decreases			
No weights	9.4	13.5	4.7
Within-good weights	9.6	13.9	4.7
Between-good weights	10.4	8.6	7.7

Note: This table reproduces the size of price changes for posted prices from Table 4, separately for price increases and decreases.

Panel A: United States



Panel B: United Kingdom

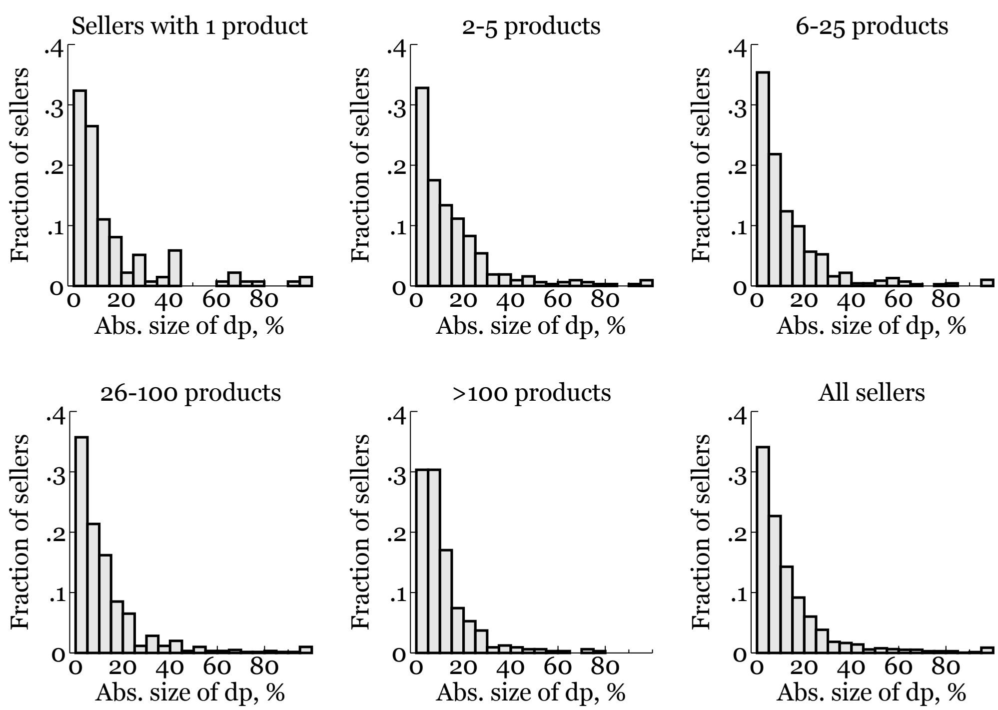


FIGURE G.5. Distribution of the Absolute Size of Posted Price Changes over Sellers: The figure plots the distribution of the absolute size of posted price change over sellers, by seller size. Changes over 100% are shown as 100%.

TABLE G.7. Duration of Product Life, weeks

	Truncated	Halftruncated			Nontruncated			Lower Bound		
	Share	Share	Mean	SD	Mean	SD	Med.	Mean	Med.	*N*
	(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 paper), and column (10) the total number of goods. To compare, the mean (median) duration in Cavallo et al. (2014) for the U.S. sample is 37 (15) weeks; for H&M and Zara only, the mean and median duration are around 10–12 weeks.

TABLE G.8. Price Stickiness by Duration of Product Life

	No Weights				Click Weighted				
	Frequency, %			Duration of Spells,	Frequency, %			Duration of Spells,	
Duration of Product Life	Mean	SD	Med.	weeks	Mean	SD	Med.	weeks	*N*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(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: The table reports the frequency of price adjustment and the duration of spells for goods with nontruncated product lives (i.e., goods which appear for the first time after our sample period starts and exit the market before the end of our sample period). To account for possible sample truncation, we drop products that enter or exit within the first or last five weeks of our data. Columns (1)–(3) report the mean, standard deviation, and median frequency of price adjustment across goods with a specified duration of life, column (4) reports the corresponding implied duration of price spells, columns (5)–(8) present the same statistics with between-good click weights, and column (9) shows the number of goods. We find little support for the idea that product life is a major determinant of price rigidity.

TABLE G.9. Synchronization Rate Based on the Fraction of Price Changes, %

	Synchronization across Sellers			Synchronization across Goods		
	Mean	SD	Med.	Mean	SD	Med.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: United States						
Posted Price						
No weights	2.0	1.0	1.7	2.6	1.5	2.3
Within weights	2.0	1.0	1.7	2.7	1.5	2.4
Between weights	1.7	1.0	1.5	1.4	1.4	0.9
Regular Price						
No weights	2.3	1.2	2.1	2.9	1.6	2.6
Within weights	2.4	1.2	2.1	3.0	1.6	2.6
Between weights	2.0	1.1	1.7	1.6	1.6	1.0
Panel B: United Kingdom						
Posted Price						
No weights	1.8	1.1	1.7	2.5	1.4	2.2
Within weights	1.8	1.1	1.7	2.6	1.4	2.3
Between weights	1.8	1.0	1.5	1.8	1.5	1.4
Regular Price						
No weights	2.1	1.2	1.9	2.7	1.5	2.4
Within weights	2.1	1.2	1.9	2.8	1.5	2.5
Between weights	2.1	1.1	1.8	2.0	1.5	1.6

Notes: This table reports an alternative measure of synchronization relative to the one in Table 6. This measure defines synchronization as a ratio of the standard deviation of the fraction of price changes over time to its mean over time (coefficient of variation), in %. A measure of zero means no synchronization (Calvo).

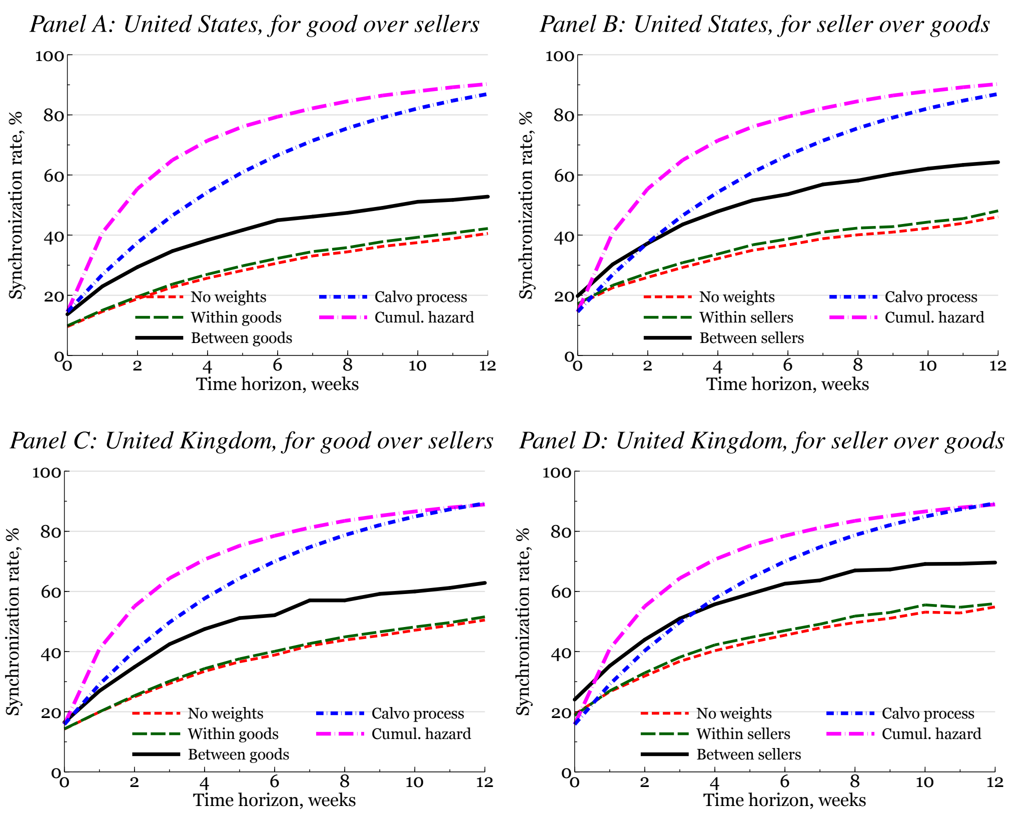


FIGURE G.6. Synchronization of *Regular* Price Changes by Time Horizon: The figure reproduces Figure 2 for regular prices.

TABLE G.10. Frequency and Synchronization of Posted-Price Increases and Decreases

	No Weights			Click Weighted			
	Mean	SD	Med.	Mean	SD	Med.	N
	(1)	(2)	(3)	(4)	(5)	(6)	(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

Note: The table reports estimates of the frequency and synchronization of posted-price increases and decreases. See notes to Tables 4 and 6.

TABLE G.11. Frequency and Synchronization of Regular Price Increases and Decreases

	No Weights			Between Weights			
	Mean	SD	Med.	Mean	SD	Med.	N
	(1)	(2)	(3)	(4)	(5)	(6)	(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

Note: The table reproduces Table G.10 for regular prices.

TABLE G.12. Predictors of Regular Price Stickiness

	Frequency of Price Changes, %			Absolute Size of Price Changes, *log points*			Cross-Seller Synchronization Rate, %		
Weights:	No	W	B	No	W	B	No	W	B
Predictors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: United States									
Log number of sellers	5.9***	7.6***	7.6***	−0.6	−0.7	−0.9	1.5***	1.7***	1.8***
	(0.5)	(0.6)	(0.5)	(0.8)	(0.8)	(0.7)	(0.6)	(0.6)	(0.5)
Herfindahl index, (0, 1]	14.6***	19.8***	20.7***	−5.0***	−5.6***	−5.0***	8.4***	10.2***	10.6***
	(2.1)	(2.5)	(2.2)	(1.8)	(1.8)	(1.5)	(2.5)	(2.6)	(2.3)
Log total clicks	−2.7***	−2.0***	−2.0***	−0.2	−0.2	−0.1	−0.5*	−0.3	−0.1
	(0.3)	(0.3)	(0.2)	(0.3)	(0.4)	(0.3)	(0.3)	(0.3)	(0.3)
Log median price	1.8***	1.0*	0.9	−9.8***	−9.9***	−9.7***	1.6**	1.7***	1.8***
	(0.6)	(0.6)	(0.6)	(0.9)	(0.7)	(0.7)	(0.8)	(0.6)	(0.6)
Log median price, squared	−0.2***	−0.2**	−0.2**	0.8***	0.8***	0.8***	−0.1	−0.1	−0.1
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
Share of price points	−5.9***	−6.4***	−6.2***	7.4***	7.3***	6.5***	−1.3	−1.2	−1.0
	(1.1)	(1.0)	(0.9)	(1.2)	(1.1)	(1.1)	(1.0)	(0.9)	(0.9)
R^2	0.06	0.08	0.09	0.12	0.12	0.13	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	2.6***	3.8***	4.6***	−0.8	−0.8	−1.0*	2.0	2.2	2.8**
	(1.0)	(1.0)	(1.0)	(0.5)	(0.5)	(0.5)	(1.3)	(1.4)	(1.2)
Herfindahl index, (0, 1]	15.7***	19.1***	20.3***	−5.3***	−5.4***	−5.4***	8.6*	11.2**	11.9**
	(3.2)	(3.4)	(3.2)	(1.1)	(1.2)	(1.2)	(5.0)	(5.4)	(5.2)
Log total clicks	−0.5	−0.4	−0.7**	0.3*	0.4**	0.5***	−1.7***	−1.6***	−1.4***
	(0.3)	(0.3)	(0.3)	(0.2)	(0.2)	(0.2)	(0.6)	(0.6)	(0.5)
Log median price	4.4***	4.6***	4.3***	−3.9***	−4.3***	−4.6***	3.2**	3.1**	3.3***
	(1.0)	(1.0)	(0.9)	(0.5)	(0.5)	(0.5)	(1.5)	(1.4)	(1.2)
Log median price, squared	−0.5***	−0.5***	−0.5***	0.3***	0.4***	0.4***	−0.3	−0.2	−0.3
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)	(0.2)
Share of price points	−15.3***	−14.0***	−13.5***	11.5***	10.8***	10.6***	−12.8***	−10.4***	−9.5***
	(1.4)	(1.1)	(1.1)	(1.0)	(1.0)	(0.9)	(1.9)	(1.8)	(1.5)
R^2	0.10	0.10	0.11	0.11	0.11	0.11	0.06	0.06	0.06
N	7,738	7,738	7,738	8,990	8,990	8,990	4,005	4,005	4,005

Notes: The table reproduces Table 7 for regular prices. "W" stands for within weights and "B" stands for between weights.

TABLE G.13. Predictors of Frequency of Sales

	One-Week Filter				Two-Week Filter			
Imputation:	N		Y		N		Y	
Weights:	N	Y	N	Y	N	Y	N	Y
Predictors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: United States								
Log number of sellers	0.74***	0.85***	0.86***	1.04***	1.17***	1.35***	1.20***	1.50***
	(0.07)	(0.07)	(0.07)	(0.06)	(0.08)	(0.08)	(0.11)	(0.08)
Herfindahl index, $(0,1]$	1.48***	1.93***	1.36***	1.89***	2.59***	3.31***	2.09***	3.01***
	(0.21)	(0.23)	(0.21)	(0.18)	(0.30)	(0.30)	(0.28)	(0.24)
Log total clicks	−0.30***	−0.17***	−0.39***	−0.37***	−0.44***	−0.28***	−0.50***	−0.48***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)
Log median price	−0.01	−0.04	0.03	−0.03	−0.09	−0.13	0.03	−0.10
	(0.08)	(0.07)	(0.06)	(0.08)	(0.10)	(0.10)	(0.10)	(0.14)
Log median price, sq.	−0.01	−0.01	−0.01	−0.01	−0.00	−0.00	−0.01	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Share of price points	−0.04	−0.09	0.24**	0.16	−0.08	−0.16	0.33**	0.23
	(0.12)	(0.12)	(0.10)	(0.10)	(0.16)	(0.17)	(0.14)	(0.14)
R^2	0.02	0.03	0.02	0.03	0.02	0.04	0.03	0.04
N	10,567	10,567	21,452	21,452	10,518	10,518	21,291	21,291
Panel B: United Kingdom								
Log number of sellers	0.15	0.33***	0.25**	0.44***	0.44***	0.71***	0.28**	0.59***
	(0.11)	(0.11)	(0.11)	(0.10)	(0.14)	(0.13)	(0.14)	(0.13)
Herfindahl index, $(0,1]$	0.59*	1.06***	0.99***	1.31***	1.72***	2.43***	1.40***	1.97***
	(0.33)	(0.34)	(0.29)	(0.29)	(0.46)	(0.51)	(0.36)	(0.39)
Log total clicks	0.05	0.04	0.04	−0.03	0.01	−0.00	0.10**	−0.01
	(0.06)	(0.05)	(0.04)	(0.03)	(0.07)	(0.05)	(0.05)	(0.04)
Log median price	0.24	0.25	−0.10	−0.05	0.12	0.17	−0.13	−0.05
	(0.17)	(0.18)	(0.10)	(0.11)	(0.14)	(0.15)	(0.11)	(0.13)
Log median price, sq.	−0.03**	−0.04*	0.00	−0.00	−0.02*	−0.03*	0.00	−0.00
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Share of price points	−0.54***	−0.35**	−0.52***	−0.42***	−0.81***	−0.58***	−0.81***	−0.69***
	(0.17)	(0.17)	(0.16)	(0.16)	(0.22)	(0.18)	(0.20)	(0.19)
R^2	0.01	0.02	0.01	0.01	0.02	0.03	0.01	0.02
N	4,464	4,464	10,754	10,754	4,440	4,440	10,651	10,651

Notes: The table presents the determinants of the frequency of sales.

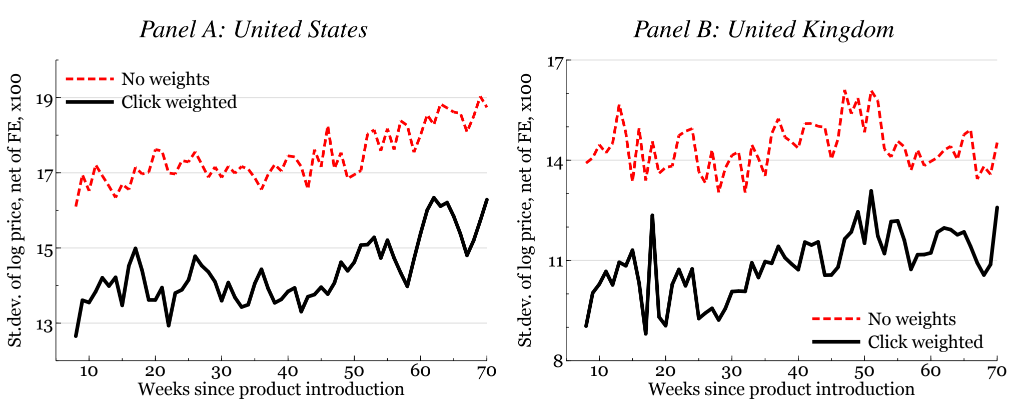


FIGURE G.7. Cross-Seller Dispersion of Posted Prices Net of Seller Effects over Product Life: The figure plots the raw and click-weighted mean over goods of the standard deviation of log price, net of seller fixed effects, for posted prices against the time passed since product introduction. Goods introduced 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. To construct this figure, we drop one outlier, a product in Media, which would cause an idiosyncratic spike in the U.S. click-weighted CV at week 44.

TABLE G.14. Average Dispersion of Posted Prices across Sellers (Alternative Measures)

	CV (1)	std(log p) (2)	VI (3)	IQR (4)	Range (5)	Gap (6)	N (7)
			Panel A: United States, actual prices				
No weights	21.5	23.6	24.4	34.6	40.7	27.6	
Within weights	21.4	22.9	23.3	32.0	40.7	27.6	29,753
Between 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 weights		20.7	17.5	28.9	36.8	25.1	29,753
Between 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 weights	19.4	20.7	19.2	28.8	34.3	26.7	17,715
Between 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 weights		16.0	12.6	22.2	26.9	20.4	17,715
Between 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, std(log p), 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. The VI is the log difference between the average and minimum price. (It 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). The IQR is computed as the log difference between the 75th and 25th percentile; the range as the log difference between the highest and lowest price; and the gap as the log difference between the two lowest prices. See Table 8 in the main text.

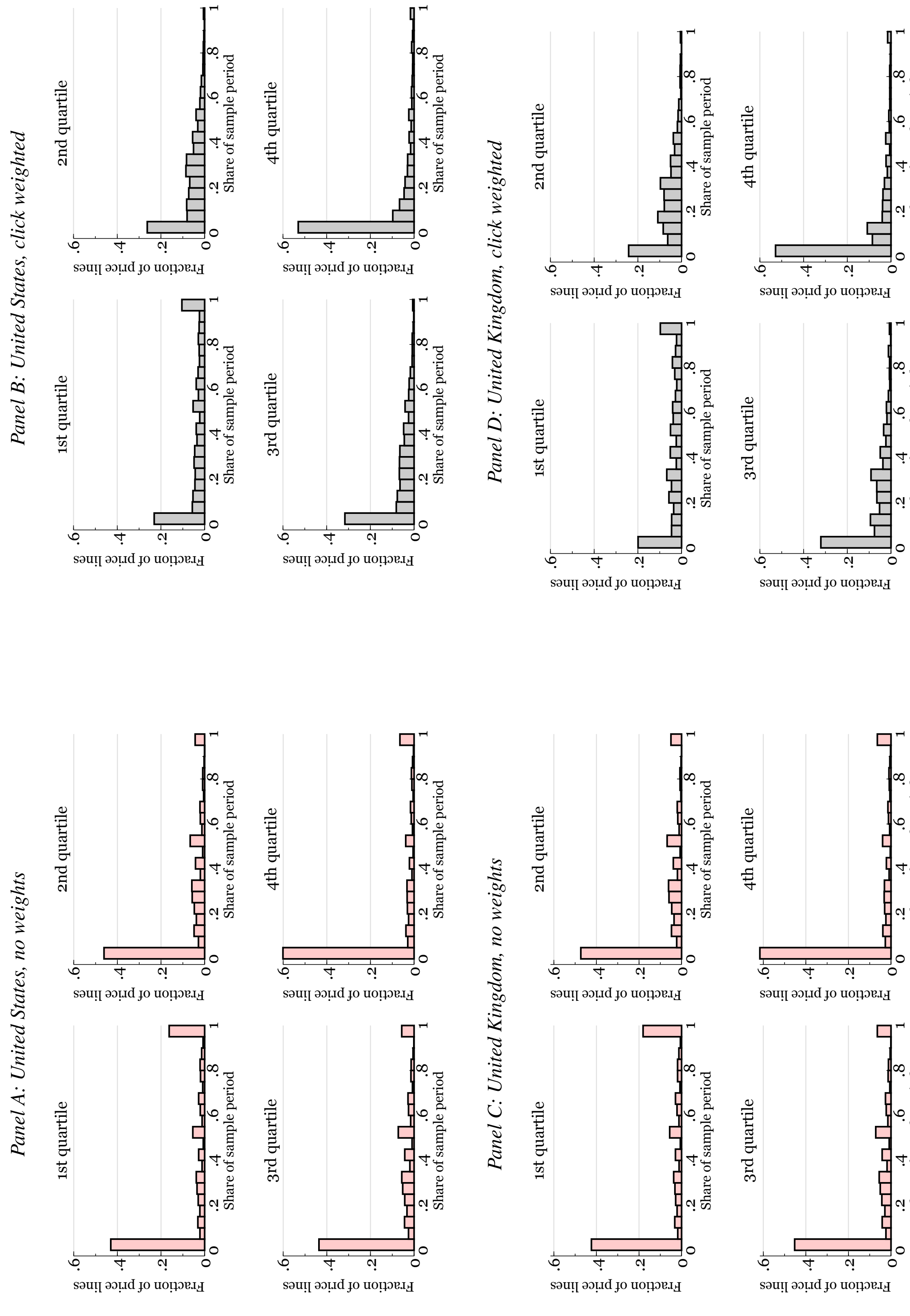


FIGURE G.8. Is Price Dispersion Spatial or Temporal? For each price line (a time-series of prices for a good–seller), we compute the share of sample period spent in each of the 4 quartiles of cross-seller price distribution. This exercise is similar to Figure 4 in Lach (2002). The figure then shows the distribution across price lines. Table 9 quantifies the height of the first (<5%) and the last (>95%) bars for each panel.

TABLE G.15. 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	0.23					−1.70	−0.34					−2.09**
	(2.10)					(1.20)	(1.81)					(0.89)
Log total clicks	0.47					2.55***	0.18					1.93***
	(1.09)					(0.69)	(0.94)					(0.53)
Log median price	−4.87***					−2.86***	−3.97***					−2.06***
	(0.78)					(0.60)	(0.62)					(0.51)
Share of price points	−1.54					−9.25***	−0.72					−6.55***
	(3.53)					(2.33)	(2.87)					(1.91)
Frequency of regular price changes		0.09***	0.20***	0.09***	0.19***	0.21***		0.07***	0.17***	0.07***	0.16***	0.17***
		(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***	0.57***		0.47***	0.58***	0.55***	0.60***	0.54***
		(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***	−0.18**			−0.19**		−0.25***	−0.15**
			(0.10)		(0.10)	(0.07)			(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	0.36	0.10	0.20	0.29	0.24	0.33	0.37
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	−6.65***					−5.69***	−3.37***					−2.64**
	(1.66)					(1.63)	(0.99)					(1.27)
Log total clicks	2.69***					3.26***	1.27***					1.86***
	(0.66)					(0.81)	(0.44)					(0.56)
Log median price	−4.04***					−2.28***	−2.58***					−1.57***
	(1.27)					(0.50)	(0.70)					(0.34)
Share of price points	−4.99***					−5.85**	−1.13					0.45
	(1.38)					(2.54)	(1.07)					(1.95)
Frequency of regular price changes		0.10***	0.24***	0.09**	0.24***	0.21***		0.06***	0.13***	0.04***	0.11***	0.12***
		(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***	0.52***		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)	(0.10)
Frequency of sales			0.10		−0.14	−0.14			0.22		−0.03	0.03
			(0.35)		(0.10)	(0.09)			(0.32)		(0.06)	(0.05)
Absolute size of sales			0.14**		0.11**	0.10**			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	0.31	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

Note: The table reproduces Table 10 without click weighting.

TABLE G.16. Predictors of Posted Price Dispersion, by measure

	CV (1)	std(log p) (2)	VI (3)	IQR (4)	Range (5)	Gap (6)
			Panel A: United States			
Log number of sellers	−2.88***	−3.49***	−2.89	−2.36**	−3.44	−7.88***
	(0.82)	(1.01)	(1.75)	(1.16)	(2.47)	(1.87)
Log total clicks	4.68***	4.98***	8.78***	5.37***	16.80***	5.46***
	(0.80)	(0.91)	(1.69)	(1.33)	(2.37)	(1.33)
Log median price	−3.79***	−3.85***	−5.59***	−4.08***	−9.77***	−3.65***
	(0.37)	(0.48)	(0.87)	(0.54)	(1.11)	(0.81)
Share of price points	−6.27***	−6.96***	−9.27***	−8.19***	−15.68***	−6.42**
	(1.44)	(1.75)	(3.23)	(2.01)	(4.17)	(2.91)
Frequency of reg. price changes	0.31***	0.37***	0.49***	0.50***	0.73***	0.50***
	(0.06)	(0.08)	(0.13)	(0.12)	(0.18)	(0.10)
Absolute size of reg. price changes	0.23***	0.29***	0.42***	0.46***	0.53***	0.33***
	(0.04)	(0.06)	(0.11)	(0.09)	(0.15)	(0.08)
Frequency of sales	−0.23***	−0.30***	−0.37***	−0.32***	−0.36**	−0.39***
	(0.06)	(0.07)	(0.11)	(0.10)	(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)
Sync. of posted price changes	−0.02	−0.01	0.00	−0.01	−0.00	−0.05
	(0.03)	(0.03)	(0.04)	(0.05)	(0.07)	(0.04)
R^2	0.32	0.29	0.24	0.25	0.32	0.22
N	3,349	3,349	3,349	3,349	3,349	3,349
			Panel B: United Kingdom			
Log number of sellers	−7.01***	−5.40***	−2.81	−3.28*	−10.76***	−10.81***
	(1.51)	(1.42)	(1.93)	(1.69)	(2.86)	(2.65)
Log total clicks	3.90***	2.92***	4.25***	1.06	14.00***	5.11***
	(0.81)	(0.77)	(1.41)	(1.10)	(2.22)	(1.80)
Log median price	−3.58***	−3.00***	−3.83***	−3.00***	−7.67***	−3.23***
	(0.44)	(0.40)	(0.62)	(0.53)	(0.96)	(0.58)
Share of price points	−1.79	−1.28	−3.15	−2.26	−1.79	−4.07
	(2.05)	(1.82)	(2.19)	(2.30)	(4.25)	(2.60)
Frequency of reg. price changes	0.14**	0.16**	0.16**	0.19***	0.32**	0.26***
	(0.07)	(0.06)	(0.07)	(0.07)	(0.14)	(0.10)
Absolute size of reg. price changes	0.09	0.10	0.09	0.12	0.15	0.17*
	(0.06)	(0.06)	(0.09)	(0.08)	(0.13)	(0.10)
Frequency of sales	−0.30***	−0.27***	−0.19	−0.29**	−0.24	−0.29**
	(0.07)	(0.08)	(0.14)	(0.12)	(0.18)	(0.13)
Absolute size of sales	0.25*	0.21**	0.27**	0.16**	0.45**	0.34**
	(0.13)	(0.10)	(0.13)	(0.07)	(0.20)	(0.16)
Sync. of posted price changes	−0.07***	−0.07***	−0.07***	−0.11***	−0.13***	−0.10***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)
R^2	0.29	0.24	0.15	0.17	0.27	0.19
N	840	840	840	840	840	840

Note: The table reproduces column (6) of Table 10 for different measures of price dispersion.

References

Calvo, Guillermo A. (1983). “Staggered Prices in a Utility-Maximizing Framework.” *Journal of Monetary Economics*, 12(3), 383–398.

Cavallo, Alberto F., Brent Neiman, and Roberto Rigobon (2014). “Currency Unions, Product Introductions, and the Real Exchange Rate.” *Quarterly Journal of Economics*, 129(2), 529–595.

CPC Strategy (2014). “The Comparison Shopping Report Q2 2014.” Available at http://www.cpcstrategy.com/comparison-shopping/the-comparison-shopping-report-q2-2014/.

CPC Strategy (2017). “2016 Google Shopping Performance by Category.” Available at http://www.cpcstrategy.com/blog/2017/01/2016-google-shopping-performance-across-categories/.

Kryvtsov, Oleksiy and Nicolas Vincent (2014). “On the Importance of Sales for Aggregate Price Flexibility.” Bank of Canada Working Paper No. 14-45.

Lach, Saul (2002). “Existence and Persistence of Price Dispersion: An Empirical Analysis.” *Review of Economics and Statistics*, 84(3), 433–444.

Nakamura, Emi and Jón Steinsson (2008). “Five Facts about Prices: A Reevaluation of Menu Cost Models.” *Quarterly Journal of Economics*, 123(4), 1415–1464.