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QUANTUM PRICES

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ABSTRACT

This paper studies pricing in the fashion retail industry. Online data was collected for approximately 350,000 distinct products from over 65 retailers in the U.S. and the U.K. We present evidence that a fair fraction of retailers implement an extreme form of price stickiness that we describe as quantum prices: a large number of different products are priced using just a small number of sparse prices, with price changes occurring rarely and in large increments. Normalized price clustering measures are used to show that retailers use quantum prices within- and across- categories, and this clustering is not explained by popular prices, ranges of prices, assortment size, or digit endings. This pricing strategy is consistent with a behavioral model where fewer prices makes price advertising more effective. An implication of this model is that advertising is increasingly effective when the same prices are used across product lines, i.e. for new products. Finally, quantum prices affect product introductions and price adjustment strategies at the firm level, while it creates larger deviations of the law of one price and hinders the computation of inflation at the macro level.

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1 Introduction

The Internet has had a fundamental impact on the way retailers engage with their consumers. First, consumers often observe prices across locations, making geographical price discrimination harder. Old brick-and-mortar retailers were small local monopolies that had the ability to decide the prices and products' offerings, which implied that uniform prices were rare. Second, and equally important, the internet allowed retailers to organize the data differently. Since the Egyptian land register, created around 3000 BC — the first known land ownership record — the data has been organized around two paradigms: geography and socio-economic conditions. This structure is informative because a family's location or economic conditions are good predictors of their customs and purchases. In other words, it is an indicator of preferences. With the introduction of the internet, however, it is now possible to directly observe consumers' behaviors. Every purchase, trip taken, website visited, music listened, movies watched, searches googled, are breadcrumbs left behind that describe aspects of the personality and preferences. Therefore, clustering the data along the actual behavior constitutes a better estimate of preferences.¹

These two features have changed how retailers engage with customers. We study the fashion industry and observe three distinct pricing behaviors, which we denote as follows: Traditional, Platform, and Quantum Pricing strategies. Traditional pricing stores —such as Louis Vuitton, Dolce Gabana, Ralph Lauren, Reiss— focus on obfuscating prices from the consumer. These retailers will often make prices the least salient attribute. In many cases, products have no tags attached, or prices are carefully hidden from the shopping experience. Platform pricing retailers —such as Amazon, Walmart, Wayfair, Google— emphasize their business in growing the network and thereby expanding its market share. They tend to have two sources of revenues, namely an attractive mark-up to the product and the revenue from utilizing the consumer information. Their prices are often decided by advanced algorithms and their distribution is dense, almost continuous on a price line.² The nature of the competition implies that few retailers can follow this approach because only a few can capture the whole network. These two strategies have received considerable attention in the literature.

Our paper is focused on characterizing and rationalizing a new form of pricing: the *Quantum Pricing* strategy. The quantum pricing is followed by a vast number of firms, including some of the leading and most successful retailers —such as Apple, Zara, H&M, Ikea,

¹For example, Netflix might observe that two individuals have similar tastes for movies; although ages and locations can be different, one is married, and the other one is not even thinking about the idea (Bennett, Lanning, et al. (2007)).

²This behavior stands in sharp contrast with the traditional marketing literature. See Monroe (1973); Dickson and Sawyer (1990); Lichtenstein, Ridgway, and Netemeyer (1993); Schindler (1991); Schindler and Kirby (1997); Stiving (2000); Anderson and Simester (2003).

Bonobos, and Uniqlo. In order to maximize information recall and advertising effectiveness, retailers tend to cluster prices massively. Even within narrowly defined categories (e.g., jeans) products and prices are clustered along price points that are far from each other and that are sticky over time. In fact, product introductions tend to occur at those price points, and even in some occasions discounts are set to match those existing lower prices. We therefore define *quantum prices* as the property of a firm’s pricing strategy of using sparse, clustered, and sticky values, to price large and diverse product lines.³

We study pricing strategies in the fashion industry in the U.S. and the U.K.⁴ We collect online data from 54 retailers in the U.S. and 40 retailers in the U.K, with a total of close to 230,000 and 190,000 distinct products, respectively. This represents a significant share of the apparel, footwear, and accessories industries in both countries, and to the authors’ knowledge is the largest data collection effort in this sector.⁵ In order to study pricing, we need to be able to identify which products are relatively similar to each other. To address this problem, we design an unsupervised machine learning classifier that, reading HTML code and product-level descriptions, allows us to classify each item into twelve categories that are consistent across retailers and over time. The categories are: accessories, bags, bottoms, dresses, jewelry, outerwear, shoes, sports, suits, tees, tops, and underwear. Broadly speaking, we could interpret a retailer-category (e.g., Zara Underwear) as the relevant choice space of a consumer who is a store buying a specific product.

This paper makes three contributions, which we summarize as follows. First, we document the existence of quantum prices or price clustering in the fashion industry. The stylized fact is documented within retailer-categories as well as across retailer-category pairs.⁶ Note that, because some categories are already relatively broad (e.g., sweaters and shirts are Tops), our findings are lower bounds to what would be found using more narrowly defined categories. Descriptive evidence shows that the median store has 2,496 distinct items in the U.S. and 2,678 items in the U.K., and the median store has 83 distinct prices in the U.S. and 60 prices in the U.K. The average probability that two items in a retailer-category have the same price is close to 10%. And the average probability that two items from different categories

³The term is reminiscent of quantum mechanics, where the electrons jump from one level of energy to another in discrete, non-divisible quanta. Prices in fashion retail can be very sticky, and move in discrete and large quantities.

⁴Fashion retail represents a significant portion of the economy. The combined market of apparel, footwear, bags, and accessories is about \$380 billion sales in the U.S., and £55 billion sales in the U.K. The U.S. is the second largest market, next to China, and accounts for about 20% of world sales in the sector. The internet channel accounts for about 17% of sales, but is growing rapidly (2012-2017 CAGR of 20%). Estimates obtained from Euromonitor industry reports dated 2017 and 2018.

⁵Related work using smaller datasets in online apparel are Cavallo, Neiman, and Rigobon (2014), Gorodnichenko, Sheremirov, and Talavera (2014).

⁶In our analyses we use a cross-section of items that excludes clustering from duplicates in terms of time, color varieties, and sizes.

within a retailer have the same price is about 5%. These estimates already provide motivation for the practice of using just a handful of prices for large and diverse assortments.

A number of statistical techniques are used to test the robustness of the observed price clustering. For example, clustering could be explained by a corporate policy to use \$9 dollar endings. Thus we use a normalized price clustering index that removes the effects from popular prices, price endings, ranges of prices, or number of products. The index is a modification of the geographical concentration index introduced in Ellison and Glaeser (1997). This measure takes the price distribution of each retailer-category, and controls for shares of products concentrated on, for example, certain digit endings or popular prices in the overall category. We find that about 25% of the retailer-categories have little to no clustering, and this fraction increases to 45% when we control for price digits. Therefore, rightmost digits account for a portion of the price clustering in the data; however, about half of the remaining retailer-categories still exhibit statistically large clustering, including 22% of them which are found to be remarkably concentrated. Price clustering is also observed using an unsupervised machine learning approach. The method estimates the price clusters in the data through a trade-off in the within-cluster variation and between-cluster variation. We find retailers that concentrate prices in a few discrete clusters, and that price clusters have economically meaningful differences between each other. The median price differential between centroids (mid-points) is 30% and 21% in the U.S. and the U.K., respectively.

Moreover, quantum prices are documented in the time-series. Using data collected across collections, we show that the quantum prices are sticky and, in fact, retailers will consistently introduce new products at those quanta. This suggests a new of menu cost stickiness, i.e. a cost to opening a new price bucket in the distribution. The stickiness is different from canonical menu cost models (e.g., Golosov and Lucas Jr (2007)), because apparel products tend to have a short duration, often do not experience any price increase, and the main pricing decision takes place at the time of a product introduction. This stickiness stands in contrast to models that assume firms optimize prices from a relatively unrestricted domain of positive numbers.

These pricing observations are not oddities associated with isolated firms. Quantum prices are observed in a wide range of retailers, and the data is representative of the apparel industry in terms of revenue market shares, as well as in terms of the large firm heterogeneity. The data includes department stores, luxury retailers, medium- to low- end pricing retailers, and fast fashion. For example, the data includes Louis Vuitton, Forever 21, GAP, Walmart, Victoria's Secret, and Zara.⁷ Moreover, all of the retailers sell online and offline; and the

⁷The size of some of these retailers is remarkable. For instance, Louis Vuitton had £16 billion sales in fashion and leather goods; Uniqlo had \$17 billion sales and operates over 3,000 stores in 18 countries; Inditex had €25 billion sales and operates over 7,000 stores in 58 countries; Nike had \$34 billion sales. Estimates obtained from

regular prices are the same in both channels. More importantly, some of the firms are among the largest or most popular retailers worldwide, and pricing is hardly an improvised managerial outcome.

The second contribution is to present a simple framework that rationalizes quantum prices. We discuss models *à la* convenient prices, demand uncertainty, and salience, and show that their predictions cannot fully explain the stylized facts. Pricing in fast-turnover products like apparel, and the relationship between advertising and the distribution of unique prices, has received little attention. We propose a behavioral model where using fewer prices makes price advertising more effective. And the advertising becomes increasingly effective when the same prices are used not only within a category, but also across categories and even across different seasons. In other words, there is a menu cost to introducing a new price (to the price distribution) for product introductions. This menu cost, together with consumers' costly price awareness, predicts few sticky prices. The model does not suggest that retailers should always follow these strategies. For example, everyday low-price retailers, or high-end retailers appealing to a wide customer base, are not expected to benefit from this strategy. But it can be optimal for retailers that need to inform prices of fast turnover assortments to price-sensitive consumers.

Finally, we discuss macroeconomic implications of quantum prices.⁸ We discuss three such implications. The price stickiness in quantum pricing will be a source of lumpy price adjustments. We find suggestive evidence that, although quantum retailers use existing prices for new products, they will change the product mix across price buckets. For example, a retailer will put a larger (lower) fraction of new products into the more expensive (cheaper) prices. Thus, the observed prices are the same but the proportion of products in each bucket changes. Such form of price adjustment will affect the measurement of inflation. We show that when retailers practice quantum pricing, a larger number of products sampled are needed to better estimate the aggregate inflation rate. Quantum pricing produces more noise and wider ranges of inflation estimates for a given subsample of products, compared to when the prices are more uniformly distributed. Finally, we report large deviations from the law of one price using matched products collected the same day between the U.S. online store and the U.K. online store. A restricted price distribution relates to larger deviations in relative prices.

The rest of the paper is structured as follows. Section 1.1 reviews the literature. Sections 2 and 3 describe the online data and the classification methodology, respectively.

FY2017 annual reports.

⁸There are also relevant micro implications which are briefly mentioned. If prices belong to a discrete and sparse space, products can be designed to hit specific points. Therefore, quantum prices affect the attributes of product creation, the advertising strategies, and how to convey information about quality differences. See Monroe (1979); Milgrom and Roberts (1986); Schindler (1991); Stiving (2000).

Sections 4 and 5 document price clustering. Section 6 discusses the advertising framework. Section 7 discusses macro implications. And Section 8 concludes.

1.1 Related literature

This paper relates to several strands of literature. Methodologically, the motivation of using online data to study pricing strategies, price stickiness, and price adjustment is similar to that in Cavallo, Neiman, and Rigobon (2014), Gorodnichenko, Sheremirov, and Talavera (2014), and Cavallo (2018). Our work contributes to these papers in that we document pricing in the fashion retail industry, as well as novel forms of price stickiness using product-level data.

The machine learning classifier to categorize products relates to previous efforts to categorize unstructured online data. For example, Cavallo (2012), Cavallo and Rigobon (2016), Aparicio and Bertolotto (2016), and Aparicio and Cavallo (2017) categorize online products in order to construct price indices using CPI weights. Our work contributes to this literature in that we have a richer and more representative amount of data in apparel, and are able to construct specific sub-categories within apparel that are consistent across retailers, time, and countries.

Evidence of price points in the distribution of prices relates to a body of literature on uniform prices in retail. There is work on uniform prices in retail chains (DellaVigna and Gentzkow (2017)), online dynamic pricing (Weisstein, Monroe, and Kukar-Kinney (2013)), managerial costs or consumer fairness concerns (Leslie (2004); Orbach and Einav (2007)), consumer fairness concerns on prices for different sizes (Anderson and Simester (2008)), homogenous consumer preferences for flavors (Draganska and Jain (2006)), adverse quality signaling for lower-priced goods (Anderson and Simester (2001)). Our research provides evidence that uniform pricing extends beyond varieties of the same good, and that such price points have micro- and macro- implications.

Our main framework of price advertising relates to an extensive literature in marketing (Lal and Matutes (1994); Wernerfelt (1994); Simester (1995); Shin (2005); Rhodes (2014)). However, these papers do not explore the fashion retail industry, which is characterized by large assortments and fast-turnover products, and where the need (and the strategies) to inform consumers are different from traditional retail. We contribute to this literature with a framework that considers the effectiveness of the distribution of unique prices, and why for some firms there is a menu cost to introducing new prices.

We consider complementary explanations to quantum prices. One relates to demand uncertainty (Ilut, Valchev, and Vincent (2016)); firms have used certain prices before, and are reluctant to experiment with new prices. We also consider a case where consumers face bounded rationality. For example, Hauser and Wernerfelt (1990); Iyengar and Lepper

(2000); Alba, Hutchinson, and Jr. (1991); Roberts and Lattin (1997); Eliaz and Spiegler (2011); Piccione and Spiegler (2012) study situations where the consumers' decision is affected by price framing, price recall, price formats, or the size of the consideration sets.

That firms limit the number of prices within a category due to overload or bounded comparability concerns is not unreasonable given the surprising number of options in apparel. For example, Forever 21 sells about 2,000 different styles of dresses on a given day. Even in a narrower sub-category, like casual dresses, there are 450 options. Consumers cannot possibly compare all product attributes; in fact, a consumer cannot even take more than a few dresses to the fitting room. Therefore, we expect consumers to rely on decision heuristics to screen out products. One alternative is that firms use few prices in order to shift attention away from prices (Prelec and Loewenstein (1998)), which makes consumers less price sensitive. This model predicts a portion of the observed price clustering; but may not capture why prices are different across stores, but are the same across diverse items and even across collections.

Our evidence of price stickiness relates to a large literature on price stickiness in retail, and managerial costs of updating prices. See, for example, Levy, Bergen, Dutta, and Venable (1997); Blinder, Canetti, Lebow, and Rudd (1998); Zbaracki, Ritson, Levy, Dutta, and Bergen (2004); Nakamura and Steinsson (2008); Klenow and Malin (2010); Bhattarai and Schoenle (2014); Gorodnichenko, Sheremirov, and Talavera (2014); Ellison, Snyder, and Zhang (2018). We show that the existence of quantum prices can be thought of as an extreme form of price stickiness, and thus has implications for strategies of price adjustments, inflation measurement, and frictions between countries.

Price points in the distribution can be related to a literature that associates price endings with consumer demand, price recall, or product perceptions. See Monroe (1973); Dickson and Sawyer (1990); Lichtenstein, Ridgway, and Netemeyer (1993); Schindler and Kirby (1997); Thomas and Morwitz (2005). Our work also relates to a growing strand of literature on price endings or round prices in supermarket products and price rigidity (Kashyap (1995); Levy, Bergen, Dutta, and Venable (1997); Knotek (2008, 2011); Levy, Lee, Chen, Kauffman, and Bergen (2011); Ater and Gerlitz (2017); Snir, Levy, and Chen (2017)). Although this paper studies a different industry, our findings support the view that final digits account for a large share of the observed price clustering. But after controlling for price endings a significant price clustering is observed.

2 Online data

We collect online data from 53 fashion retailers in the U.S. and 40 retailers in the U.K. These retailers are representative of the apparel market overall, i.e. we cover the largest firms in terms of market share and a wide heterogeneity in terms of style, item composition, branding, and consumers. See Appendix A.1 for the complete list of retailers.

Online data is collected as follows. A script is designed to search the HyperText Markup Language (HTML) public code of a retailer’s website. The program automatically stores the data of each item, including product description, ID, price, sale price, promotion description, new arrivals indicator, and sales indicator. The ID is an item-specific identifier assigned by the retailer. Products that come in different colors will often have the same or very similar ID, which we use to keep only one of them. This allows to rule out price clustering that would arise from near perfect substitutes. Additional details about collecting online retail data can be found in Cavallo and Rigobon (2016); Aparicio and Cavallo (2017).

Due to the large scope of retailers and computational limitations, we collect data once per month during 6 months for most of the retailers, during 1 year for a subset of the retailers, and during 2 years for a few of the latter retailers. The panel is not balanced across retailers since the web-scraping script can occasionally fail. For the most parts of the analyses, we concentrate on a cross-section of items across retailers from a 6 month period. This removes any price clustering that could be driven by counting the same products multiple times.

The apparel sector is characterized by some distinctive features. Products have a short duration, which ranges from a few weeks to several months (e.g., Caro and Gallien (2010); Cavallo, Neiman, and Rigobon (2014)). This likely produces an asymmetric price stickiness during the life of a good. Products are introduced at a certain price $p^{t=1}$ and often do not experience any price increase. However, products do experience either temporal or permanent discounts towards the end of the season. If discounts are permanent, items have a sale price until it is discontinued, $p^{t=1} > p_s^{t>1}$. And if discounts are temporal, the price will return to the regular price, $p^{t=1} = p^{t=3} > p_s^{t=2}$. In this paper we focus on the regular price, or introduction price, which we consider the most important pricing decision. Sales at the full price account for the largest share of revenue (Ghemawat, Nueno, and Dailey (2003)). Moreover, in the regulatory filings, firms often attribute lower financial returns to excessive markdowns.

Table 1: Summary Statistics

		US	UK
(i)	Time period	March 2017 to May 2018	March 2017 to May 2018
(ii)	Average months per retailer ^a	4.6	4.5
(ii)	Observations ^b	241,928	199,619
(iii)	Retailers	54	40
(iv)	Distinct goods	230,717	188,558
(v)	Average distinct goods ^c	4,278	4,718
(vi)	Distinct goods (10%pct.)	1,279	1,122
(vii)	Distinct goods (90%pct.)	7,463	13,800
(viii)	Distinct prices ^d	1,126	827
(ix)	Distance between prices (%) ^e	13	13
(x)	Average Items / Prices ^f	49	87
(xi)	Items / Prices (10%pct.)	11	9
(xii)	Items / Prices (90%pct.)	92	192

Notes: ^aEqual weight average across retailers. ^bExcludes duplicates in terms of product, category, country, retailer. For example, the same product collected in two different months will appear only once. ^cEqual weight average across retailers. ^dEqual weight across retailers. Average distinct prices rounded to the nearest integer. ^eAverage distance across consecutive prices. Computed as equal weight average across retailers. ^fThe U.K. data includes a larger fraction of retailers that sell large assortments, and therefore the ratio is larger than in the U.S.

Table 1 provides summary statistics of the data coverage. We have a cross-section of over 230,000 and 188,000 distinct products in the U.S. and the U.K., respectively. There are on average over 4,000 distinct products in each retailer, but there is a large heterogeneity. The 10th and 90th percentile store has 1,279 and 7,463 distinct products in the U.S., respectively. This illustrates the diversity in the retailers covered, since some fashion retailers sell very few items (e.g., Hermes) while others sell extraordinary large assortments (e.g., Zara). There is also heterogeneity in the relationship between prices and products. For example, the 10th and 90th percentile store in the U.K. sells 9 and 192 products per price, respectively.

3 Classification

An initial requirement to identify what classes of products have certain prices. However, scraped online data is not structured this way. Data is collected without labels, product

names are often inconsistent across retailers, and therefore we need classification rules that can group similar items together. These classifications are necessary to study cross-section and time-series pricing. For example, clustering that takes place at a popular price $\$x$ should receive little weight; but *what* is a popular price must be learned from the overall category price distribution across retailers.

Table 2: Classification Summary

	US	UK
(i) Average categories per retailer	11.5	11.5
(ii) Observations to be classified ^a	505,522	450,468
(iii) Classification output (%)		
Accessories	7.3	6.7
Bags	6.1	5.7
Bottoms	15.4	13.6
Dresses	7.5	7.3
Jewelry	4.1	3.6
Outerwear	7.1	8.1
Shoes	10.8	11.7
Sports	3.9	3.3
Suits	2.3	2.5
Tees	13.7	11.7
Tops	16.9	18.9
Underwear	2.9	5.7
Unclassified ^b	2.2	1.6
(iv) Retailer-Category pairs ^c	504	372

Notes: ^aTotal number of observations excluding those that are duplicates in terms of product ID, month, category, retailer, country. ^bObservations that did not get classified are removed from the analysis. Unclassified observations are due to unrecognizable text (e.g. product descriptions or HTML text that do not contain useful information), or due to items that fall outside apparel (e.g., beauty products). ^cA retailer-category pair is the finest level of analysis.

We construct a semi-supervised machine learning classifier, based on decision trees, that groups items into twelve categories: accessories, bags, bottoms, dresses, jewelry, outerwear, shoes, sports, suits, tees, tops, and underwear. The approach is semi-supervised because there is no unequivocal procedure to validate the classification. We rely on the retailers' webpage categories and our interpretation of the product description to create these classification rules. Moreover, due to the large quantity of data, we cannot manually assign

labels to every single product. Instead we design rules to check random portions of the data or products that exhibit dissimilar characteristics to those in their group (e.g., items that are too expensive in the category). See Appendix A.2 for additional details.

The output is a classifier which can consistently categorize products across retailers and across collections. Our approach relates to previous efforts in the literature using online data for inflation measurement (Cavallo (2012); Cavallo and Rigobon (2016)), forecasting CPI inflation (Aparicio and Bertolotto (2016)), and retail pricing (Aparicio and Cavallo (2017)), although we focus on a significantly larger share of the clothing industry, and therefore construct relatively narrow sub-categories.

Table 2 provides summary statistics on the classification output. Line (iii) shows that there is a fair fraction of products in each category. However, there is still space to sub-divide overweighted categories like Bottoms or Tops. Line (iv) shows that there are in total 504 and 372 retailer-category pairs in the U.S. and the U.K., respectively.

4 Evidence of price clustering

This Section presents formal evidence of quantum prices or price clustering in fashion retail. We show results using a series of clustering measures computed at the retailer or retailer-category level.

4.1 Descriptive evidence

Table 1 showed that the data covers over 230,000 different items and 1,110 different round prices in the U.S. This implies that there are about 200 items per price in the overall market. This suggests that many items in the same retailer-category will have the same price.

Figure 1 shows the probability that two distinct items in the same retailer-category have the same price. The median probability is close to 10%. Some of these magnitudes are surprisingly large when we consider that some categories are relatively broad, and thus a lower bound to what we could find in more narrowly defined categories (e.g., Jeans as opposed to Bottoms). Item misclassification should, in any case, push the probabilities downwards. Therefore, for this probability to be this large it needs to be the case that even different items like sweaters and shirts (or jeans and chinos), which belong to the same category, have the same price.

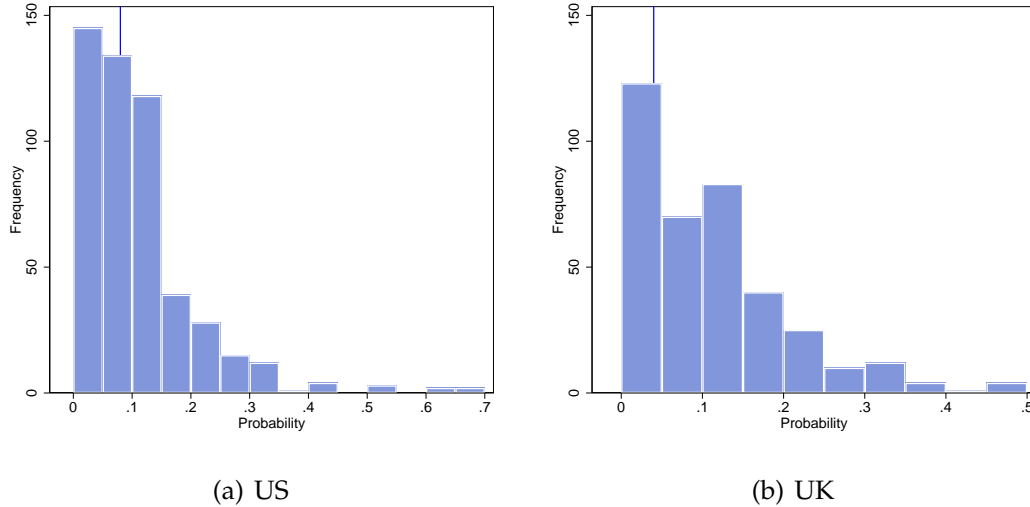


Figure 1: Probability that two items have the same price

Notes: Histogram of the probability that two different items in the same retailer-category have the same price. Probability calculated at the retailer-category level.

Appendix A.3 shows results of this probability computed at the retailer level (across categories). The average probability across retailers is 5.2% in the U.S. and 5.3% in the U.K. Although magnitudes are much smaller, there is a fair amount of retailers that use the same prices across categories. The heterogeneity in pricing across retailers is reinforced in Appendix A.4. We find substantial variation of the probabilities (that two items in the retailer-category have the same price) across the number of distinct products. For example, there are many retailer-categories where the probability is 20%, and the number of distinct product varies from less than 100 to over 1,000.

4.2 Normalized measure

Not all prices are equally good in practice. For example, a body of literature argues that consumers practice left-to-right processing for multiple-digit prices, and due to processing costs and lower returns to rightmost digits, consumers either drop-off rightmost digits or overweight the left ones (e.g., Schindler and Kirby (1997); Thomas and Morwitz (2005)). For these reasons, \$19.99 might be perceived as having a lower price differential with respect to \$19.00 than with respect to \$20.99.⁹ Therefore, we would like to measure price clustering after controlling for prices that are popular in the category or the retailer, or that may arise mechanically from the number of products or from a range of good prices.

⁹For evidence of price endings or round prices, see Kashyap (1995); Knotek (2011); Levy, Lee, Chen, Kauffman, and Bergen (2011).

We construct a normalized clustering index that builds on [Ellison and Glaeser \(1997\)](#).^{10,11} The core of this index lies in comparing the observed price frequencies in a given retailer-category against the observed price frequency in the overall category. Intuitively, we want to penalize for clustering that occurs at certain prices (e.g., Zara Underwear) which are popular in the category (Underwear). Formally, the index in the retailer-category i is defined as follow:

$$index_i = \frac{\sum_{b=\underline{b}}^{\bar{b}} (s_{i,b} - x_{c,b})^2 - (1 - \sum_{b=\underline{b}}^{\bar{b}} x_{c,b}^2)1/N_i}{(1 - \sum_{b=\underline{b}}^{\bar{b}} x_{c,b}^2)(1 - 1/N_i)} \quad (1)$$

We bin the distribution of prices into buckets of 1 dollar (or 1 pound), i.e. prices are rounded to the nearest integer. This allows to more conservatively control for price endings, because prices like \$19.90 and \$19.50 will be treated as the same, and therefore penalized according to the greater overall frequency of \$20. In eq. (1), $s_{i,b}$ is the share of items in retailer-category i at bucket b , and $x_{c,b}$ is the share of items in category c at bucket b . The sum goes from the minimum price in category c , \underline{b}_c , to the maximum price in category c , \bar{b}_c . Finally, N_i is number of distinct products in retailer-category i , and the term $\frac{1}{N_i}$ controls for the number of products.

The index can be interpreted as the excess probability that two items in the same group will have the same price, given the size of the retailer-category N_i , and the empirical distribution of prices in the category. Because the index is normalized to be between 0 and 1, values close to 0 should be interpreted as retailer-categories not exhibiting *excess* price clustering. Values above 0.025 indicate statistically large price clustering ([Ellison and Glaeser \(1997\)](#)).

The results are shown in the histogram in Figure 2. We find a fraction of retailer-categories with no more than the expected clustering, as well as a fair share of cases with medium to large clustering. The mean and median in the U.S. are 0.098 and 0.075, respectively, both of which are considered large estimates of price concentration.

The normalized measure is substantially larger than those that would be expected if prices were drawn from a Normal or uniform distribution with the same empirical parameters. Prices out of the uniform distribution are restricted to 10 dollar multiples, which increases its clustering and thus provides a stricter benchmark. See Appendix A.5 for additional evidence. The mean values are 0.010, 0.052, and 0.098 for the Normal, uniform, and

¹⁰[Ellison and Glaeser \(1997\)](#) measure geographic concentration across manufacturing firms in the U.S., and would like to control for regions that are naturally better for certain industries (in our case, an industry is a retailer-category).

¹¹We find that the clustering results using eq. (1) and its modifications are quantitatively similar when computed using subsets of retailers or reduced datasets within retailers.

data-based indices.

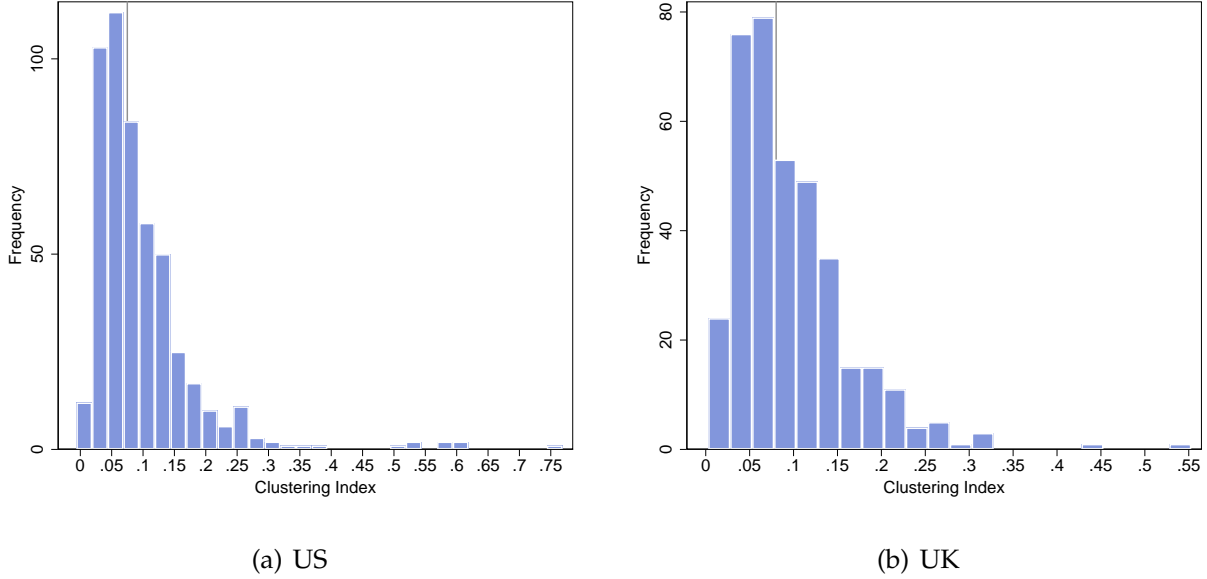


Figure 2: Normalized price clustering

Note that eq. (1) compares each retailer-category price bin share against the category price bin share (the first term in the numerator). We could, however, replace the category price bin share, i.e. $x_{c,b}$, with a series of alternative price market shares, and evaluate changes in the clustering index. We discuss three alternatives.

First, we could use the price shares that would be observed under a Normal distribution. We define $x_{c,b} = \Phi(b) - \Phi(b-1)$, where $\Phi(\cdot)$ refers to the CDF from a Normal distribution with μ as the average price in the category and σ as the standard deviation of the prices in the category (equally weighed retailers). Clustering estimates are comparable to Figure 2, and therefore shown in Appendix A.6 in the Appendix. The mean and median in the U.S. are 0.106 and 0.083, respectively.

Second, we could more severely control for prices and price levels (ranges of good prices, or cheap and expensive products relative to others in the category) as follows. We run retailer-category Poisson regressions of price counts on price, price squared, and category shares.

$$S_{i,b} = \alpha_i + \beta_{i,1}bin_{i,b} + \beta_{i,2}bin_{i,b}^2 + X_{c,b} + e_i \quad (2)$$

$S_{i,b}$ denotes the count of items in retailer-category i priced at bin b (instead of $s_{i,b}$, which are shares), $bin_{i,b}$ is the price bin b , $bin_{i,b}^2$ is the price bin squared, and $X_{c,b}$ are count of items in category c priced at bin b . Once we estimate regression in eq. (2), we obtain predicted counts, $\hat{S}_{i,b}$, and convert these to predicted shares, $\hat{s}_{i,b}$, using the sum of predicted counts, \hat{N}_i .

These predicted shares are used in eq. (1) instead of the price shares $x_{c,b}$, and the normalized index is recalculated. Counts of 0 items are ignored in the regressions, and forced to predict a share equal to 0.

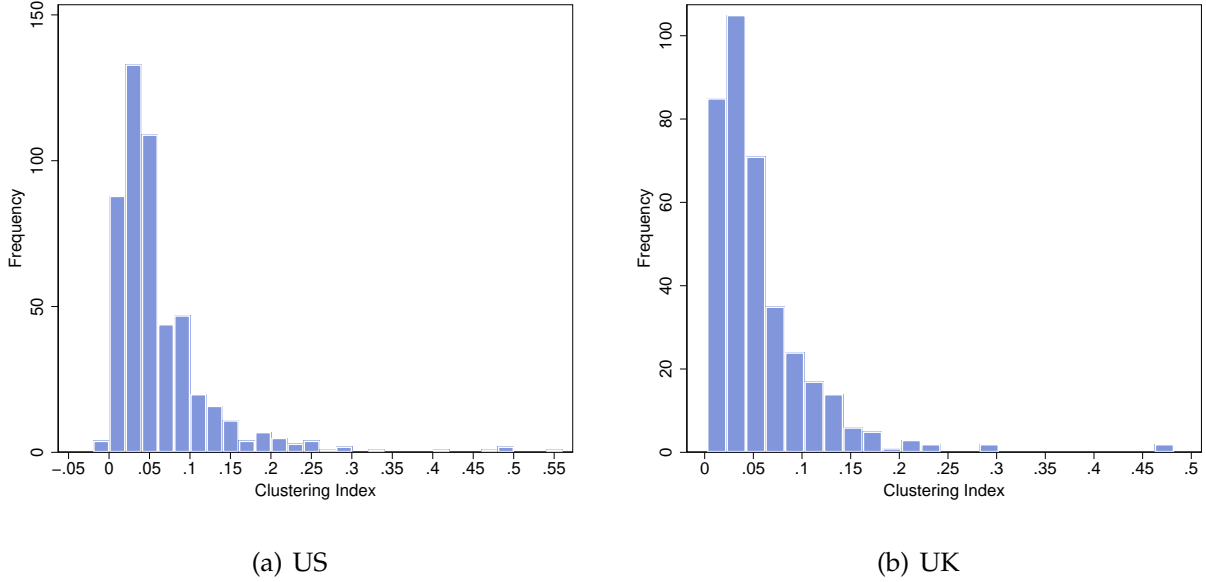


Figure 3: Strict normalized price clustering

Notes: Histogram of the strict normalized price clustering index that controls for prices, ranges of prices, and category counts. Index computed at the retailer-category level. Details in the main text.

The results in Figure 3 show that some fraction of firms, after controlling for these practices, have little to no clustering. But there is still a large number of retailer-categories that exhibit substantial price clustering. We view this as the preferred specification that captures the true price clustering in the data.

The more features we include in a regression like eq. (2), the more stringent the clustering measure, and therefore the smaller the excess price clustering that will be estimated in the data. For instance, we can investigate the portion of the true price clustering that is due to a firm having firm-category specific price endings policies. The third variant does exactly this. We included price ending (integer) dummy variables in the regressions, i.e. the terms $\sum_{j=0}^8 \beta_{i,E_j} \text{End}_{i,j}$. Estimates are shown in Appendix A.7. We now find a larger number of retailer-categories with close to zero price clustering, suggesting that rightmost digits is a relevant pricing concentration practice. However, half of the retailer-categories still exhibit price clustering that cannot be attributed to price endings.

Table 3: Summary statistics on the normalized clustering index

		Index (1)	Index (2)	Index (3)	Index (4)
US					
(i)	Mean	0.075	0.083	0.044	0.025
(ii)	Median	0.098	0.106	0.063	0.038
(iii)	Percent of cases where:				
	< 0	0.2	0	0.8	3
	[0, 0.025)	5.4	7.9	23.6	46.8
	[0.025, 0.05)	23.6	19.4	34.5	27.8
	> 0.05	70.8	72.6	41.1	22.4
UK					
(i)	Mean	0.08	0.09	0.041	0.019
(ii)	Median	0.097	0.107	0.057	0.029
(iii)	Percent of cases where:				
	< 0	0	0	0	5.6
	[0, 0.025)	5.9	8.1	26.9	54.3
	[0.025, 0.05)	19.4	18.5	33.3	24.7
	> 0.05	74.7	73.4	39.8	15.3

Notes: Index (1) is the baseline normalized index in eq. (1). Index (2) is the normalized index using price bin shares from a Normal distribution. Index (3) is the preferred normalized index that controls for prices, range of prices, popular prices. Index (4) is similar to (3) and adds price ending dummies. Indices are defined in the main text.

Table 3 provides summary statistics of the normalized price clustering indices. Note that the indices decrease from (1) to (3) and (4) as we sequentially control for additional pricing features. In some cases the clustering index can be slightly less than 0 if a retailer-category exhibits less price clustering than what is expected. Extreme cases like these could be retailer-categories where there is close to one price per product. Column (3) shows that the mean and median of the preferred measure of price clustering is 0.044 and 0.063 in the U.S., and 0.041 and 0.057 in the U.K., respectively. And there is a considerable fraction of cases with clustering greater than 0.05, i.e. 41% in the U.S. and 40% in the U.K. Even in the stringent case that controls for price endings dummies, the mean estimates are 0.038 in the U.S. and 0.029 in the U.K.

Table 4: Examples of price clustering

	Retailer	$\frac{\text{Items}^a}{\text{Prices}}$	Prob. ^b	Index(1) ^c	Index (2) ^d
US					
(i)	Low clustering				
	Louis Vuitton	2.8	0.02	0.04	0.02
	Aritzia	8.5	0.05	0.05	0.03
(ii)	Medium clustering				
	Gap	20.5	0.16	0.11	0.05
	Victoria Secret	7.6	0.08	0.08	0.05
(iii)	High clustering				
	Bonobos	18.5	0.21	0.22	0.16
	Uniqlo	30.7	0.34	0.31	0.21
UK					
(iv)	Low clustering				
	Gucci	4.5	0.02	0.06	0.03
	Ralph Lauren	5.1	0.04	0.06	0.03
(v)	Medium clustering				
	Burberry	7.3	0.08	0.09	0.05
	HM	75.1	0.15	0.08	0.05
(vi)	High clustering				
	Zara	85.7	0.2	0.13	0.07
	Uterque	13.2	0.17	0.19	0.12

Notes: Selected retailers among those that exhibit low, medium, and high price clustering. The following measures are within-retailer across-category averages. ^aThe number of distinct items per distinct price. ^bProbability that the price of two distinct items in the same category is the same. ^cNormalized clustering measure as defined in equation (1). ^dPreferred normalized measure that accounts for prices, ranges of prices, popular prices. Details in the main text.

The results so far document that there are different classes of retailers in terms of pricing behaviors. There is a group of retailers that exhibit little if any price clustering. In fact, these might even exhibit less clustering than what we would expect given the price distribution of the category. Many of these retailers fall into what we describe as traditional or platform retailers. Examples are Louis Vuitton and Walmart, respectively. Another set of retailers have price clustering explained by price levels, popular prices, or price endings, and thus controlling for these brings the excess clustering down. A third set of retailers continues to exhibit substantial clustering not driven by these features. These are the retailers which clearly fall into the quantum pricing strategy. Table 4 provides selected examples of retailers and their estimated clustering measures. Section 6 discusses why a retailer might benefit from using a handful of prices.

Our results suggest that price endings are a major driver of price clustering, and thus contribute to prior literature (e.g., [Stiving and Winer \(1997\)](#); [Schindler and Kirby \(1997\)](#)). However, we continue to find substantial price clustering after controlling for digit endings. A few potential reasons might help explain why. First, the data includes all items in a large share of the apparel industry. Price endings can be more prevalent in advertised items, but when we consider entire catalogs we find that all digit endings are used. This is important because it is unlikely that there is a kink in the demand in Abercrombie at the \$8 ending but at the \$9 in Uniqlo, and such kink would not exist at \$9 and \$8, respectively. Second, price endings are less commonly thought at the integer level ([Thomas and Morwitz \(2005\)](#)). This would exacerbate price rigidity (from \$29 to \$39 there a 35% difference). In fact, about 51% of the over 230,000 products in the U.S. have a non-zero decimal digit. Lastly, because sales are commonplace in apparel, if price endings were important to revenue then one might expect a similar strategy in sale prices. But many fashion retailers set sale prices as percentages or direct price points; and other than a higher frequency of \$9 in sales, we find no strong relationship between price endings in regular prices and sales. See Appendix [A.8](#).

4.3 Correlated clustering across categories and retailers

The clustering measures can also be computed within retailers and across categories, as well as across retailers and within categories. For example, comparing prices between two categories within the same retailer would estimate the extent to which there are correlated quantum prices. We discuss three results.

First, we compute the probability that two random items, in different categories but in the same retailer, have the same price. This empirical probability is computed sampling two items for every within-retailer category-category pair. In total there are 2,217 pairs in the U.S. and 1,646 in the U.K. We find a surprising amount of correlated clustering, especially if we consider that some categories are relatively broad (e.g., sweaters and shirts in Tops). For example, in the U.S. there are over 500 retailer category-category pairs (about 25% of total) with more than 5% estimated probability. In the U.S., the mean is 3%, the median is 2%, and the 90th percentile is 10%; in the U.K., the mean is 5%, the median is 2%, and the 90th percentile is 12%. See results in Appendix [A.9](#).

Second, we implement the normalized measure in eq. (1) within-retailer and across-categories, as well as across-retailers and within-retailers. Estimates are expected to be lower because items in two different categories cannot in general be more concentrated than they are in their own category. The normalized measure of correlated clustering is based on a modification of [Ellison and Glaeser \(1997\)](#); [Ellison, Glaeser, and Kerr \(2010\)](#), who estimate geographic concentration across manufacturing plants from different industrial sectors. The

normalized index is computed as follows:

$$index_{i,j}^c = \frac{\sum_{b=\underline{b}}^{\bar{b}} (s_{i,b} - x_b)(s_{j,b} - x_b)}{1 - \sum_{b=\underline{b}}^{\bar{b}} x_b^2} \quad (3)$$

Where i and j denote two categories within the same retailer, and x_b is the average price bin share between the two categories at price bucket b . The sums go from the minimum to the maximum prices observed in either category.

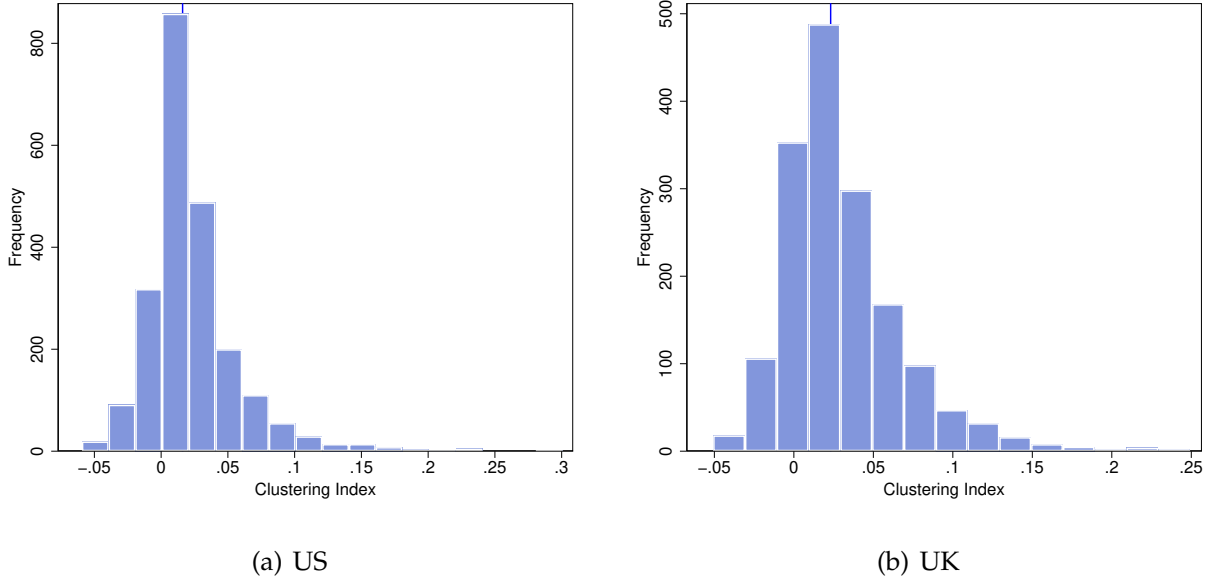


Figure 4: Correlated price clustering

Notes: Histogram of the normalized price clustering measure computed within-retailer and across-categories. Clustering truncated at 0.3 for better visualization. Vertical line denotes the median correlated clustering.

Figure 4 shows remarkable correlated clustering across categories. For example, there are 325 category pairs (about 15%) with clustering above 0.05 in the U.S. The mean is 0.023 in the U.S and 0.031 in the U.K. This reinforces the evidence that some retailers use the same prices for very different types of products. Appendix A.9 shows which category pairs tend to be on average more correlated. The average is 0.018 and the median is 0.016, computed across 74 category pairs in the U.S. (excluding same category pairs). For instance, dresses-swimwear have a negative correlated clustering measure (-0.013), but dresses-tops (0.064) or sports-tees (0.060) have large estimates. Note that this measure is only large when different categories use the exact same price, not a similar price.

Finally, we calculate the normalized correlated clustering index in eq. (3) within-

category and across-retailers, in order to examine if retailers use the same prices for similar items. Appendix A.10 indicates no evidence of correlated clustering across retailers. For computational reasons the results are available for a random fraction of the retailers in each country. There are in total 832 and 1,475 within-category retailer-retailer pairs in the U.S. and the U.K., respectively. The estimates are close to 0 in both countries. For example, the mean and median in the U.S. is 0 and 0.002, respectively. The lack of evidence echoes the limited advantage of price endings. If some prices were particularly appealing to consumers then one might expect different retailers concentrating on the same prices.

In summary, we found a statistically large degree of price clustering within a retailer-category, a significant but smaller degree across categories within the same retailer, and no clustering across retailers within the same category. Appendix A.11 overlaps the clustering measure distributions at the three levels.

4.4 Robustness: ML clustering

Previous analyses in this Section showed evidence of price clustering using predefined buckets of prices. But are these price buckets economically meaningful? For instance, some of these price buckets can be too close from each other, and we might want to consider those as belonging to a same price cluster. We use an unsupervised machine learning approach to address this question.

We define a clustering index borrowing ideas from the popular k -means literature (for a review see Friedman, Hastie, and Tibshirani (2001)) and from the CH index (Caliński and Harabasz (1974)). See Appendix A.12 for methodological details. We define a ratio $\kappa(k) \equiv \frac{\overline{WC}(n_k, k)}{\overline{BC}(k)}$, which relates the within-cluster variation (a series of price buckets within cluster k) to the between-cluster variation (centroids k and $k - 1$). This method accomplishes two things. First, it determines the optimal number of price clusters in the data according to a standard trade-off. And second, we demand that clusters be separated at least 5% from each other.

Figure 5 shows the results of k_i^* for all retailer-categories i in the U.S., the corresponding average distance between consecutive centroids (in percentage), and the ratio of k^* to the maximum possible of clusters.¹² Results for the U.K. are shown in Appendix A.12. Overall we find results that are qualitatively similar to those in the previous analyses. We would expect this because the strict normalized measure, defined in eq. (1) and eq. (2), also controls for prices that are too close to each other.

¹²Due to the 5% threshold, the maximum number of clusters is not the number of distinct prices, i.e. $\#b$. The maximum k^* is $\lfloor \frac{\log(b^{max}/b^{min})}{\log(1.05)} \rfloor + 1$.

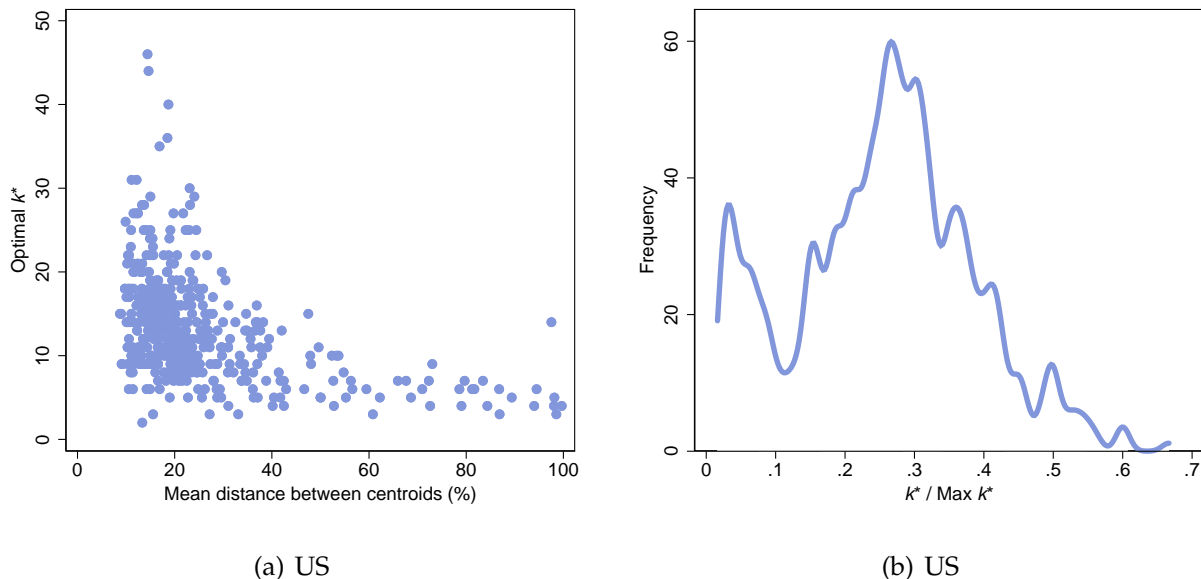


Figure 5: Optimal number of price clusters in the data

There is a large share of retailer-categories that exhibit medium to substantial price clustering. These are captured by those having a low ratio of k^* relative to the maximum possible k . Then there is another set of cases that are poorly clustered, and tend to exhibit large k^* . And importantly, for the vast majority of the cases the price clusters tend to be meaningfully separated from each other. Panel (a) shows many cases where the average distance between centroids is between 10% and 30%. In fact, the mean and median average distance between centroids is 70% and 21% in the U.S., and 67% and 21% in the U.K., respectively.

5 Pricing dynamics of price clustering

Section 4 showed evidence of price clustering in the cross-section. However, this clustering fades if retailers simply select new quantum prices every time. We now show that the quantum prices are very sticky across collections. Retailers are not only reluctant to create new prices throughout the life of a product, but also use the same prices for product introductions.

5.1 New prices

Products in apparel are often characterized by little, if any, upward price changes and a short product life. This raises the question of which prices are retailers choosing throughout

collections.¹³ In addition, there is substantial seasonality in prices, as measured by the monthly inflation rate in clothing. The average absolute non-seasonally adjusted monthly inflation rate is about 1.9% in the U.S. and 1.8% in the U.K.¹⁴ Therefore, a priori there is no reason why we should not expect very different, seasonal prices as the assortment composition varies over time. However, we find that the set of prices is remarkably stable.

Table 5: Price stickiness

	<i>m</i> months after				
	<i>m</i> = 1	<i>m</i> = 2	<i>m</i> = 3	<i>m</i> = 4	<i>m</i> = 5
(i) Share of common prices^a					
<i>p</i> 10%	0.73	0.63	0.57	0.48	0.41
Median	0.91	0.89	0.86	0.81	0.75
Average	0.91	0.87	0.86	0.83	0.76
<i>p</i> 90%	1.0	1.0	1.0	0.99	0.92

Notes: Results are averages across retailer-categories in the U.S. ^aRatio of common prices (between the prices observed in the first month and month *m*) to the prices in month *m*.

We take the prices in each retailer-category’s initial scraping month, and compare these with the prices observed 1 to 5 months later. This measures the likelihood that retailers use different prices over time in a given category. Table 5 shows a significantly large share of common prices, relative to the first month. The mean and median number of distinct prices that each retailer uses in the initial month is 41 and 32 in the U.S., and it is 49 and 30 in the U.K., respectively.

The estimates can be interpreted as follows. The share of common prices measures the ratio of common prices (between the first month and *m* months after) to the distinct prices in month *m*. For example, in half of the retailer-categories over 75% of the prices observed 5 months later were exactly the same to those in the first month.

5.2 Product introductions

The results in Table 5 include both products whose price is changing as well as prices from new products. Table 6 replicates the analysis but only for product introductions in each of

¹³We document that the mean product life is 3.1 months in the U.S. and 3.2 months in the U.K. In addition, we document asymmetric frequencies of price changes. Only 5.3% of the products have a regular price change, whereas close to 70% experience a sale price. Estimates are comparable to Nakamura and Steinsson (2008) and Cavallo, Neiman, and Rigobon (2014). See Appendix A.16.

¹⁴See Appendix A.17. Estimates during 2017-2019 obtained from the Bureau of Labor Statistics (U.S.) and Office for National Statistics (U.K.).

the 1 to 5 following months.

We find that the vast majority of products are introduced at the existing prices. For example, the average probability that a new product in month 5 comes in at an existing price is 0.91. Moreover, the 90th percentile probability is 1, which means that there is a fair share of retailer-categories pairs where there is no single product introduction with a new price. Similar results are found in the U.K. retailers (Appendix A.18).

Table 6: Product introductions

	<i>m</i> months after				
	<i>m</i> = 1	<i>m</i> = 2	<i>m</i> = 3	<i>m</i> = 4	<i>m</i> = 5
(i) Prob introducing a new good at existing prices^a					
<i>p</i> 10%	0.61	0.53	0.48	0.55	0.60
Median	0.96	0.96	0.93	0.93	0.92
Average	0.96	0.93	0.91	0.93	0.91
<i>p</i> 90%	1	1	1	1	1

Notes: Summary statistics on the probabilities across retailer-categories in the U.S. ^aProbability that the price of a product introduction in month *m* was among the observed prices in the first month.

We now study whether the price stickiness probabilities (line (i) in Table 6) are related to the clustering measures. We run OLS regressions at the retailer-category level, where the dependent variable is defined as the average of these *m*-based probabilities. Regressions are run jointly for all group pairs in the U.S. and the U.K.

Table 7 shows that the baseline clustering index (Section 4) is related to higher price stickiness. Columns (1) to (3) show that higher price clustering relates to higher probabilities that products will be introduced at the existing prices.

We also find that measures of price advertising and fast-inventory turnover (fast-fashion retailers) are related to a higher price stickiness.¹⁵ The price advertising indicator was constructed as follows. Throughout 2017 and 2018 we enrolled in e-mail newsletters from most of the retailers, and recorded whether these included price points or not (promotions in terms of percentages that did not include price points were classified as non price advertisers). We also complemented the newsletters with a simple online exercise: for each retailer we checked whether the landing page included price points or not. These two sources are surprisingly similar. According to this measure, 36% of the retailers in the data engage

¹⁵The results are similar for the remaining clustering measures. See Appendix A.19 for additional specifications.

in price advertising. Fast-fashion retailers are identified following [Caro and Martínez-de Albéniz \(2015\)](#) and industry reports.

Table 7: Predictors of quantum stickiness

VARIABLES	(1) <i>prob.</i>	(2) <i>prob.</i>	(3) <i>prob.</i>
Probability of product introduction at existing price			
Cluster index ^a	0.590*** (0.179)	0.570*** (0.176)	0.528*** (0.176)
Price ad		0.0412** (0.0191)	
Fast fashion			0.0542*** (0.0197)
log (N)	YES	YES	YES
Country FE	YES	YES	YES
Cat. FE	YES	YES	YES
Observations	782	782	782
R ²	0.260	0.271	0.274

Notes: ^aNormalized clustered index that controls for popular prices, price ranges, and number of products. Price advertising and fast fashion are binary indicators as described in the main text. Standard errors clustered at the retailer-country level. *** p<0.01, ** p<0.05, * p<0.1

6 Theories of quantum prices

A variety of models can rationalize different aspects of price clustering as an optimal pricing strategy. We first discuss a behavioral advertising model, and then outline four alternative frameworks.

6.1 Advertising effectiveness

We propose a simple model in partial equilibrium where price clustering makes advertising more effective. And it is increasingly effective when the same prices are used over time, i.e. in product introductions. This suggests that there is a menu cost to introducing new prices.

Apparel companies invest substantially on media advertisement ([Ghemawat, Nueno,](#)

and Dailey (2003); Wall Street Journal (2017)).¹⁶ However, only some retailers are salient about prices.¹⁷ Just consider two opposite examples. In Uniqlo, prices have a central role in advertising and signage strategies. This is true online as well as in brick-and-mortar stores. Prices are prominently displayed in the ads, promotions, and signs across the store. In fact, there are employees (*runners*) who go around the store rearranging items such that prices, sizes, and colors are in the right location and visible to the consumer. Louis Vuitton, on the other hand, makes prices the least possible salient attribute. Price labels are carefully obfuscated, you often need to ask for help to a merchant, there are no markdown racks, and prices are never displayed in the ads.¹⁸

Although there is extensive literature on whether and how the advertising should include prices (Lal and Matutes (1994); Simester (1995); Anderson and Simester (1998); Shin (2005); Bagwell (2007)), the distribution of unique prices, the stickiness, and the role of memory has received little attention. A relevant exception is Rhodes (2014), which introduces a model where consumers update beliefs on prices based on the advertised prices.

Consider a retailer that sells a multi-product assortment C . Let C be defined as follows.

$$C \equiv \{(x_{1,1}, \dots, x_{1,N_1}), \dots, (x_{M,1}, \dots, x_{M,N_M})\}$$

$x_{i,m}$ is product i in category m and N_m is the number of products in this category. Then $N = N_1 + \dots + N_M$ denotes the number of products in the catalog. The cost of advertising is $g(A)$, where A denotes the number of distinct prices and products included in the advertisement. We can think of A as bits of information competing for a space in the ad. As illustrated in Appendix A.13, with or without prices, newsletters only advertise a handful of items.

There are two types of consumers. A fraction λ are price-sensitive, of which γ_{ps} are informed and $(1 - \gamma_{ps})$ are only aware through advertising. And a fraction $(1 - \lambda)$ are quality-sensitive (γ_{qs} are informed). Consumers' product or price memory, or brand positioning awareness, fades over time but is updated with new advertisements.¹⁹ Recall, r , decays exponentially. An initial ad reaches $r_1 = r_0$ of the $(1 - \gamma)$ uninformed. In the next period, if no new ad is seen, then $r_t = r_0 \alpha^{t-1}$; and when the same ad is seen, then $r_t = r_0 \alpha^{t-1} (1 - \beta) + \beta$;

¹⁶For example, Abercrombie & Fitch Co. and Victoria's Secret each spent 3% of net sales in paid advertisements.

¹⁷See Appendix A.13 for visual examples of ads with and without prices. One image advertises 35 jeans at \$35 each; the second image advertises bags without prices.

¹⁸Louis Vuitton prices are visible in the webpage. Goyard is an extreme example of traditional price obfuscation. Goyard produces luxury bags, but neither the products nor the prices are displayed online. In fact, the webpage makes the following statement: "Goyard products are available exclusively at Goyard boutiques worldwide. Goyard does not engage in any form of e-commerce."

¹⁹For evidence on price recall, see Monroe (1973); Dickson and Sawyer (1990); Lichtenstein, Ridgway, and Netemeyer (1993); Monroe and Lee (1999). See Brown (1969) for early evidence that consumers associated low-price advertising with general low prices.

where $\alpha, \beta < 1$.

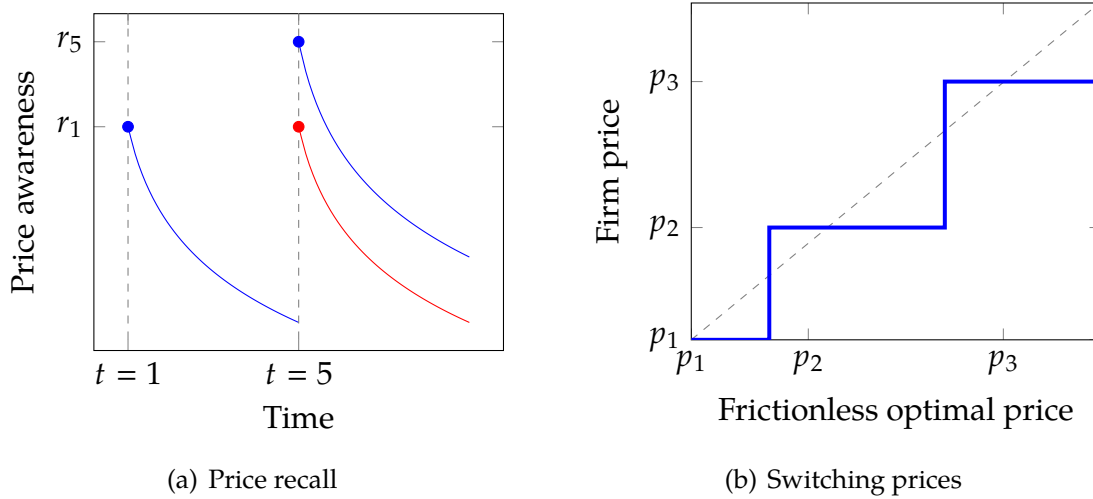


Figure 6: Price recall and advertising

Notes: Panel (a) shows the relationship between price awareness and advertising. At time $t = 5$, the retailer can advertise a different price (red) and achieve r_1 awareness, or advertise the same price (blue) and increase awareness to r_5 . Fewer prices allows to more effectively advertise different products together, and, if done over time, to more consistently build a price positioning. Panel (b) shows three advertised prices p_1, p_2, p_3 . The retailer will stick to the advertised price p_1 and, if switching to a different price, it will jump discretely to p_2 which has been used before.

Panel (a) in Figure 6 illustrates the case. An initial ad of x, p reaches r_1 price awareness. Price recall starts fading afterwards until the retailer sends out a new advertisement. If the retailer advertises a new price, p' , awareness jumps back to the r_1 level; while advertising the old price, p , it increases to r_5 . This can be thought of as a menu cost to introducing a new price; it is the cost of giving away the price positioning that has been achieved through signage and advertising.^{20,21}

²⁰Bananas at Trader Joe's is an extreme case of building price reference. The price, 19 cents each, has been the same for years (Forbes (2018)). And modifying this price will not go unnoticed. See also Voss, Parasuraman, and Grewal (1998), and references therein, for a discussion of price expectation, brand loyalty, and repurchase behavior.

²¹One might be tempted to jam or saturate the consumer with advertising to boost recall, but this is likely to increase dissatisfaction. This can be related to the empirical evidence on *pulsing*, i.e. advertising that oscillates from high to low levels (Dubé, Hitsch, and Manchanda (2005)).

The problem of the firm is to choose prices and advertising as follows:

$$\begin{aligned} \max_{A, \tilde{p}} \sum_m \sum_i^{N_m} (p_{i_m} - c_{i_m}) & \left\{ \lambda \left[(\gamma_{ps} + (1 - \gamma_{ps})1(i_m \in A)) \right] \right\} D_{ps}(p_{i_m}) + \\ & (p_{i_m} - c_{i_m}) \left\{ (1 - \lambda) \left[(\gamma_{qs} + (1 - \gamma_{qs})1(i_m \in A)) \right] \right\} D_{qs}(p_{i_m}) - g(A) \end{aligned} \quad (4)$$

where p_{i_m} and c_{i_m} are the price and cost of product i in category m ; $1(i_m \in A)$ is an indicator variable if product (or price) i_m was included in the advertisement. For tractability $D_j(p_{i_m})$ is a linear demand, $1 - b_j p_{i_m}$, for $j = ps, qs$.

The model allows for simple predictions that reflect institutional details of price setters in the industry. For example, when consumers are price-sensitive and informed, retailers do not cluster prices. Platform strategy retailers (e.g., Walmart's every day low prices), focus on getting the lowest price, and therefore have no incentives to stick to price points over time. When consumers are price-sensitive, uninformed, and advertising is costly, firms cluster prices. Retailers like Uniqlo and Zara will use few prices for advertising efficiencies, and it will be costly to use different prices for new products. When retailers have both price- and quality- sensitive consumers, firms will not cluster prices. Retailers like Ralph Lauren and Armani have low/high labels and a wide price distribution to attract a broad customer base. We formalize some of these cases as follows.

Result 1. *In a single-period two-product problem, for a set of parameters where consumers are price-sensitive and advertising is costly, it is optimal to cluster prices: $p_1^* = p_2^*$.*

Details in Appendix A.15.

In Result 1, the retailer clusters prices but also restricts the product space. The retailer could produce a high-quality product; but its core demand is price-sensitive, and therefore it is better off selling low-price products at the same price. Price clustering allows to more efficiently inform consumers about cross-section of products.

Result 2. *In a single-period two-product problem, for a set of parameters where there are price- and quality- sensitive consumers, it is not optimal to cluster prices: $p_1^* < p_2^*$.*

Details in Appendix A.15.

In Result 2, the retailer produces high-end and low-end products to appeal to both types of consumers. This resembles the standard vertical differentiation solution.

Result 3. *In a two-period two-product problem, for a set of parameters where consumers are price-sensitive and uninformed, and there are advertising efficiencies over time, it is optimal to use sticky prices: $p_1^{t_1} = p_2^{t_2} = p^*$.*

Details in Appendix A.15.

In Result 3, the retailer overcomes uninformed consumers using sticky prices. A new product is introduced in each period at the same price. Sticky prices allow to build brand or price awareness. The effect is expected to be larger with more products (cross-section information gains).

Result 4. *In a two-period problem, two products in t_1 and one product in t_2 , for a set of parameters where consumers are price-sensitive and uninformed, it is optimal to switch price to advertised prices: $p_3^{t_2} = p_2^{t_1}$.*

Details in Appendix A.15.

In Result 4, the retailer is first selling two products at different prices (costs are such that $p_1^{t_1^*} < p_2^{t_1^*}$). In the second period, the retailer faces unanticipated increased cost for a new product. Instead of setting the frictionless $p_3^{t_2^*} < p_2^{t_1^*}$, it is optimal to jump to the advertised $p_2^{t_1^*}$. This is illustrated in Panel (b) in Figure 6. The retailer jumps between advertised prices instead of introducing new prices.

A behavioral model with price memory and advertising costs can rationalize price clustering within- and across- categories. And predicts a reluctance to introduce new prices over time, even for product introductions. In fact, price adjustments should be lumpy: if switching a portion of new products to a different price, these will jump to an existing clustered price. In Section 7 we discuss evidence of price stickiness.

6.2 Convenient prices

We now consider a model following Knotek (2008) where there are convenient prices. These are prices that for different reasons facilitate a transaction (e.g., round numbers to avoid change in coins). This generates demand kinks at prices that a retailer is more likely to use.²² These can also be thought of as price cliffs, which generate discontinuous drops in demand. We modify the model to multi-product, multi-category retailers. Consider a firm that sells N_m products in category m . Each period $t = 1, 2, \dots$ there is an optimal set of prices, $p_{m,t}^*(\Omega)$, that the firm would like to set in the absence of frictions, e.g. corporate policies on prices points, consumers' reaction to price digits. Ω denotes a set of state variables such as marginal costs, competitors' prices. The firm incurs a loss, $n(p, \Omega)$, when setting prices that are not optimal. In addition, there is a set of convenient prices, $p^\#$; and there is a loss, $h(p, p^\#)$,

²²Prices that are "better" than others can more generally be related to a literature on price endings, convenient prices, or round prices (Kashyap (1995); Blinder, Canetti, Lebow, and Rudd (1998); Anderson and Simester (2003); Knotek (2008); Levy, Lee, Chen, Kauffman, and Bergen (2011); Knotek (2011)).

associated to setting a price p that is not convenient. Each period, the firm's profits are:

$$\Pi_t(p, p^\#, \Omega) = \sum_m \sum_{i=1}^n (p_{i_m} - c_{i_m}) q_i(p_i) - n(p_{i_m}, \Omega) - h(p_{i_m}, p^\#) - A_{i_m} 1(p_{i_m} \neq p_{i_m}^{t-1}) \quad (5)$$

where $A_{i,t}$ is a menu cost to a price change. The problem of the firm is to choose the set of prices p that satisfies:

$$p \in \arg \max_{\tilde{p}} V(\tilde{p}, p^\#, \Omega), \text{ where } V(p, p^\#, \Omega) \equiv \max_{\tilde{p}} \Pi_t(\tilde{p}, p^\#, \Omega) + \beta E [V(\tilde{p}, p^\#, \Omega)] \quad (6)$$

When the menu cost is small, convenient prices are far apart, or the inconvenience loss are small, the firm sometimes charges inconvenient prices, $\tilde{p} \notin p^\#$. But when these are large costs, the firm jumps from one price to another. Appendix A.14 illustrates this scenario.

A model like this would predict some price clustering. In Section 4 we documented that some firms rely on price endings to cluster prices products within- and across- categories. And the model would predict price rigidity at more convenient prices. However, the quantum prices that we observe are often far apart from each other, which the model predicts should lead to less clustered prices. This model does not capture why the set of clustered prices and the digit endings are different across retailers; or why some retailers are not clustering prices at all, including retailers positioned in similar price ranges. In addition, we do not find evidence that price endings in regular prices are related to endings in sale prices.

6.3 Demand uncertainty

It is possible to rationalize price clustering is as an optimal strategy to overcome demand uncertainty. Ilut, Valchev, and Vincent (2016) presents a model where ambiguity-averse retailers face an uncertain demand. Firms use demand at previously observed prices to update priors on future demand, which generates kinks in the expected profits, and therefore a discrete and sparse distribution of prices. We modify the model to multi-product retailers as follows. The firm faces a demand for product i , expressed in logs, as follows:

$$q(p_{i_m,t}) = g(p_{i_m,t}) + z_{i_m,t} + x(p_{m,t}) \quad (7)$$

where $p_{i_m,t}$ is the price of product i in category m at time t . There are three components in (7). $g(p_{i_m,t})$ is a known time-invariant function. For example, $g(p_{i_m,t}) = a_{m,0} - a_{m,1}p_{i_m,t}$, where $a_{m,0}$ and $a_{m,1}$ are unknown parameters and can vary across categories. $z_{i_m,t}$ is an iid time-specific price-insensitive shock, e.g. certain styles become more fashionable and receive higher demand. And $x(p_{m,t})$ is an unknown function, but that firms learn about using past

observations; it is common to products in the same category. Therefore, the firm’s time t profits are:

$$\Pi_t = \sum_m \sum_{i=1}^n (P_{i_m} - C_{i_m}) e^{q(p_{i_m,t})} \quad (8)$$

In this model, retailers observe total quantities sold, $q(p_{i_m,t})$, but not its underlying components. The retailer is uncertain about the distribution where $x(p_{m,t})$ has been drawn. However, it considers a set of priors, Υ_0 ; and each prior in Υ_0 is a Gaussian Process distribution. Firms decide prices at time t with information on the history of quantities $q^{t-1} = [q(p_1), \dots, q(p_{t-1})]$ and its corresponding prices $p^{t-1} = [p_1, \dots, p_{t-1}]$. The retailer updates expected demand conditional on (q^{t-1}, p^{t-1}) .

The result of this model is that retailers are averse to experimenting with new prices. Firms have used prices p^{t-1} in the past, and use these to form beliefs that attenuate demand uncertainty. And these kinks in the expected profits would predict a reluctance to change or introduce new prices. Appendix A.14 illustrates this case.

This framework provides several predictions that are consistent with the evidence. In Section 7 we show that fashion items rarely experience price increases, and a large set of retailers use the same prices, observed months ago, for new products. The pricing strategy also exhibits price memory, i.e. if there are price adjustments, when the distribution is very clustered, these price changes are more likely to occur between the set of previously observed prices. However, the model is a single-product monopolist; and it is unclear why retailers that sell hundreds or thousands of products do not experiment with some products. In addition, it does not capture the cross-section price clustering and the large heterogeneity in price distributions across retailers (e.g., why only some retailers are averse to demand uncertainty).²³

6.4 Salience and price sensitivity

A demand-side behavioral explanation can be that price clustering makes consumers *less* price sensitive. This can be articulated in a model where consumers are boundedly rational, and because there is limited ability to compare all possible attributes, consumers use heuristics to reduce consideration sets prior to making a decision. See, for example, [Eliaz and Spiegel \(2011\)](#); [Piccione and Spiegel \(2012\)](#); [Bordalo, Gennaioli, and Shleifer \(2013, 2015\)](#).

Decision heuristics in apparel are not unrealistic. On a given day, Forever 21 can sell over 2,000 different dresses; during three months Zara offers 10,000 unique products. It is

²³[Ilut, Valchev, and Vincent \(2016\)](#) consider a single-product monopolist, and focus on scanner data in supermarkets and convenience stores. Their results need not translate to a different industry such as fashion retail where a brand’s assortment tends to be substantially larger.

unfeasible for a consumer to compare prices, colors, styles, and sizes available for all possible options. In fact, there is a limited number of items you can bring to the fitting room.²⁴ This may explain why retailers that sell large assortments do not simply group all jeans together in one spot and all sweaters in another spot.

Consider a model where consumers follow a two-stage decision process. First, consumers' attention overweights the most salient attribute of the choice set. And then consumers decide the best product from a menu based on the selected attribute. Interestingly, this model can be applied within- and across- retailers. Consider first the former case.

Consumers evaluate N products in a choice set $C \equiv \{(x_1, p_1), \dots, (x_N, p_N)\}$, where x captures the horizontal differentiation of a product and p is the price. The relevant choice set, C , is defined by all the products in the same category. Let (\bar{x}, \bar{p}) be the reference product with average attributes $\bar{x} \equiv \frac{\sum_i x_i}{N}$ and $\bar{p} \equiv \frac{\sum_i p_i}{N}$. In the first stage, consumers decide the screening attribute. Assume consumers pick x if there is more variation in x than in p , and pick p otherwise.²⁵ When many different products have the same price, consumers focus on the horizontal attribute x . This allows to shift attention away from prices, and possibly make consumers less price sensitive.²⁶

The model can include more than one retailer. The consumer evaluates N products from a choice set $C \equiv \{(x_i, p_i)\}$, where $i \in N$, and N is the number of distinct products in one category, across retailers in a relevant price range. Consider $N = 3$ and two firms located in a circular city choose attributes (x, p) . Firm 1 sells two products $\{(x_1, p_1), (x_2, p_2)\}$ and firm 2 sells product $\{(x_3, p_3)\}$. There can be multiple equilibria but there is one where firm 1 chooses to cluster prices, $p_1 = p_2$, while $x_1 \neq x_2 \neq x_3$, to soften price competition. Attributes are such that there is more variation in x than in p , and therefore consumers choose the best product from the menu according to x . Intuitively, firm 1 could increase p_2 but would trigger firm 2 to cut p_3 .

We documented price clustering within-retailer within-category, which could be interpreted as an effort to shift attention away from prices, especially in large assortments. Interestingly, the model allows to have consumers in certain price ranges to be more price sensitive than others, e.g. price sensitivity diminishes for more expensive, high-quality goods, and therefore high-end retailers have less incentives to cluster prices. In unreported

²⁴Moreover, there is evidence that in certain domains having too many choices can deter purchases or reduce consumer satisfaction (Iyengar and Lepper (2000)). Whether and how choice overload manifests often depends on consumers' articulated preferences, how choices are displayed or removed, frequency of purchase, and search costs (e.g., for a review see Scheibehenne, Greifeneder, and Todd (2010); Chernev, Böckenholt, and Goodman (2015)). The effects of adding more options are therefore a priori ambiguous.

²⁵This is similar to the salience function $\sigma(\cdot)$ in Bordalo, Gennaioli, and Shleifer (2013). Variation in the x attribute can be related to how dense or sparse is the produce space (Bertini, Wathieu, and Iyengar (2012)).

²⁶See also Kaul and Wittink (1995) for a discussion of price advertising and price sensitivity. Shifting attention away from prices can temporarily avoid the cost of paying (Prelec and Loewenstein (1998)).

regressions, we find that the clustering measures in Section 4 are lower for more expensive retailers (as measured by the median price in their assortment). But the model does not capture why retailers use the exact same prices and not just similar prices; or why retailers use the same prices across categories. In addition, many of the price clustered retailers dedicate efforts in actually making prices salient: large signage costs, price image featured in the stores, and price advertising campaigns. It is possible that building a price image allows to form a store-specific reference price, and what draws attention to price is seeing a different price. This price image can also serve as a commitment or signaling device to lower price competition between stores. These extensions could be captured including an advertising channel to the model.

6.5 Managerial inattention

A supply-side explanation to quantum prices could be managerial costs of setting prices for a large number of products. We could think of a pricing problem where each unique price represents a state, or a scenario, and it is costly for managers to strategize on multiple states (Fershtman and Kalai (1993); Bloom and Van Reenen (2007)). Such managerial inattention is exacerbated when the number of products is large, when there are frequent sales, and when collections arrive faster, because pricing decisions have to be made more frequently and on large assortments.

For example, fast-fashion retailers have shorten design-to-shelve times to a few weeks (Ghemawat, Nueno, and Dailey (2003); Cachon and Swinney (2011)). Quantum prices allows to streamline the pricing process for short-cycle products which are constantly being replaced by new ones. Similarly, fewer prices allows to reduce managerial costs associated to markdown pricing. In fact, we have found evidence that fast-fashion retailers tend to exhibit larger price clustering measures, as well as larger measures of price stickiness introductions.

However, the price clustering measures control for the number of products, and price clustering is observed in both small and large assortment retailers. Clustering prices is not necessarily a less demanding task. Price tags have to be printed for all new products, and therefore the managerial cost of setting a new price or an old price should be about the same. Managerial inattention could, however, affect price stickiness of price changes (Ellison, Snyder, and Zhang (2018)). Finally, many of the quantum strategy retailers are among the most popular and profitable firms worldwide. And given the size of these retailers (see Section 1 for a few examples), pricing is hardly left improvised.

6.6 Summary

Table 8 summarizes the clustering predictions. The models of convenient prices, demand uncertainty, salience, and inattention (6.2-6.5) predict forms of price clustering that are consistent with the data. These can generally account for within- category clustering and price change stickiness, but are limited in predicting across- category clustering, sticky product introductions, and the large heterogeneity in pricing behaviors across retailers.

In general, 6.2-6.5 do not capture the advertising role in setting prices. Retailers often sell large and diverse assortments, often of short duration, and branded products gives them control over the final price. Retailers are in the constant need of informing consumers about new collections, and doing so is costly. One strategy is to pick a niche of prices and stick to these for different products and over time. In fact, Section 7 shows that retailers engaging in price advertising or price clustering are more likely to use the same prices over time, even for product introductions. Consistent with the advertising model, this suggests a menu cost to introducing new prices which is different from the traditional within-product price change stickiness due to menu costs, staggered contracts, or price point rigidity (Nakamura and Steinsson (2008); Klenow and Kryvtsov (2008); Blinder, Canetti, Lebow, and Rudd (1998)). See Appendix A.15 for potential extensions on the advertising model.

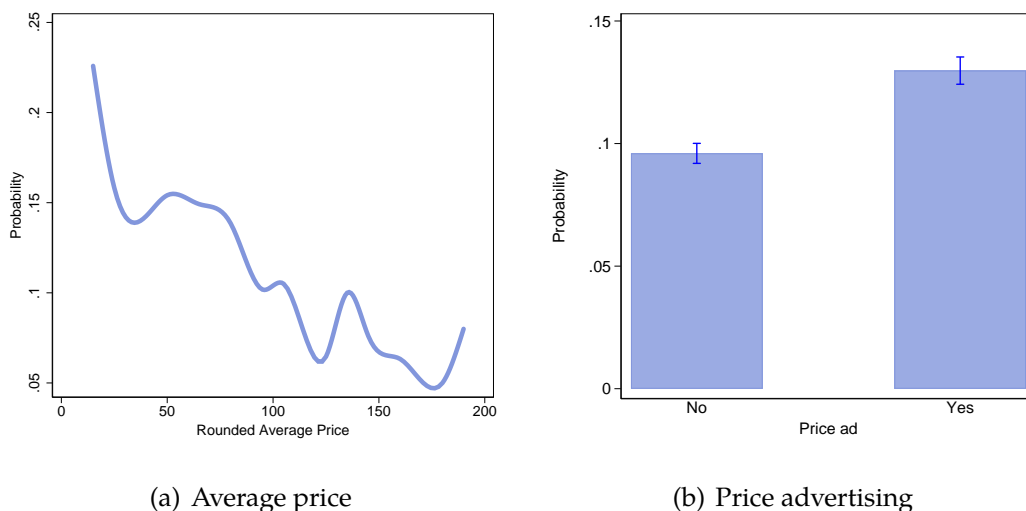


Figure 7: Relationship between clustering and advertising

Notes: The clustering measure is the probability that two items in the same retailer-category have the same price (Section 4). Panel (a) shows the relationship between the average price (rounded to the nearest 10 multiple) and price clustering. Panel (b) shows the relationship between price advertising and clustering. Price advertising indicator as defined in the text. Error bars are SEMs.

In Panel (a) Figure 7 we show that clustering decreases with the average price; con-

Table 8: Theories of quantum prices

	Clustering ^a	Advertised Products ^b	Expensive/Cheap ^c	Across Retailers ^d	Stickiness ^e
Advertising	Within- and across-category	Higher clustering	Higher for low-price retailers	+/-	Few price changes, sticky introductions
Convenient prices	Within- and across-category	+/-	+/-	Same prices	Few price changes
Demand uncertainty	Within-category	+/-	+/-	Same prices	Few price changes, sticky introductions
Salience and sensitivity	Within-category	Higher clustering	Higher for low-price retailers	+/-	+/-
Managerial inattention	Within- and across-category	+/-	Higher for low-revenue retailers	Same prices	Few price changes

Notes: Model predictions in terms of clustering dimensions (columns). ^a Expected form of price clustering. ^b Expected clustering for advertised products. ^c Expected clustering across cheap or expensive retailers. ^d Expected observed prices across retailers. ^e Expected forms of price stickiness.

sistent with the notion that firms use clustering when faced with more price-sensitive consumers. We also find evidence that price advertising is related to statistically significant higher clustering measures. Visual evidence is showed in Panel (b) Figure 7. Similar results are obtained using regressions of the price clustering measures on the price advertising indicator, and controlling for number of products, categories, and country.

7 Macroeconomic implications: A case study

Sections 4 and 5 showed that quantum strategy retailers use a handful of prices for large and diverse assortments, and that such strategy is sticky over time. Section 6 discussed that quantum pricing can be an optimal strategy to increase advertising effectiveness. Moreover, because price recall and brand perceptions are costly to build and depend on past prices, the advertising becomes increasingly effective when the same prices are used over time.

What are the macroeconomic implications of quantum prices?²⁷ A formal study of the matter is beyond the scope of this paper due to data limitations. First, we have focused on the fashion retail sector only.²⁸ Addressing this question requires gathering datasets across different industries. The data collected by national statistical offices, however, is not a good source for this purpose because very few items from each store are actually sampled. Our approach has been to collect all the available items within a store and only by doing so we were able to report the existence of quantum prices. The second limitation is that we lack units sold. Future research should study the relationship between quantum prices and consumer behavior. However, for illustrative purposes in this section we study the macro implications as if the data from a couple of stores were representative of the aggregate. The purpose is to explore potential macroeconomic implications using a case study of two retailers. We first show suggestive evidence of price adjustment strategies, and how this introduces noise in measuring aggregate inflation. Finally, we show deviations from the Law of One Price using matched products between the U.S. and the U.K.

²⁷Quantum prices can be interpreted as an extreme form of price stickiness. The stickiness is different from canonical time-dependent or state-dependent models. In time-dependent models, the timing of price changes is exogenous, and in state-dependent models, firms choose when and by how much to change prices due to menu costs (Klenow and Kryvtsov (2008)). In this paper, quantum price stickiness is interpreted as closer to state-dependent pricing, because firms decide how to change prices given quantum prices, or how to introduce a new quantum price. But still it suggests a new form of menu cost, namely the cost of introducing a new price. For evience on price stickiness in retail see, for example, Mankiw (1985); Levy, Bergen, Dutta, and Venable (1997); Blinder, Canetti, Lebow, and Rudd (1998); Nakamura and Steinsson (2008); Klenow and Malin (2010); Kehoe and Midrigan (2015); Gorodnichenko and Talavera (2017); Cavallo (2018).

²⁸We have found anecdotal evidence of comparable pricing practices in electronics, personal care products, and services such as cable, phone, hotels, insurance, and financial services. We have not seen similar behaviors in perishables, fuel, education, and health care. Still, the macroeconomic implications obviously depend on how prevalent quantum prices are in each of these sectors and also at the aggregate level.

7.1 Product mix and inflation measurement

Inflation in the U.S. and the U.K. has been hovering around 2%, and input prices often experience large price swings.²⁹ Although we lack unit costs in the data, it is reasonable to assume that cost shocks are expected, to some degree, to impact final prices. And we have documented that a fraction of fashion retailers tend to use existing prices for product introductions. Therefore, one might ask, how retailers adjust their average prices with a constrained price grid.

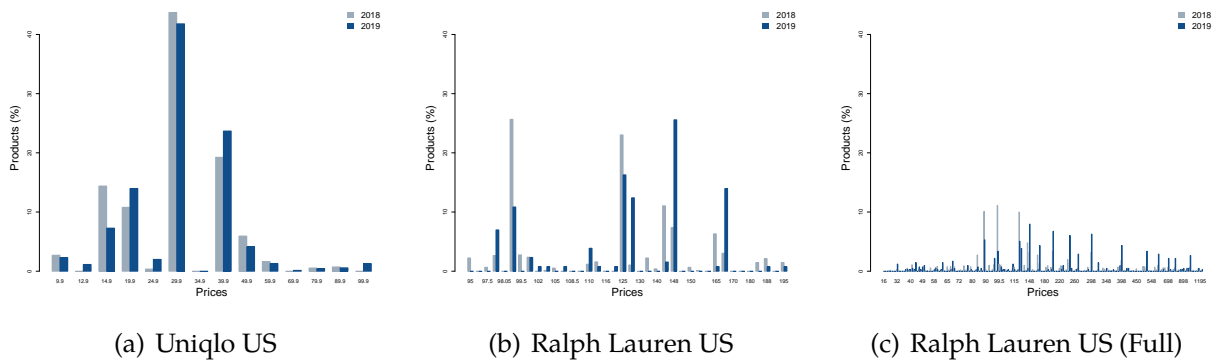


Figure 8: Price adjustment

Notes: Panels (a) and (b) show the price distribution of the same categories and time periods in Uniqlo U.S. and Ralph Lauren U.S., respectively. The bars sum up to 100% each year. Data from the same month is used across the two years to account for seasonality. Results are similar using different months or years.

We focus on a case study using two stylized retailers: Uniqlo and Ralph Lauren. Panel (a) in Figure 8 compares the prices observed in Uniqlo U.S. between the same categories over two years (same month). Uniqlo, which is characterized by strong measures of price clustering (Table 4), appears to adjust prices by changing shares of products in the existing prices. In fact, quantum prices are so sticky that over 90% of the change in the price distribution occurs via modifying the product shares in the old prices. This evidence is consistent with the advertising model that predicts, in price advertisers or price-sensitive retailers, large and discrete price jumps for product introductions.

On the other hand, in Panel (b) showing Ralph Lauren U.S., prices are spread out across many points in a price grid. In fact, the price range showed is restricted for comparison purposes; the entire price distribution is significantly wider (Panel (c)). This is consistent with retailers which serve both price- and quality- sensitive consumers, and thus implement

²⁹For example, cotton prices increased 20% year-on-year as of April 2018. But then prices decreased 26% year-on-year as of July 2019. See [Financial Times \(2018\)](#); [Bloomberg \(2018, 2019\)](#).

different labels or quality ladders to appeal aspirational entry-level consumers at lower price points, as well luxury- or status- seeking consumers at very high prices (Moon, Herman, Kussmann, Penick, and Wojewoda (2004); Han, Nunes, and Drèze (2010); Kapferer and Bastien (2012)). In this example, changes in the price distribution are more evenly split between shares in the same prices and new price buckets (close to 50% each).

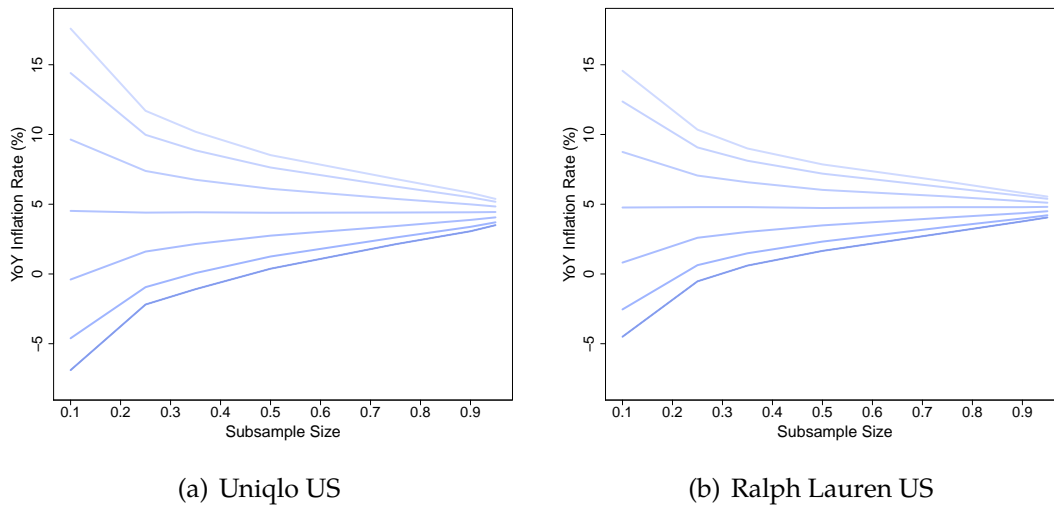


Figure 9: Measuring inflation

Notes: Panels (a) and (b) show the estimated inflation rates in Uniqlo US and Ralph Lauren US, respectively, obtained through simulating an increasing percent of sampled products. Products are sampled with no replacement. Each specification is repeated 10,000 times. Lines denote the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentile of the inflation estimate. For instance, the top line denotes the 95th percentile of the distribution of inflation rate estimates across each subsample size.

For the computation of the aggregate inflation instead of using the full distribution from Ralph Lauren we use a much tighter set (Panel (b)). Notice that the price distribution in Uniqlo expands prices from 9.9 to 99.9 (so a tenfold increase) while the smaller set from Ralph Lauren expands from 95 to 195. A smaller relative spread, but similar nominal spread. Even though both distributions are about 100 dollars wide, Uniqlo has significantly less possible prices than Ralph Lauren. These lumpy distributions introduce a friction that affects the sampling error when measuring inflation. For concreteness in the exposition, we focus on the two stylized retailers. We begin by observing that, year on year, both retailers exhibit an approximately 5% inflation rate in a relatively similar price range. Since products tend to have a short life, the inflation rate is computed using average prices (Aparicio and Cavallo (2017)). Suppose we sample a given percent of products, how does quantum prices affect the computation of inflation?

We find that the existence of price clusters leads to a significantly larger noise and wider range of inflation estimates. In other words, a representative subsample requires a larger number of products to obtain a sensible inflation rate. The reason is that when prices are distributed continuously many prices can change by a small amount, and therefore the average inflation does not require to collect many of those individual prices. However, when the store follows a quantum strategy, the distribution becomes more discrete, and sampled observations will either have zero or large inflation.

We compute the inflation rate using a sample of 10% to 95% of the products. We then obtain the percentiles of the distribution in each of the sample specifications. Although both retailers exhibit a similar year-on-year inflation rate, price clusters introduce more noise and a wider range of inflation estimates. This effect is consistently observed across the ladder of sampling. For instance, with a subsample of 25%, the 10th- and 90th- percentile inflation rate is -2.2% and 11.7% in Uniqlo, compared to -0.5% and 10.2% in Ralph Lauren, respectively. The standard deviation in this specification is 31% larger with price clustering (4.3% compared to 3.2%, respectively). See Figure 9. Panels (a) and (b) show the inflation estimates in Uniqlo and Ralph Lauren, respectively.

7.1.1 Price advertisers

The observation about the changes in the price distribution can be extended to more retailers. We use data on all retailers for which we have one year of data and thus comparable seasons year-on-year. The change in the price distributions in each retailer-category is decomposed as follows. Let $w_{i,1}$ and $w_{i,2}$ denote the shares of products located in price i (no rounding) in time 1 and time 2, respectively. The change in the price distribution is decomposed into:

$$\sum_{i=p^{\min}}^{p^{\max}} |w_{i,2} - w_{i,1}| = \underbrace{\sum |w_{i,2} - w_{i,1}|_{w_1 \cap w_2 \neq \emptyset}}_{\text{shares of products in same prices}} + \underbrace{\sum |w_{i,2} - w_{i,1}|_{w_1 \cap w_2 = \emptyset}}_{\text{shares of products in different prices}} \quad (9)$$

The term in the left computes the sum of the absolute differences between the shares of products in the price buckets with observations in both periods. The term in the right computes the sum of the absolute differences located in prices that are observed in only one of the periods. We then compute the fraction that each term represents in the price change distribution. The measure is computed for all retailer-categories.

The median proportion of the shares in the same price bins is 0.6, and tends to be larger for price clustered and price advertiser retailers. Figure 10 shows that the fraction of the change in prices through existing prices is significantly higher for retailers that price advertise. The mean share is 0.45 for non price advertiser retailers and 0.80 for price adver-

tisers.³⁰ Appendix A.20 shows the histogram of the proportion accounted for the left term in eq. (9).

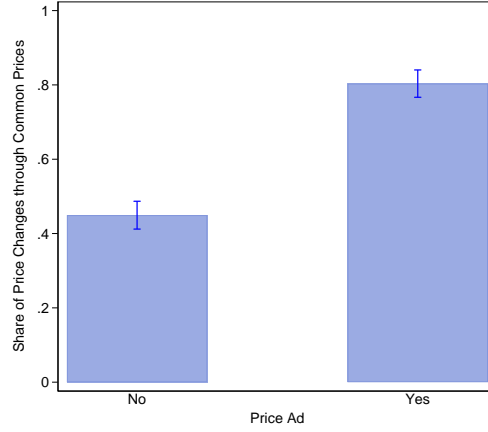


Figure 10: Changing product mix and price advertising

Notes: Shows the average change in the price distribution that comes through modifying shares of products in the old prices. The measure is first calculated for all retailer-categories and then the average is reported across price- and non price- advertiser retailers. Error bars are SEMs.

We propose a second measure of support in the distribution across periods. Similarly, $w_{i,1}$ and $w_{i,2}$ denote the shares of products located in price i (no rounding) in time 1 and time 2, respectively. The minimum support in the price distribution can be computed as:

$$\sum_{i=p^{\min}}^{p^{\max}} \min_w (w_{i,1} - w_{i,2}) \quad (10)$$

For every single price in the distribution of the retailer-category, we identify the minimum share of products located at that price (between the first and second period). For instance, if $w_{12.4,1} = 0.15$ and $w_{12.4,2} = 0$, then we obtain 0. We then sum these minimum shares across all possible prices. The results are similar to Figure 10. The average support for non price advertisers is 44% and for price advertisers it is 78%.

Pricing through product mix can be a source of lumpy price adjustments, i.e. either very small or very large. Appendix A.20 shows larger lumpy price adjustments for price

³⁰We also decompose the change in the average price between the 2017/2018 collections into the change in price for the products using common prices, and the change in price for products using different prices. We compute the absolute value of the sum of these two terms, and obtain the fraction accounted by each term. The mean and median of the share of the price change due to existing prices is 0.51 and 0.53, respectively. This measure is statistically higher for price advertiser retailers, i.e. the observed changes in the average prices is driven by the existing prices.

advertising retailers.³¹ Lumpy adjustments predict either 0 or economically large changes, which is what the Figure shows. For example, over 50% of the retailer-category pairs in price advertising retailers have exactly 0 change in the median price (compared to less than 20% for non-price advertising retailers). The average absolute change, conditional on being different from zero, is 21% and 13% for price and non-price advertisers, respectively.

7.2 Law of one price

One alternative for fashion retailers to reduce the frictions from quantum pricing is to design items to hit specific prices. The ability to learn costs and/or demand and modify assortments is an advantage that is often not feasible for traditional retailers that sell the same product lines over time. In fact, fast-fashion retailers are known to have short time-to-market and to efficiently manage inventories and styles within the season (Ghemawat, Nueno, and Dailey (2003); Caro and Gallien (2007, 2012); Caro and Martínez-de Albéniz (2015)).

However, multi-national retailers cannot perfectly produce for a specific quantum price. First, quantum prices are different across countries, and within a country prices are separated by non-trivial price increments. Second, there are exchange rate movements which implies that products will not be introduced at the targeted prices. And third, there are country-level taste differences. Therefore, despite lower price setting costs in fashion retail (i.e., products are new and price tags need to be printed), price clustering is expected to generate good-level deviations from the law of one price (LOP). The data allows to test for product-level LOP because each product has a unique ID which can be utilized to perfectly match the same product in the U.S. online store and the U.K. online store on the same day.

The implications in terms of LOP can be visualized in Figure 11. We focus on the stylized retailers Uniqlo and Ralph Lauren.³² In particular, we compute the percent of products assigned to each combination of U.S. dollars and U.K. prices. Darker regions indicate a larger share of products assigned to a given bucket. We pool all products throughout the collection period. The heatmaps can be related to the price distributions in Figure 8. Panel (a), which corresponds to Uniqlo, depicts large and discrete price increments between prices. In fact, a handful of buckets are enough to characterize Uniqlo's pricing across countries. In contrast, Ralph Lauren in Panel (b) exhibits a richer range of prices to accommodate exchange rate and taste changes.

³¹We calculate the change in the median price, in absolute value, in the same retailer-category, the same month (hence season), between two consecutive years. Similar results are obtained computing the median price change between product replacements. Replacements are matched using the closest introduction in terms of price.

³²Overall, using data from all retailers, we find large good-level deviations from the LOP. The mean absolute good-level deviation is 0.20 log points. We also find that products introduced in the first price bucket in each retailer-category in the U.S. are in general not priced in similar price buckets in the U.K. See Appendix A.21.

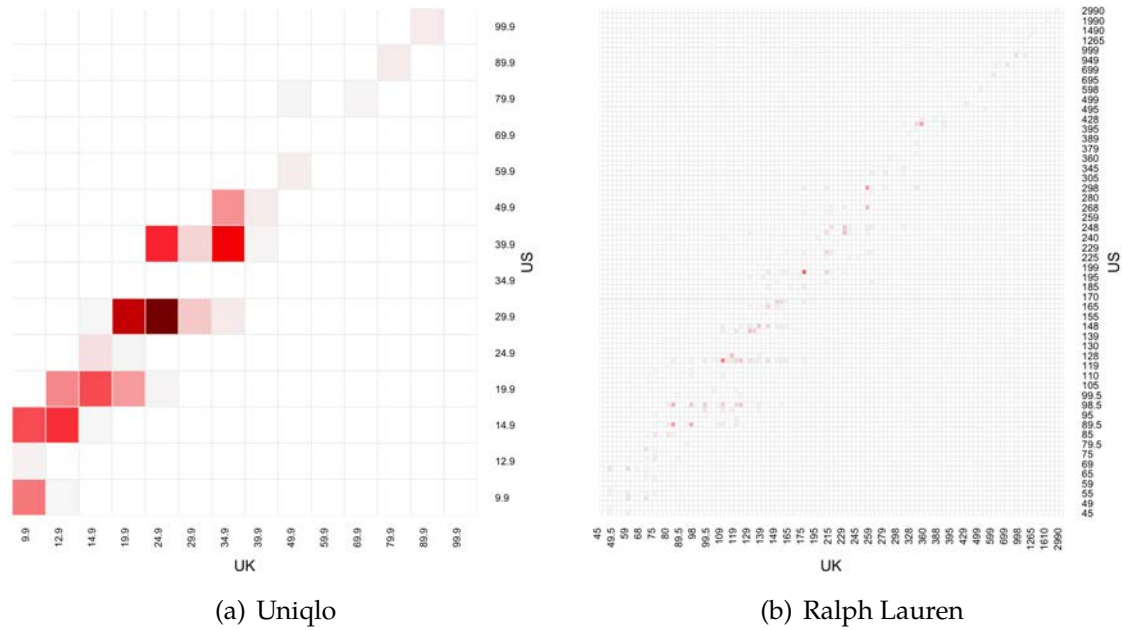


Figure 11: Law of One Price

Notes: Panels (a) and (b) show a heatmap that represents the proportion of matched products allocated in each combination of U.S. dollars and U.K. pounds. In both panels the color key goes from the same range of 0% to 20% of products. Darker regions indicate larger proportion of products in a price bucket.

Finally, we quantify these intuitions by running a fixed-effects regression of relative prices and evaluating the residuals. In particular, we regress $Relative_{i,t} = \alpha + \gamma_t + \epsilon_{i,t}$, where $Relative_{i,t}$ denotes p_{UK}/p_{US} (the product-level ratio of U.K. and U.S. price). Monthly fixed effects are included to control for exchange rate movements. Confirming our visual impressions in Figures 8 and 11, quantum pricing relates to large deviations from the law of one price. The MSE is 67.8% larger in Uniqlo’s, compared to Ralph Lauren’s case.

8 Conclusions

This paper used a novel dataset with over 350,000 different products from over 65 retailers in the U.S. and the U.K. to study pricing strategies in the fashion retail industry. The data collection combines three pieces that are rarely available together: (i) a large scale cross-section of products that are representative of the heterogeneity in the sector; (ii) a time-series of collections; and (iii) thousands of matched products across countries.

We show evidence that a fraction of retailers practice what we define as quantum prices: prices that are sparse, clustered, far apart from each other, and assigned to large and diverse assortments. Price clustering can be articulated as an optimal pricing strategy to

increase advertising effectiveness. This form of pricing represents a remarkable source of price stickiness, suggesting a menu cost to introducing new prices, which has implications for product introductions, lumpy price adjustments, inflation measurement, and international pricing frictions.

There are additional implications not analyzed in this paper, which we view as interesting areas of research. The fact that products are introduced at sticky prices suggests that retailers might nonetheless redesign product attributes to target specific prices. A body of literature in marketing and operations highlights the retailers' ability to optimize assortments via learning demand (Caro and Gallien (2007, 2010); Cachon and Swinney (2011)). However, learning the optimal price distribution has received little attention. Future research should explore relationships with cost shocks, differences across industries, product line design, and consumer decisions.

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A Appendix

A.1 Retailers

Table 9: List of Retailers

US	UK
Abercrombie, Adidas, Aeropostale, All Saints, American Eagle Ann Taylor, Aritzia, Armani, Banana Republic, Benetton, Bonobos, Brooks Brothers, Burberry, Calvin Klein, Club Monaco, Coach, Dolce Gabana, Dr Martens, Eddie Bauer, Express, Fendi, Forever, Free People, Gap, Gucci, Guess, Hermes, Hollister, JCrew, Kenneth Cole, Lacoste, Levi's, Louis Vuitton, Massimo Dutti, Michael Kors, Nike, Old Navy, Penguin, Primark, Ralph Lauren, Reitmans, Scotch and Soda, Other Stories, Talbots, TJMaxx, Tommy Hilfiger, Ugg, Uniqlo, Urban Outfitters, Vans, Versace, Victoria Secret, Walmart, Zara	Adidas, All Saints, Armani, Benetton, Bershka, Burberry, Calvin Klein, Coach, Dior, Dolce Gabana, Esprit, Forever, Forever 21, Free People, Gucci, Hermes, H&M, Kiabi, Lacoste, Levi's, Louis Vuitton, Mango, Marks and Spencer, Massimo Dutti, Next, Nike, Oysho, Primark, Pull and Bear, Ralph Lauren, Reiss, Scotch and Soda, Stradivarius, Tommy Hilfiger, Uniqlo, Urban Outfitters, Uterque, Vans, Versace, Zara

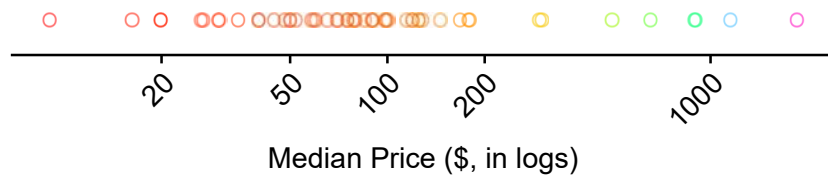


Figure 12: Retailers in a price line

Notes: For each retailer in the U.S. we compute the median price of the cross-section of distinct items. This diagram reflects the range of prices covered in the data.

A.2 Algorithm to classify products into categories

We categorize products using decision trees for classification. For a review see [Friedman, Hastie, and Tibshirani \(2001\)](#). The core objective is to provide a consistent approach to categorize products across retailers and across collections (over time) such that when new data is collected, the same classifier (or a slight improvement of it, after training with new data) can be used to assign products into the existing categories.

The classifier takes two main features: the description of the product and the retailer-specific category-related tags, both of which are retrieved from the HTML code of the website. The classifier takes the words contained in both elements and, based on a user-defined hierarchy and word frequency, it assigns products into twelve categories (and an ‘unclassified’ group). The hierarchy is important because if some items are collected next to a ‘sandals’ category HTML tag, then these products are very likely to be Shoes. The frequency is relevant because it takes into account that similar items should be categorized in the same group. For example, items that are solely described as ‘denim’ are more likely to be jeans, and therefore will be assigned to the Bottoms category.

The classifier raises a flag when the price of the item is disproportionately different from what we expect in the category, or when many similar items are not being categorized, and the decision tree is fine-tuned to start classification over. In addition, random samples of the data in each retailer are manually observed to verify that the categories assign in fact correspond to those products.

It is useful to note that the main clustering results are not sensitive to classification errors. In fact, if anything, classification errors present lower bounds to price clustering (precisely because a misclassified product will likely introduce a price-off the distribution of prices in the category). Moreover, the categories are relatively broad, which also means that price clustering would be higher under narrower categories.³³ Moreover, the main results of the paper are found using random portions of the data or random subsets of retailers.

In order to obtain a gauge a sense of accuracy, we sample random items from several retailers (100 each), which corresponds to close to 10% of the distinct retailers. We obtain an error rate of 96.2%. This magnitude can be interpreted as follows. For every 100 random items in the sample, close to four products have been assigned to the wrong category. For example, a short sleeve vest that has been classified as ‘Tees’.

³³However, also note that too narrowly defined categories will present a barrier to comparing products across retailers. For instance, if firm *A* sells backpacks and firm *B* sells totes, having those as separate categories will prevent us from comparing pricing behaviors across retailers for these set of items, even though they are very similar.

A.3 Retailer-Level Probability

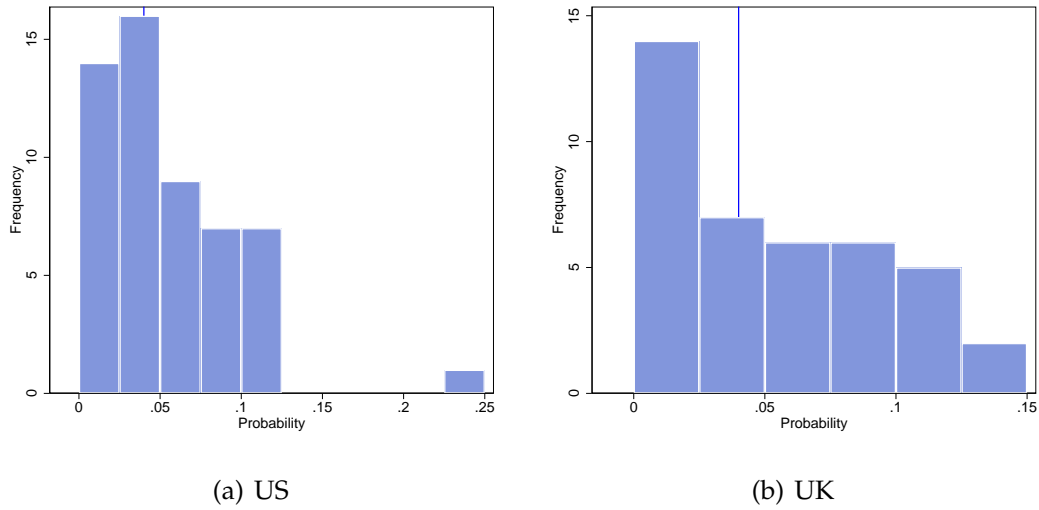


Figure 13: Probability that items have the same price

Notes: Histogram of the probability that two items, from any category in the same retailer, have the same price. Probability calculated at the retailer level. Vertical line depicts median probability.

A.4 Dispersion in Retailer-Category Probability

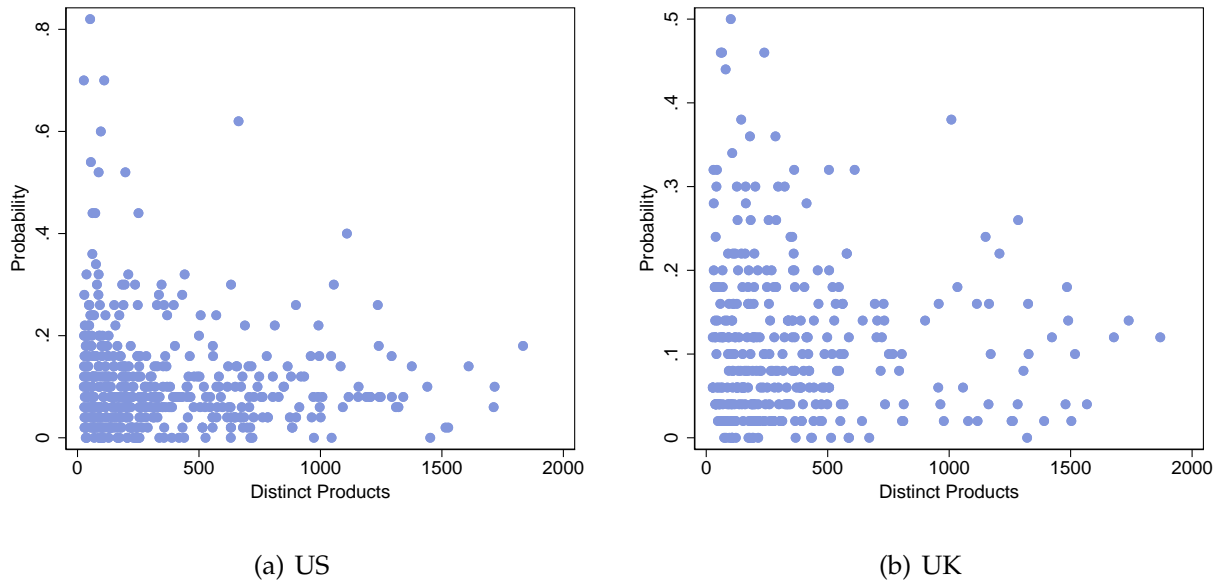


Figure 14: Probabilities of same price and distinct products

Notes: Relationship between the probability that two items in the retailer-category have the same price and the number of distinct products. The number of products is restricted to 2,000 for better visualization.

A.5 Normalized Clustering Using Different Benchmarks

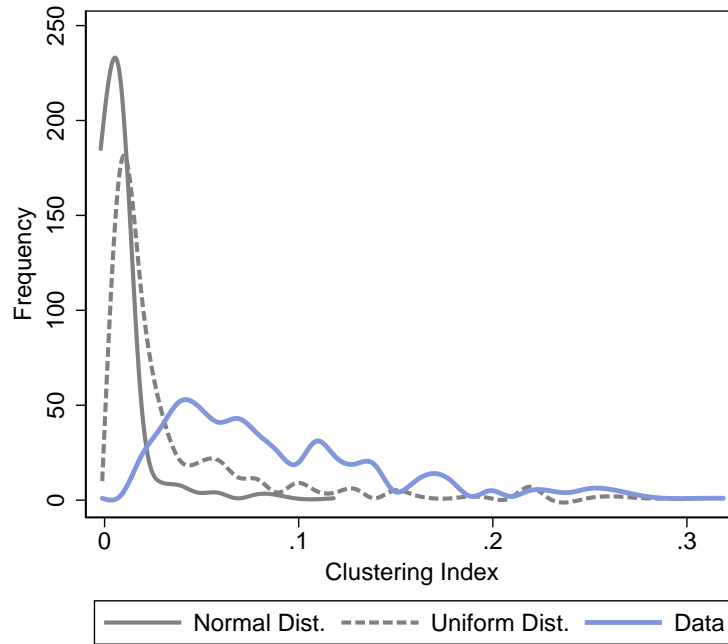


Figure 15: Normalized clustering against pricing benchmarks

Notes: We compute normalized clustering indices following equation (1). We compare the retailer-category level indices in the data with those that would be generated if prices were drawn from a Normal or Uniform distribution. Prices from the Normal distribution are rounded to the nearest integer. Prices from the Uniform distribution are rounded to the nearest integer multiple of ten. This conservatively assumes that firms can only price in 10-dollar increments.

A.6 Normalized Clustering Relative to Normal Distribution

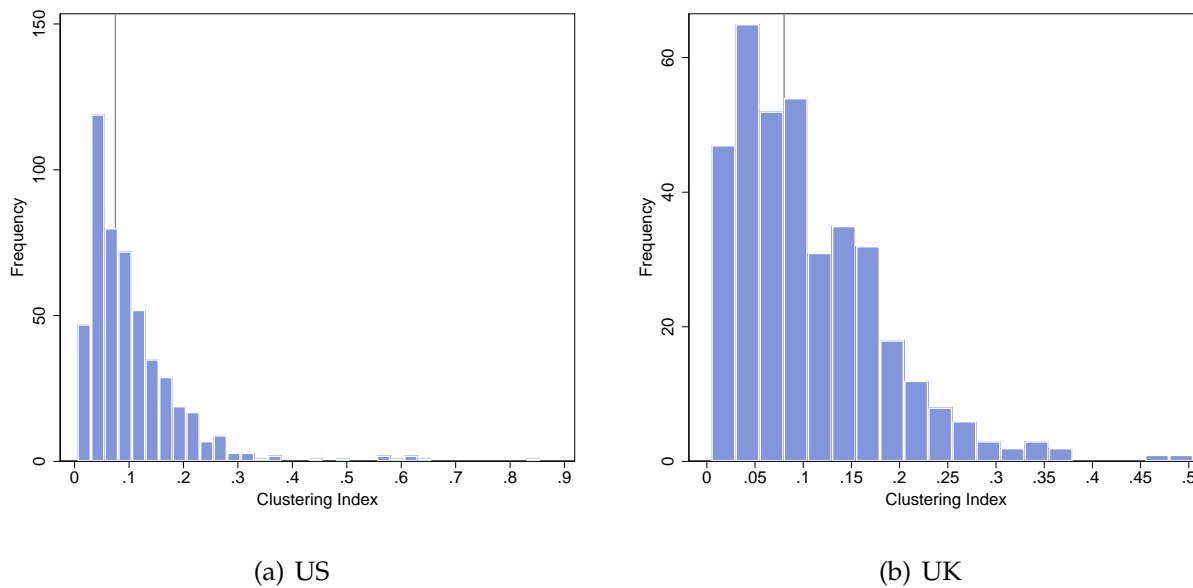


Figure 16: Normalized price clustering relative to a Normal distribution

A.7 Normalized Clustering with Price Endings

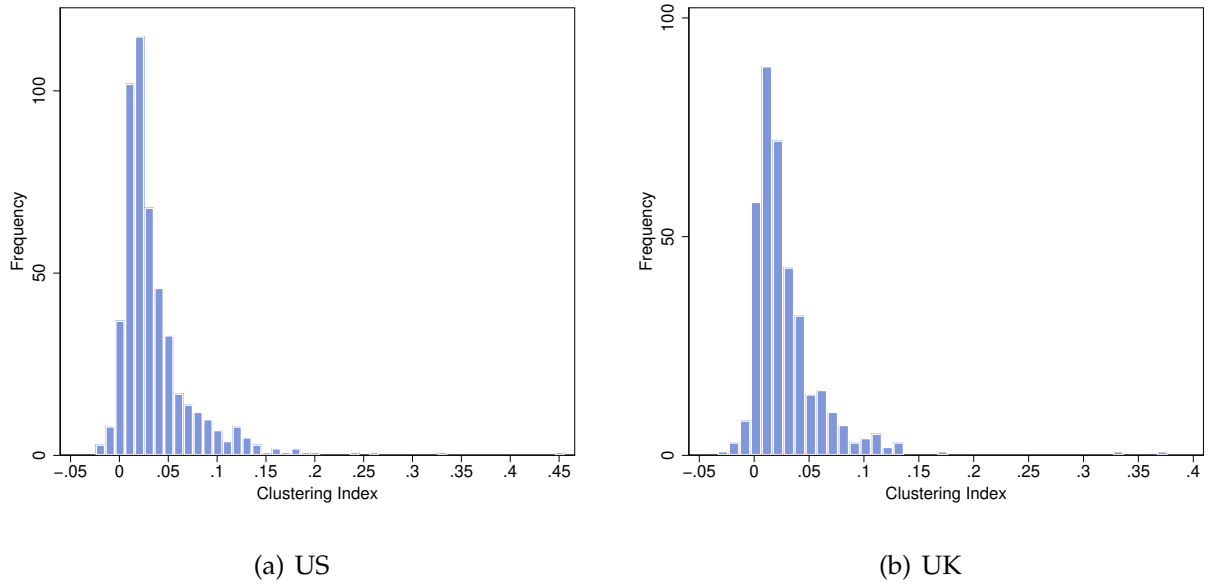


Figure 17: Normalized price clustering

Notes: Histogram of the normalized measure of price clustering that controls for prices, price levels, popular prices, and last digits. Details in the main text.

A.8 Price Endings

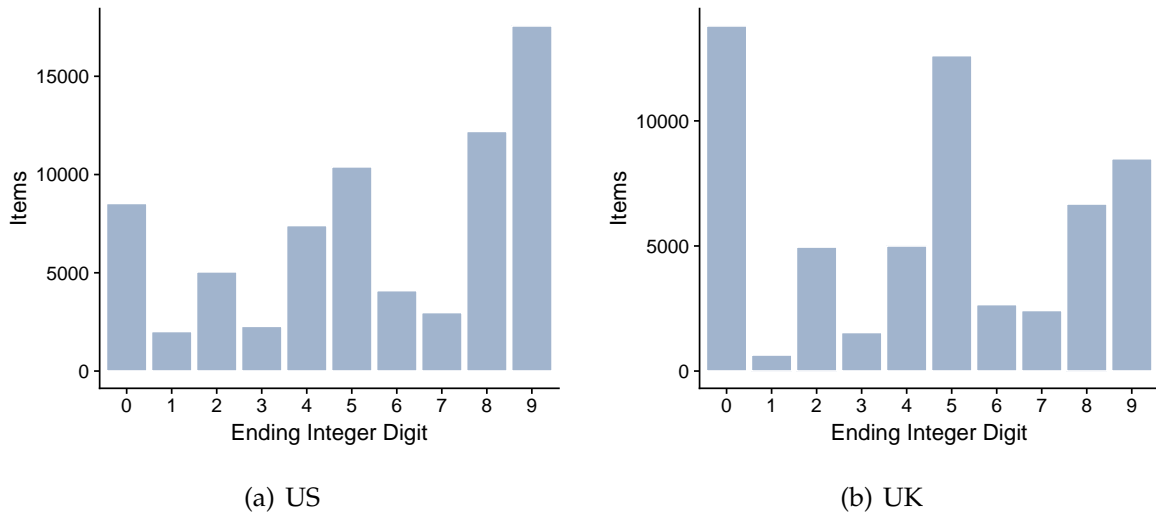


Figure 18: Price endings

Notes: Number of distinct items priced at each ending integer digit.

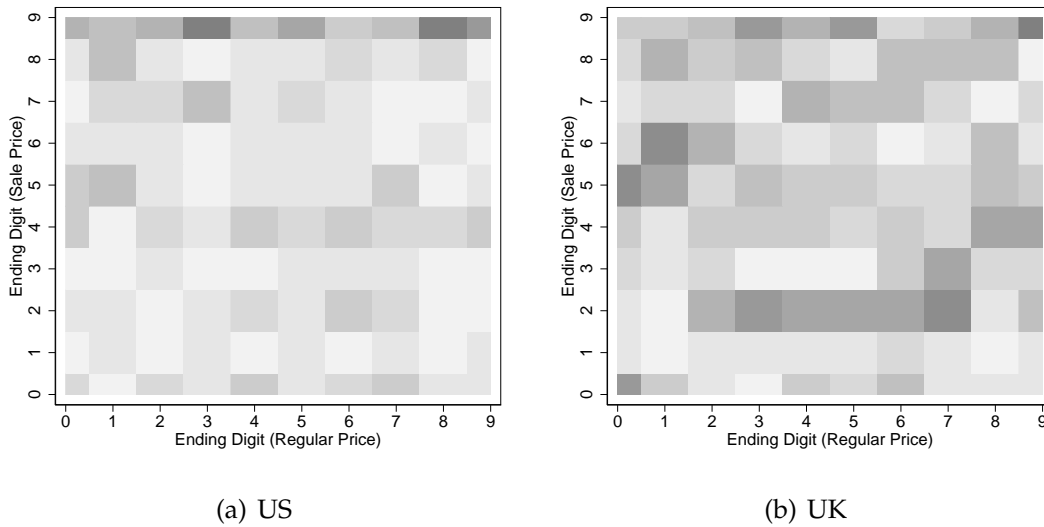


Figure 19: Price endings in regular and sale prices

Notes: Heatmap of the relationship between items at each ending integer digit in regular prices and sale prices.

A.9 Correlated Clustering: Within-Retailer, Across-Categories

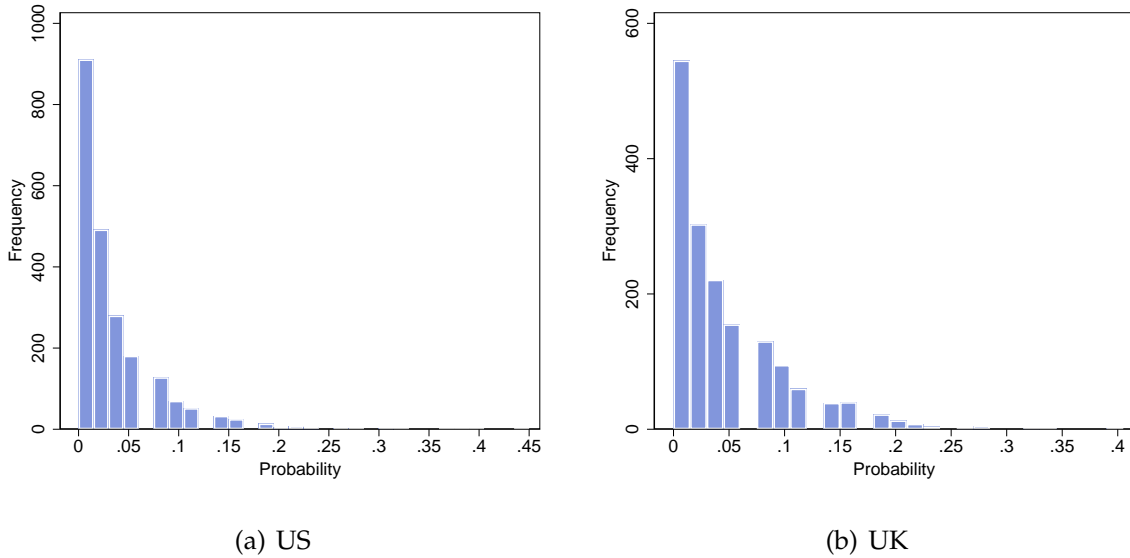


Figure 20: Probability of same price within-retailer and across-category

Notes: Histogram of the probability that two items from two different categories in the same retailer have the same price. Probability computed from each category pair within a retailer.

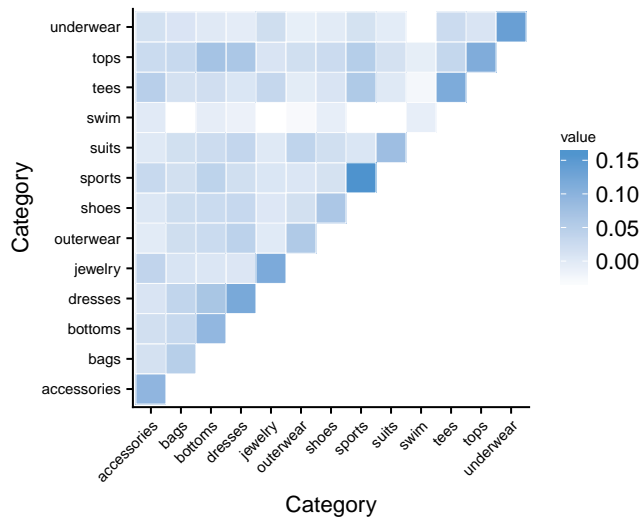


Figure 21: Same prices across categories

Notes: We compute the average of the correlated clustering measure at the category-category level across retailers in the U.S. Darker regions indicate different categories that have shares of products at the same prices.

A.10 Correlated Clustering: Across-Retailers, Within-Category

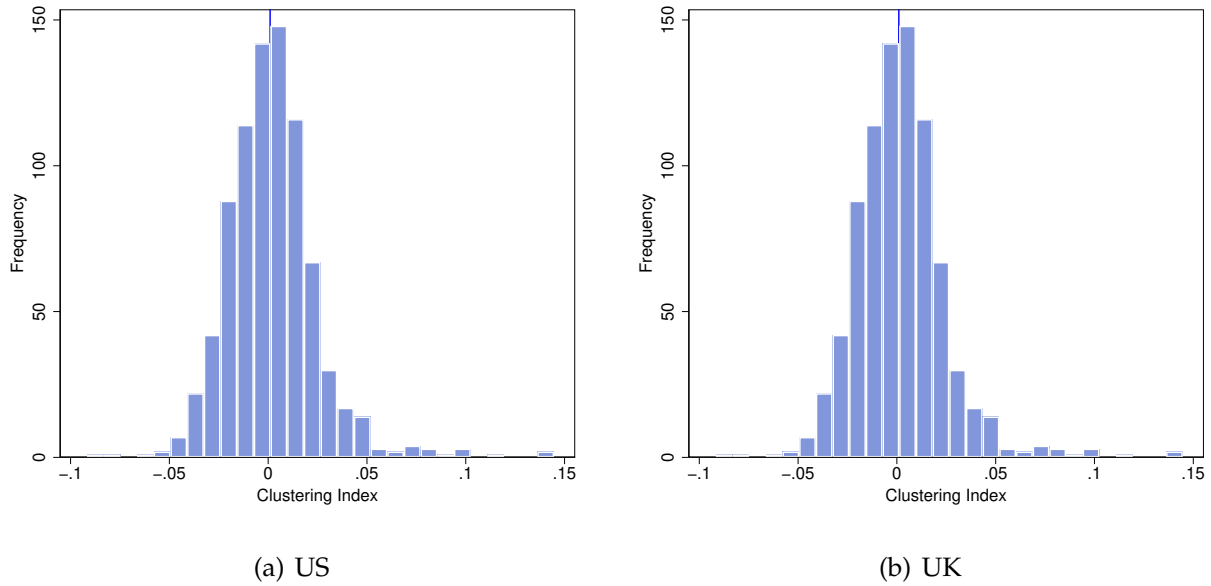


Figure 22: Normalized correlated clustering across retailers

Notes: Histogram of the normalized correlated price clustering measure. The statistic is calculated within-category for each retailer-retailer pair. For computational reasons the results are based on a random half of the retailers. Vertical line depicts the median clustering estimate. Overall there is no evidence that retailers are using the same prices for similar items.

A.11 Scope of Clustering

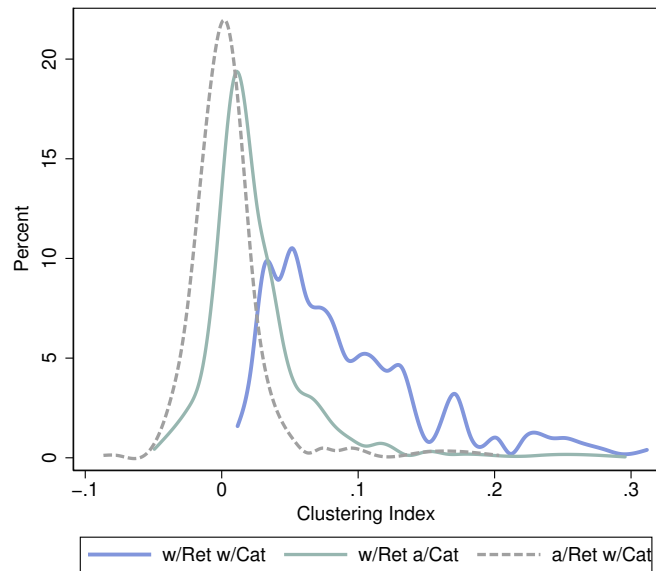


Figure 23: Scope of price clustering

Notes: Histogram overlapping the baseline clustering measure at the three levels: within a retailer category; across categories within retailer; and across retailers within category.

A.12 Robustness: ML clustering

We first motivate the analysis implementing the GAP statistic (Tibshirani, Walther, and Hastie (2001)). This method compares the within-cluster variation to the within-cluster variation that one would observe if points were uniformly distributed. In addition to having a relevant name for fashion retail, the statistic has the benefit of potentially estimating one cluster in the data. But interestingly, price points in the price distribution are so dispersed that the method tends to estimate $k_i^* = \#\{b_i\}$, that is, the optimal number of clusters k^* is found to be equal to the number of distinct prices in each retailer-category.

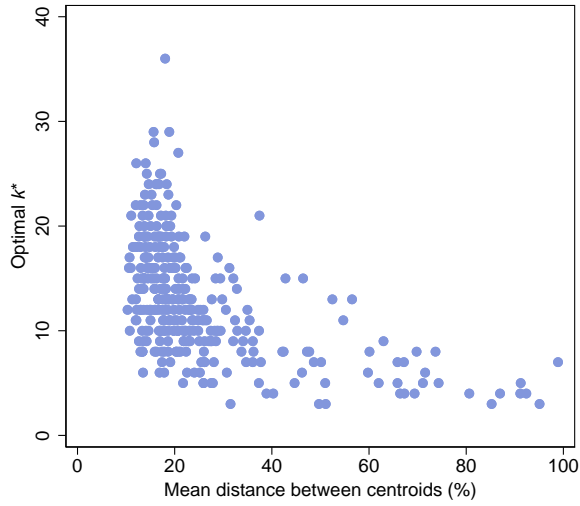
To avoid this problem we define a clustering index borrowing ideas from the k -means literature (for a review see Friedman, Hastie, and Tibshirani (2001)) and from the CH index (Caliński and Harabasz (1974)). First, we normalize prices in each retailer-category dividing prices by the median price. Second, we run the k -means algorithm to find the optimal k^* clusters; where $k \in \{1, \dots, \#b\}$, i.e. k could be as large as the number of prices. We take the estimated clusters, and compute the average within cluster absolute distance, $\overline{WC}(n_k, k)$, and the average between cluster absolute distance, $\overline{BC}(k)$.

We define the ratio $\kappa(k) \equiv \frac{\overline{WC}(n_k, k)}{\overline{BC}(k)}$. Both the numerator and the denominator decrease for each additional cluster. But because the price clustering problem is univariate, and will select as many clusters as prices are in the data, for each k we compute the minimum between-cluster percent distance, $d^{min}(k) \equiv \min_i \left\{ \left(\frac{centroid_i(k)}{centroid_{i-1}(k)} - 1 \right), \forall i \in (2, \dots, k) \right\}$. We ignore ratios $\kappa(k)$ for which $d^{min}(k) < 5\%$, and set the optimal k^* as the corresponding k to the smallest ratio of the surviving ones. That is, $k^* = \min_{\kappa} \{\kappa(2), \dots, \kappa(\hat{k})\}$, where \hat{k} is the maximum k such that its distance with the previous cluster $k - 1$ is at least 5%.

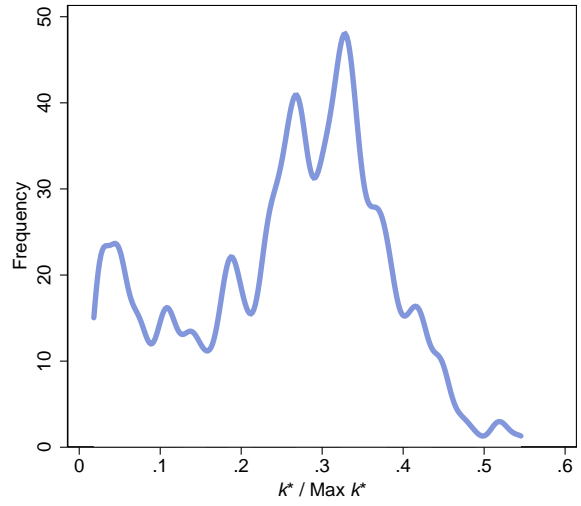
Intuitively, this approach provides two advantages. First, it determines the optimal number of price clusters in the data, where optimal refers to the traditional ratio of within-cluster dispersion to between-cluster dispersion. And second, the optimal clusters are constrained to have a meaningful difference in economic terms. For example, if we observed items at \$58 and \$59 we would like to consider these as belonging to a same cluster of price buckets.³⁴

Figure 24 shows the results for the U.K. Results for the U.S. are shown in Figure 5 in the main text.

³⁴We also measured clustering borrowing the concept of largest uniform spacings (Devroye (1981)). The index is defined as the ratio of the sum of k -th largest spacings (price differentials) and the sum that would be expected under a uniform distribution. Ratios above 1 would suggest price clustering. Again we find a large number of retailer-categories with significantly large price clustering. Results not shown.



(a) UK

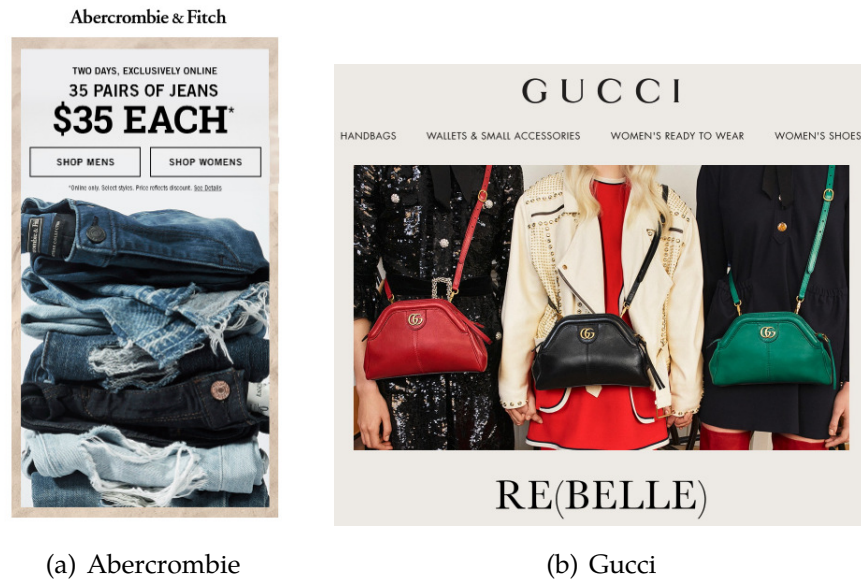


(b) UK

Figure 24: Optimal number of price clusters in the data

Notes: Results from the unsupervised machine learning approach to estimate price clusters in the data. Results for the U.K. are similar to those in the U.S. (Figure 5). Consistent with previous analyses, there is substantial price concentration, and concentration takes place in clusters that have economically meaningful price differences. See Section 4.4 for additional details.

A.13 Advertising Examples



(a) Abercrombie

(b) Gucci

Figure 25: Advertising examples

Notes: Examples from digital newsletters. Panels (a) and (b) show newsletters with and without price advertising, respectively.

A.14 Convenient Prices and Demand Uncertainty

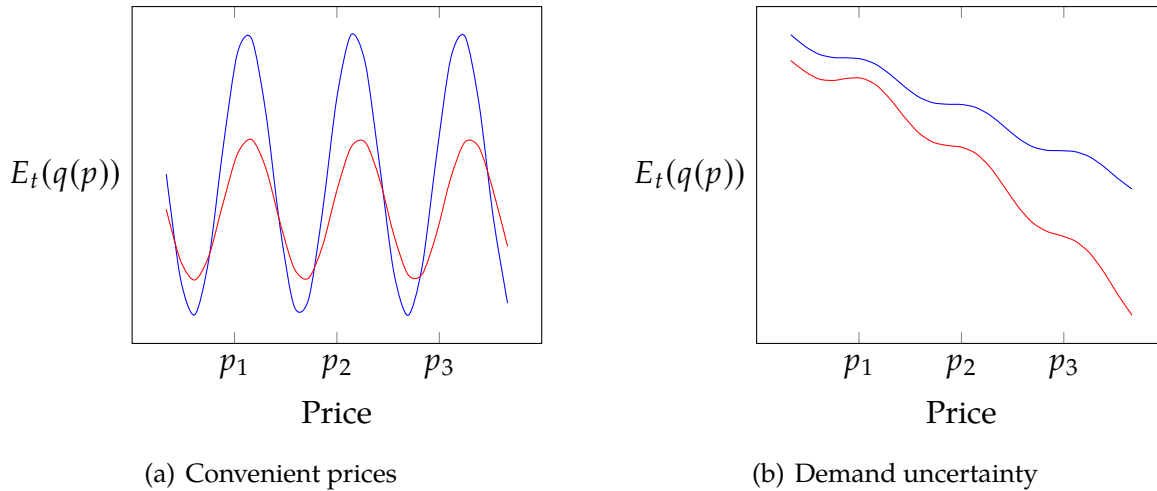


Figure 26: Price clustering due to convenient prices or demand uncertainty

Notes: Panel (a) shows demand kinks at certain convenient prices for two different products. A model following [Knotek \(2008\)](#) would generate clustering at better prices or price endings. This is consistent with some retailers whose clustering is driven by digit endings. Panel (b) shows the expected demand curves for two different products in the same category. Following [Ilut, Valchev, and Vincent \(2016\)](#), a retailer that is averse to experimenting with new prices will update its beliefs based on the three observed prices. This generates kinks in the expected profits which induces the retailer to choose the same prices for different products or for new products.

A.15 Advertising effectiveness

A.15.1 Result 1

Consumers are price-sensitive ($\lambda = 1$) and uninformed ($\gamma_{ps} = 0$). Thus the retailer advertises prices and products to attract price-sensitive consumers ($A \geq 2$). We solve for the optimal prices in three cases: (a) a single product; (b) two products at different prices; (c) two products at the same price. Consider $g(A) = \omega A^2$. When advertising is costly, the firm is better off in scenario (c): produces two products and clusters prices.

In case (a), the firm maximizes profits, $\Pi(p_1) = (p_1 - c_1) * ((1 - \gamma_{ps})1(i = 1 \in A)) * (1 - b_{ps}p_1) - \omega A^2$. Then, $p_1^* = 1/2(1/b_{ps} + c_1)$. Profits evaluated at the optimal price are, $\Pi(p_1^*) = (1/2)(1/b_{ps} - c_1) * (1/2 - b_{ps}c_1/2) - \omega A^2$.

In case (b), the problem is to $\max_{p_1, p_2} \Pi(p_1, p_2) = (p_1 - c_1) * ((1 - \gamma_{ps})1(i = 1 \in A)) * (1 - b_{ps}p_1) + (p_2 - c_2) * ((1 - \gamma_{ps})1(i = 2 \in A)) * (1 - b_{ps}p_2) - \omega A^2$. We obtain $p_1^* = 1/2(1/b_{ps} + c_1)$ and $p_2^* = 1/2(1/b_{ps} + c_2)$. Therefore, $\Pi(p_1^*, p_2^*) = (1/2)(1/b_{ps} - c_1) * (1/2 - b_{ps}c_1/2) + (1/2)(1/b_{ps} - c_2) * (1/2 - b_{ps}c_2/2) - \omega A^2$.

In case (c), the problem is to $\max_p \Pi(p) = (p - c_1) * ((1 - \gamma_{ps})1(i = 1 \in A)) * (1 - b_{ps}p) + (p - c_2) * ((1 - \gamma_{ps})1(i = 2 \in A)) * (1 - b_{ps}p) - \omega A^2$. We obtain $p^* = 1/2(1/b_{ps} + (c_1 + c_2)/2)$. Therefore, $\Pi(p^*) = (1/b_{ps} - (c_1 + c_2)/2) * (1/2 - b_{ps}(c_1 + c_2)/4) - \omega A^2$.

When advertising is sufficiently costly, $\Pi(p^*) > \Pi(p_1^*)$ and $\Pi(p^*) > \Pi(p_1^*, p_2^*)$. For example, evaluate at $c_1 = 0.2, c_2 = 0.3, b_{ps} = 0.25$. It is optimal for the firm to sell two products at the same price.

A.15.2 Result 2

There is an equal share of price- and quality- sensitive consumers ($\lambda = 0.5$); and both types are informed ($\gamma_{ps} = \gamma_{qs} = 1$). Therefore, advertising is useless ($A = 0$). We are interested in obtaining optimal prices for two cases: (a) two products at the same price; (b) two products at different prices. The firm is better off in scenario (b).

In case (b), the problem is $\max_{p_1, p_2} \Pi(p_1, p_2) = (p_1 - c_1) * \lambda * \gamma_{ps} * (1 - b_{ps}p_1) + (p_2 - c_2) * \lambda * \gamma_{qs} * (1 - b_{qs}p_2)$. Optimal prices are, $p_1^* = (1/2) * (1/b_{ps} + c_1)$ and $p_2^* = (1/2) * (1/b_{qs} + c_2)$. The firm produces a high-cost (high-quality) good to quality-sensitive consumers and a low-cost good to price-sensitive consumers. Profits in (b) are higher than what would be obtained selling two products at the same price. It is not optimal to cluster prices.

A.15.3 Result 3

Consumers are price-sensitive ($\lambda = 1$) and uninformed ($\gamma_{ps} = 0$). Therefore, the retailer must engage in advertising to reach consumers. And it sells one product in two periods, and these

products are different. The firm considers three cases: (a) advertises in $t = 1$ and not in $t = 2$; (b) advertises different prices in each period; (c) advertises the same price in $t = 1$ and $t = 2$.

Assume no present value discounting. In case (a), the problem is $\max_{p_1, p_2} r(p - c_1) * (1 - b_1 p_1) + (r\alpha)(p_2 - c_2) * (1 - b_2 p_2)$, where subscripts denote time t . We obtain prices $p_t = (1/2)(1/b_t + c_t b_t)$. Profits are $\Pi^a = r(1/2b - c_1/2) * (1/2 - c_1 b/2) + (r\alpha) * (1/2b - c_2/2) * (1/2 - c_2 b/2) - \omega A^2$, where $A = 2$ because (x_1, p_1) are advertised one time at $t = 1$. For simplicity b_t is the same in both periods.³⁵

In case (b), the problem is $\max_{p_1, p_2} r(p - c_1) * (1 - b_1 p_1) + (r)(p_2 - c_2) * (1 - b_2 p_2)$. Optimal prices are the same as (a). Profits are $\Pi^b = r(1/2b - c_1/2) * (1/2 - c_1 b/2) + (r) * (1/2b - c_2/2) * (1/2 - c_2 b/2) - \omega A^2$, where $A = 4$ because advertises attributes (x_t, p_t) in both periods. Note that, in $t = 2$, firm reaches the same fraction r of the uninformed.

In case (c), we solve for the same price in two periods, namely $\max_p r(p - c_1) * (1 - b_1 p) + (r\alpha(1 - \beta) + \beta)(p - c_2) * (1 - b_2 p)$. We obtain $p^* = [r(1 + b c_1) + (r\alpha(1 - \beta) + \beta)(1 + b c_2)] [2b(r + r\alpha(1 - \beta) + \beta)]^{-1}$. And profits are $\Pi(p^*) = r(p^* - c_1) * (1 - b_1 p^*) + (r\alpha(1 - \beta) + \beta)(p^* - c_2) * (1 - b_2 p^*) - \omega A^2$, where $A = 4$ as case (b).

The intuitions are as follows. When advertising is costly (large ω) and the rate of recall loss is small (large α), the retailer advertises in the first period to reach uninformed consumers and sets optimal prices in each period (case (a)). When advertising is not too costly and initial recall is large enough (r), the retailer advertises optimal prices in each period (case (b)). But when recall loss is large and the advertising gains from sticky prices are large (β), it is optimal to use the same price for different products over time.

We note that in simulations case (b) tends to dominate cases (a) and (c). This is expected because case (b) allows to flexibly adjust prices to cost shocks. However, sticky and clustered prices are expected to become more important once we include cross-section advertising efficiencies.

A.15.4 Result 4

Consumers are price-sensitive ($\lambda = 1$) and uninformed ($\gamma_{ps} = 0$). In the first period, c_1, c_2 , and advertising cost ω are such that is it optimal to set two different prices as opposed to clustered prices. Profits with different prices are $\Pi^{t_1}(p_1^*, p_2^*) = (r/2) * [(1/b - c_1) * (1 - b c_1) + (1/b - c_2) * (1 - b c_2)] - \omega A^2$, where $A = 4$. Profits with clustered prices are $\Pi^{t_1}(p_1^* = p_2^*) = r [(1/2b + c_2/4 - c_1 3/4) * (1/2 + b(c_1 + c_2)/4)] + r [(1/2b + c_1/4 - c_2 3/4) * (1/2 + b(c_1 + c_2)/4)] - \omega A^2$, where $A = 3$. In $t = 1$, optimal prices yield $\Pi^{t_1}(p_1^*, p_2^*) > \Pi^{t_1}(p_1^* = p_2^*)$.

³⁵We could also imagine a demand curve that reacts to price changes, even if the products are different. For example, the uninformed fraction reached by the advertisement in $t = 1$ overreacts if prices are higher in $t = 2$: $q(p_2) = 1 - b p_2$ if $p_2 \leq p_1$, or $a - b p_2$ otherwise. See the discussion in Appendix A.15.5.

In the second period, the retailer sells a single new product. Suppose that the retailer did not anticipated higher costs, and that $c_1 < c_3 < c_2$. Thus the frictionless price p_3 would be $p_1^{t_1^*} < p_3^{t_2^*} < p_2^{t_1^*}$. There are three cases: (a) sets a new optimal price and advertises accordingly; (b) uses the advertised price p_1 from $t = 1$; (c) uses the advertised price p_2 from $t = 1$.

In case (a), profits are $\Pi^{t_2}(p_3^*) = r/4b(1 - c_3)^2 - \omega A^2$. Cases (b) and (c) are similar in that the retailer takes advantage of the information gains from using advertised prices. Profits are $\Pi^{t_2}(p_3 = p_j^{t_1}) = r(r\alpha(1 - \beta) + \beta) * (p_j - c_3) * (1 - bp_j) - \omega A^2$, for $j = 1, 2$. Even if c_3 increases, for a large range of parameters of advertising gains and costs, the retailer is better off deviating from the frictionless price and jumping to $p_2^{t_1^*}$. Note that if we include products from $t = 1$, there are more incentives (due to cross-section advertising effectiveness) to stick to advertised prices.

A.15.5 Additional discussion

The model can be extended in several dimensions. It allows to include the role of promotions or markdowns. Because price advertising increases price awareness, a sale price itself is informative (e.g., advertising sale prices, instead of percentage markdowns, are informative of the size of the discounts). In fact, we find that retailers that price advertise also tend to advertise sale prices.

It also allows to incorporate changes in price sensitivity. Because price advertising creates price point awareness, prices that are different to those expected by the consumer can trigger antagonism or price sensitivity. For example, price signs can form cues to recall past prices in the store (see [Bordalo, Gennaioli, and Shleifer \(2017\)](#) for recent work on memory and choice). Therefore, a demand curve could react to changes in prices, and this reaction could be larger for stores that advertise prices.

Finally, a richer model should include the role of unadvertised items; e.g. how price advertising and the price distribution affects the perception of non-advertised products. On the one hand, advertising low prices that are not representative can be judged as misleading and reduce repeat purchases, or anchor unadvertised higher-priced items as too expensive. On the other hand, advertising high prices can simply demotivate consumers from buying. See [Monroe \(1973\)](#); [Della Bitta, Monroe, and McGinnis \(1981\)](#); [Thaler \(1985\)](#); [Kalyanaram and Winer \(1995\)](#).

A.16 Price Changes in Apparel

We use a panel data of 51 retailers in the U.S. and 37 retailers in the U.K for which we have between 2 and 7 months of data. In order to more conservatively identify the same product over time, we re-define an ID as a unique retailer, category, product name, and HTML code combination.

Table 10: Product duration and price changes

		US	UK
Product duration^a			
(i)	Mean	3.1	3.3
(ii)	Median	3.1	3.3
Products with a price change (%)			
Regular price ^b			
(iii)	Mean	5.3	7.5
(iv)	Median	1.9	3.7
Sale price ^c			
(v)	Mean	69.1	57.6
(vi)	Median	74.4	58.1
Size of sale (%)			
(vii)	Mean ^d	38.7	41.8
(viii)	<i>p</i> 75 ^e	44.6	49.0

Notes: ^aProduct duration measured in months, calculated for retailer-categories with at least 3 months of data. ^bPercent of products for which we observed a price change in the regular price (between the last and first observation). ^cPercent of products for which we observed a sale. ^dMean size of markdown, conditional on a sale, and as percent of the regular price. ^e75th percentile size of markdown. The estimates assign equal weight to each retailer-category.

Table 10 shows statistics that are consistent with the folk wisdom about apparel. First, products are generally short lived. The mean product duration is 3.1 months in the U.S. and 3.2 months in the U.K. However there is large heterogeneity; over 10% of the goods in the U.S. have a duration of less than 2 months, and another 10% have mean duration over 5 months.³⁶ This suggests that a set of products would have exhibited longer duration if our

³⁶In order to account for censoring, the duration is computed for items that could have been observed for at least 3 months. The product duration goes up to 3.4 months conditional on items for which we have at least 4 months of data. The magnitudes found here are comparable to those in Cavallo, Neiman, and Rigobon (2014), who also use online prices for a longer time period from two retailers. For example, the authors find a mean duration of 12 weeks in H&M.

data collection had covered a longer time period. Figure 27 reports the histogram of average product duration across retailer-categories.

Second, there are asymmetric price changes. Only an average 5.3% of the products have a regular price change, whereas close to 70% of the products experience a sale price.^{37,38} Therefore regular prices are very sticky in apparel, and if we observe which types of items tend to experience price increases, these are a reduced subset of longer lived items (e.g., accessories, jewelry). That markdowns are frequent (lines (v) and (vi) in Table 10) is relevant to a discussion about the extent to which ignoring discounts can overstate the estimates of price change rigidity using regular prices (Bils and Klenow (2004); Nakamura and Steinsson (2008); Kehoe and Midrigan (2015)).

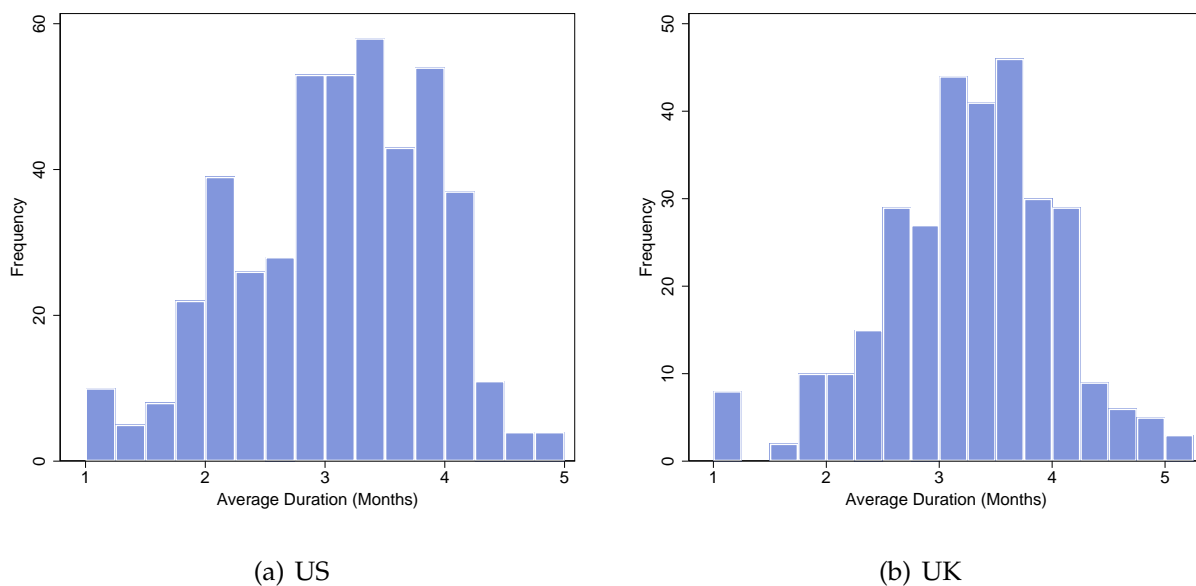


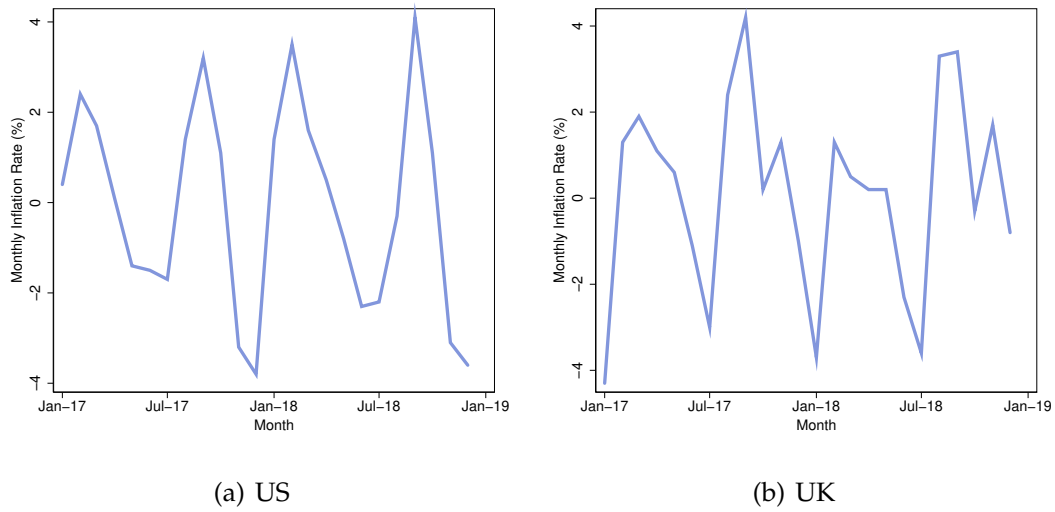
Figure 27: Histogram of average product life

Notes: Histogram of average product life in each retailer-category. Because the product duration is computed for items that could have been observed at least three months, this measure is right censored for products that should have been captured in a longer scraping period. The measure is particularly informative for the cases where the duration is shorter than five months.

³⁷These magnitudes are comparable to stickiness estimates in Nakamura and Steinsson (2008), who finds a median frequency of 3.6% price changes (excluding sales) and 87.1% of price changes due to sales, in the apparel sector.

³⁸There are a few caveats to comparing regular and sale prices which merit research on its own. Sale prices can be temporary, in which case we neglect price increases that take the form of prices reverting to the original regular price, although preliminary observations at the time of data collection suggest that this is not common. Sales behavior can be different online and offline (the latter which we do not capture). The large percentage of items on sale may not be observed in the offline stores for two reasons. It is not rare for retailers to apply online-exclusive offers. And some retailers deliberately move most of the sales to the online channel, and keep little markdowns in-store.

A.17 Inflation in Apparel



(a) US

(b) UK

Figure 28: Monthly inflation rate in apparel

Notes: Figure shows non-seasonally adjusted monthly inflation rates (%) in apparel. Obtained from the Bureau of Labor Statistics (U.S.) and Office for National Statistics (U.K.).

A.18 Prices Over Time

Table 11: Price stickiness (U.K.)

		<i>m</i> months after				
		<i>m</i> = 1	<i>m</i> = 2	<i>m</i> = 3	<i>m</i> = 4	<i>m</i> = 5
<i>Panel (A)</i>						
(i)	Share of common prices^a					
	<i>p</i> 10%	0.76	0.70	0.64	0.52	0.52
	Median	0.94	0.90	0.87	0.82	0.73
	Average	0.95	0.92	0.89	0.83	0.74
	<i>p</i> 90%	1	1	1	1	0.92
<i>Panel (B)</i>						
(ii)	Prob introducing a new good at existing prices^b					
	<i>p</i> 10%	0.67	0.55	0.54	0.50	0.68
	Median	0.98	0.97	0.97	0.94	0.91
	Average	0.97	0.94	0.94	0.93	0.92
	<i>p</i> 90%	1	1	1	1	1

Notes: Results are averages across retailer-categories in the U.K. ^aRatio of common prices (between the prices observed in the first month and month *m*) to the prices in month *m*. ^bProbability that the price of a product introduction in month *m* was among the observed prices in the first month.

A.19 Introduction Price and Price Clustering

Table 12: Predictors of quantum stickiness

VARIABLES	(1)	(2)	(3)
	<i>prob.</i>	<i>prob.</i>	<i>prob.</i>
Probability of product introduction at existing price			
Cluster index ^a	0.476*	0.454*	0.449*
	(0.243)	(0.234)	(0.237)
Price ad		0.0441**	
		(0.0198)	
Fast fashion			0.0652***
			(0.0198)
log (<i>N</i>)	YES	YES	YES
Country FE	YES	YES	YES
Cat. FE	YES	YES	YES
Observations	782	782	782
<i>R</i> ²	0.234	0.247	0.255

Notes: ^aNormalized clustered index that controls for popular prices, price ranges, digit endings, and number of products. Price advertising and fast fashion are binary indicators as described in the main text. Standard errors clustered at the retailer-country level. *** p<0.01, ** p<0.05, * p<0.1

A.20 Price Adjustments

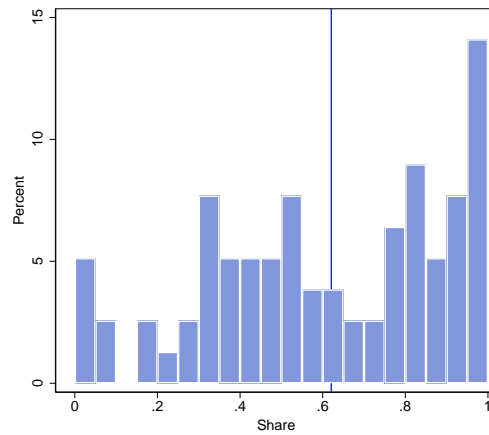


Figure 29: Changing shares of products in existing price buckets

Notes: For each retailer-category in the U.S. and the U.K. for which we have one year of data, we compare the price distribution between summer 2017 vs. summer 2018. Histogram shows the portion of the change in the price distribution that takes place via adjusting shares of products in the existing price buckets. Vertical line depicts the median share.

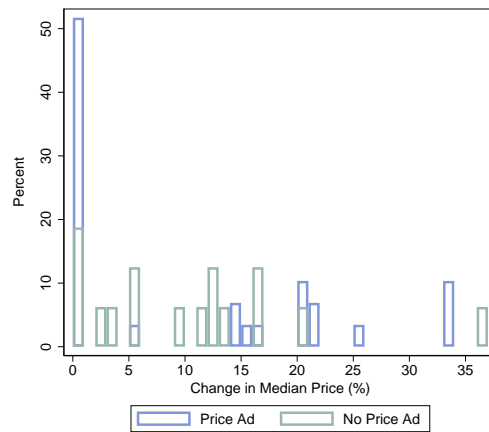


Figure 30: Lumpy price adjustments

Notes: Shows the histogram of the absolute percentage change in the median price of the same country-retailer-category, same month, between two consecutive years. For instance, one observation is the % change in the median price in HM-Shoes (U.S.) between a given month in 2017 and the same month the following year. Histogram computed separately for price advertising and non-price advertising retailers. Price changes above an absolute 40% are removed.

A.21 Law of one price

Figure 31 shows good-level deviations from the law of one price. Prices in the U.K. are inclusive of VAT (value added tax). Therefore we adjust regular prices in the U.S. by the average state sales tax of 5.1%. State-level sales taxes were obtained from the Tax Foundation. The same product is matched between the U.S. and the U.K. online stores. We first restrict to products introduced in the first price bucket in each retailer-category of the U.S. in May 2017. The first price bucket is defined as items within a 10% difference to the minimum price in each group pair. This allows to compare whether products introduced in the lowest price buckets in the U.S., were also introduced in similar price buckets in the U.K. Panel (a) in Figure 31 shows that, in general, this is not the case. Products are introduced in a wide range of cheaper and expensive prices in the U.K. This suggests that, as discussed in the main text, costs are unlikely a mechanical cause to price clustering.

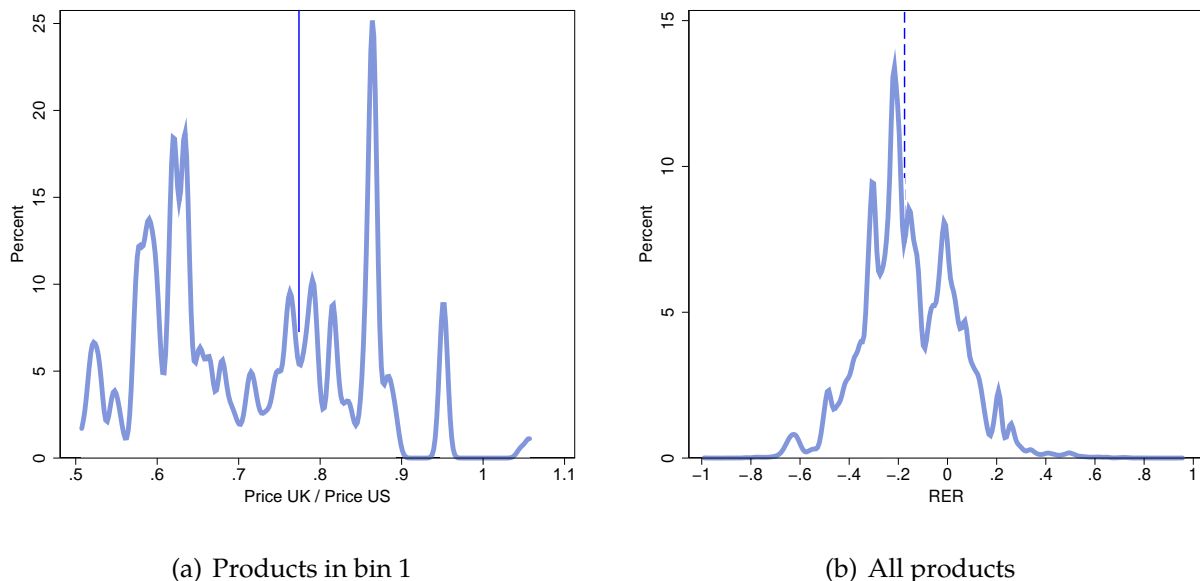


Figure 31: Histogram of deviations to law of one price

Notes: Panel (a) shows a histogram of the ratio of the U.K. price to the U.S. price for all matched products. The ratio is computed for items introduced in May 2017 in the lowest 10% price bin of each retailer-category in the U.S. The vertical line depicts the average nominal £/\$ exchange rate of 0.77. Panel (b) shows a histogram of the good-level real exchange rate. Vertical line depicts the median log deviation.

Panel (b) in Figure 31 extends the analysis to all products, price buckets, and time periods. In this case, we compute the good-level real exchange rate (RER) for each good i , which is defined as $RER_i = \log(p_{i,UK}) - e_{US,UK} - \log(p_{i,US})$; where $e_{US,UK}$ denotes the log of the value of the (average monthly) nominal exchange rate between the US and the UK.

Values close to 0 would indicate no deviation to the LOP. Once again, we find a large fraction of items that differ in prices by over 0.3 log points. The mean and median absolute good-level RER is 0.201 and 0.196 log points, respectively. These are considered relatively large deviations from the law of one price. See recent studies using micro data, e.g. [Imbs, Mumtaz, Ravn, and Rey \(2005\)](#); [Gopinath and Rigobon \(2008\)](#); [Cavallo, Neiman, and Rigobon \(2014\)](#); [Gorodnichenko and Talavera \(2017\)](#).