Submitted December 20, 2020, Revised May 16, 2021, Accepted May 21, 2021

Are Food Price Promotions Predictable? The Hazard Function of Supermarket Discounts

Hao Lan, Tim Lloyd, Wyn Morgan, Paul W. Dobson*

Abstract

Is the timing of food products going on sale, in the form of temporary price reductions, random or predictable? More specifically, are products more likely to go on sale the longer they remain non-promoted? We investigate the nature and timing of sales discounts using a large database based on weekly supermarket scanner prices covering 500 products for 137 weeks in the largest seven national retail chains in the UK. Our duration analysis of regular price spells reveals that discounting for a wide range of food products is more likely the longer they remain without a sale. However, critical differences exist between retailers following Hi-Lo or every-day-low-pricing (EDLP) policies, while the time-dependent pattern varies considerably across product categories, brand status, and discount depth.

Key words: sales, pricing policies, discounting, hazard function, supermarkets

JEL classification: L16; L66; E30.

* Corresponding Author: Paul W. Dobson, Norwich Business School, University of East Anglia; email: p.dobson@uea.ac.uk.

Author Affiliations:

Hao Lan, International Business School Suzhou, Xi’an Jiaotong Liverpool University, Suzhou, China; email: hao.lan@xjtlu.edu.cn

Tim Lloyd, Bournemouth University, Bournemouth, United Kingdom; email: tlloyd@bournemouth.ac.uk

Wyn Morgan, University of Sheffield, Sheffield, United Kingdom; email: w.morgan@sheffield.ac.uk

Paul W. Dobson, Norwich Business School and Centre for Competition Policy, University of East Anglia, United Kingdom; email: p.dobson@uea.ac.uk

1. Introduction

Sales, as price promotions offering temporary discounts, are a key element of supermarket pricing and extensively used by most grocery retailers (Anderson and Fox 2019; Fassnacht and El Husseini 2013). Eales (2016) reports that the market for groceries in the UK is one of the most highly discounted in the world, with 51% of food purchased under promotion compared to 37% in the U.S.A and 28% across Europe. Lloyd *et al*. (2014) find that around 40% of the annual variation in UK food prices is attributable to sales, which compares with between 25-50% in the U.S.A. (Hosken and Reiffen 2004; Kaplan and Menzio 2015; Anderson *et al*. 2017).

While attractive to consumers, and potentially increasing overall food demand, discounting has knock-on consequences for all stages of the food supply chain in respect of supply planning and inventory management. Effects can be pernicious in cases where retailers oblige their suppliers, unexpectedly and often retrospectively, to fund promotions to consumers. Such practices have attracted the attention of antitrust regulators owing to their detrimental impacts on the efficiency and viability of food producers (Competition Commission 2008, para 9.45) and as a result have been outlawed under the Fair Dealing provisions in the UK's Groceries Supply Code of Practice (GSCOP 2009). Promotions can also exacerbate demand swings if consumers lie in wait for predictable discounts and time their purchases strategically, leading to 'stock-outs', especially for storable products (Liu and Balachander 2014).

However, the extent to which sales are outwardly predictable or random is not clear from either existing theory or evidence. For instance, there is a stark contrast in theories of sales behaviour between static price competition models (which view sales as randomized pricing events to soften head-to-head competition, e.g., Varian 1980) and dynamic models (which view sales as occurring in predictable cycles and thus time dependent, e.g., Sobel 1984). State-dependent models can act as a bridge between the two approaches, demonstrating that product characteristics or market circumstances can influence whether sales are likely to be random or predictable events (e.g., Hosken and Reiffen 2007). Even so, whether sales overall are inclined more towards being random or predictable is unclear when there are contrasting effects. For example, storable products might be suitable for periodic sales as a device for intertemporal price discrimination, but if they are undifferentiated then randomizing sales might be a way to soften their competition. Accordingly, it is not just one attribute, like storability, that might be important but a range of characteristics, such as product type (e.g., fresh or frozen) and their brand status (national brand or private label) that might lend some products to be discounted frequently. Additionally, beyond the specifics of the product itself, the types of retailers and consumers in the market are also influential in shaping the frequency of sales. In particular, retailers can vary across a spectrum of marketing positions, ranging from frequent users of price promotions (Hi-Lo pricing) to the infrequent use that characterizes an Every-Day-Low Pricing (EDLP) marketing strategy (Fassnacht and El Husseini 2013).

Existing empirical evidence generally rejects sales behaviour as being random but offers inconsistent evidence on the form of time dependence. For instance, Pesendorfer (2002) finds a positive correlation between the probability of a sale and the time elapsed since the last sale. However, Berck *et al*. (2008) find the exact opposite, suggesting that the inconsistency of time-dependence may be due to state-dependent influence such as the mixture of the format and brand status of the products. Both studies use a probit framework, although each restricts attention to a specific grocery product category (respectively, tomato ketchup and orange juice), so findings may differ across a broader set of product categories sold in supermarkets.

Given the conflicting findings, we examine the timing of discounts using a more extensive and broader dataset. Rather than restricting ourselves to just one or two product markets, we analyse an extensive sample of prices based on UK supermarket scanner data for barcode-specific food products across a broad range of food categories and across all established national retail chains. These data enable us to broaden the scope of our investigation to examine a number of important state-dependent factors, emphasizing the fact that sales are likely to be more product and retailer specific, to better identify and understand sales patterns.

Our data relate to UK food retailing which is a large market (worth over £100bn annually and serving over 60m people) dominated by a small set of nationally-operating chain-store retailers, accounting for around two-thirds of all food sales and over four-fifths of supermarket sales (Competition Commission 2000; 2003; 2008; Dobson *et al*. 2003; Nielsen 2012). An interesting feature of the UK market is that the leading retailers adopt essentially national price promotions but with differentiated strategies. UK retailers are spread along a spectrum of price promotion positions, ranging from extreme Hi-Lo pricing to strict EDLP pricing (Chakraborty *et al.* 2014; Lan and Dobson 2017). For the UK, we have average weekly price data at chain level on over 500 matched products (either identically packaged national brands or chain-equivalent private label goods, making up 82% and 18% of the sample respectively), sold over a two-and-a-half-year period by all seven main supermarket groups.

Our work also differs from these previous studies in an important methodological respect. Rather than use a probit model, we conduct a duration analysis using the hazard function, which has the advantage of allowing micro-level market heterogeneities (such as product and retailer characteristics) to directly affect the likelihood of a sale. While the approach is common in macroeconomics (e.g., Nakamura and Steinsson 2008; Klenow and Malin 2011; de Prince 2018) where the focus is on the microeconomic foundations of inflation, we apply it to analyse the behaviour of sales in food retailing. To our knowledge, this is the first article to conduct a duration analysis to examine the timing of discounts that takes into account the effect of these micro-level market heterogeneities. As in the macroeconomics literature, doing so is pivotal to the conclusions that are drawn and provides an explanation that could help reconcile the contradictory results obtained in earlier studies (de Prince 2018).

The article proceeds as follows. Section 2 reviews the theoretical and empirical background, highlighting the contrasting results that have emerged. Section 3 outlines the data and the context of UK supermarket competition, which is central to our findings. Section 4 explains the methodology used for the duration analysis. Section 5 reports and discusses the results of the duration analysis. Section 6 concludes with the article's key insights. An online appendix provides additional details of the dataset and further details on the empirical analysis and checks.

2. Theoretical and empirical background

Price promotions (sales) are common in retailing. They are traditionally associated in retailing with stock clearances (Lazear 1986), inventory management (Pashigian and Bowen 1991) or as penetration pricing for new product introduction (Bass 1980). However, in the context of grocery retailing, temporary sales feature on continuously stocked products for a variety of other purposes, notably promoting the price image of the retailer (e.g., with loss leader discounts), appealing to specific (deal prone) consumers (as a segmentation device), and for differentiating on price to stand apart from rivals (Anderson and Fox 2019).

The theoretical and empirical literature focusing on sales has been notable for a series of developments. Berck *et al*. (2008) reviewed key sales theories and tested a number of derived hypotheses using supermarket scanner data from the US orange juice sector, testing for dynamic patterns of sales, brand heterogeneity and the role of retailer decisions. In this spirit, we propose a number of hypotheses, some novel, informed by the findings of the recent literature about multiproduct retailer pricing and taking account of the growing concentration and differentiation of food retail markets. Specifically, we propose testing four broad hypotheses, along with more specific sub-hypotheses in respect of different state dependent factors, as follows.

Hypothesis 1 (Time dependence): Sales are more likely the longer it has been since the last

sale

This well-established hypothesis has been tested extensively in the literature using different econometric approaches and data sets. Theoretical support for the hypothesis comes from a number of dynamic sales models, including Conlisk *et al.* (1984), Sobel (1984), and Pesendorfer (2002). Such models assume that consumers are heterogeneous with varying tastes and knowledge about prices in the market, which allows for intertemporal price discrimination between those willing to buy at regular high prices and those prepared to wait for discounted low prices, such as with seasonal sales. The implication is that discounting will be cyclical and so a sale becomes more likely the longer the time since the last sale. Furthermore, this cyclical pattern may be reinforced by consumer expectations and habit formation for buying on deal (Anderson and Fox 2019). The alternative hypothesis is that sales are random and reflect attempts to differentiate prices to soften competition. This is the approach taken by Varian (1980) in viewing competitive promotions as mixed strategies, with similar perspectives offered by Narasimhan (1984), Raju et al. (1990), Rao (1991), Simester (1997), Anderson and Kumar (2007), and Sinitsyn (2008). However, Sinitsyn (2017) explains that sales need to be pre-scheduled, so time-dependency pressures may dominate the inclination to randomize.

The empirical literature presents contradictory findings, perhaps best illustrated by Pesendorfer (2002) and Berck *et al.* (2008). Specifically, Pesendorfer (2002), using U.S. tomato ketchup data, finds that a product is *more* likely to be on sale the longer is has been since the last sale. Berck *et al.* (2008), examining U.S. fresh and concentrated orange juice data, find that a product is *less* likely to be on sale the longer it has been since the last sale. Using a sample of fresh and long-life milk, Bakucs and Ferto (2015) find evidence pointing to perishability determining the nature of the relationship. One aim of our study is to examine which of these outcomes represents the more general case across a wide range of food products when appropriate controls are in place rather than attempt to generalize findings based on a specific product category.

Hypothesis 2 (Sales in rival retailers): Sales of the same products in rival retailers make sales more likely

A key aspect of the sales profile of a product is the potential for the staggering of sales across retailers (i.e., with a product promoted in one retailer at a time) which can influence the time dependence of sales. Staggering indicates that sales are coordinated in a de-synchronized manner across retail chains due to retailer or/and manufacturer price-setting behaviour. For example, Lach and Tsiddon (1996) and Berck *et al*. (2008) highlight the importance of this feature when accounting for the effects of brand status, notably national brands versus private label. In particular, Berck *et al.* (2008) concluded that national brand sales are more likely to cause subsequent sales of other brands in the same product category. This might also suit retailers when staggered sales for given brands relaxes competition by allowing retailers to be operating with different special offers at any given time, while helping with the long-term planning of promotions in providing a steady stream and rotation of special offers from week to week (Anderson and Fox 2019). These perspectives on the staggering of sales contrast with the view of sales as being randomized as mixed strategy outcomes (Varian 1980) or synchronized in recurring cycles for intertemporal price discrimination (Albrecht *et al.* 2013). Accordingly, controlling for rival effects on the same (or equivalent in the case of private label) products could be important in conducting duration analysis to assess the predictability of sales.

Hypothesis 3 (State dependence): Sales are state dependent

Supermarket food retailing is complex given that there are a handful of differentiated retailers selling manifold types of products. Thus, sales might be state dependent – the prediction depends on a variety of micro-level heterogeneities. We focus attention on four specific features.

Hypothesis 3-1 (Storability): Storable products are promoted more than perishable ones.

Reviewing the literature, state-dependence of sales is mostly an empirical outcome. Hosken and Reiffen (2004) initially investigated a broad range of grocery products in the US using micro-level grocery price data and show that sales are more randomized in perishable goods but time-dependent in durable goods. Hosken and Reiffen (2007) use these insights to develop a theoretical model where they derive a Markov perfect equilibrium in which the relevant state variable is consumer inventory, predicting that storable goods will exhibit long periods of stable prices followed by significant but short-lived price reductions, whereas prices for perishable goods will move more frequently but by smaller amounts.

Recent theoretical developments in pricing amongst multiproduct retailers strengthens explanations of product heterogeneity. Retailers could use sales as a loss-leader strategy applied to known value items to signal the overall store price image (Rhodes 2014); or on goods where cherry-picking consumers are prepared to search for the lowest prices (Shelegia 2012); or to offer tempting treats to drive impulse sales (Johnson 2017). Notably, the timing and sequencing of price promotions depends on the structure and composition of product lines across product categories (Simester 1997; Jing and Zhang 2011; Sinitsyn 2012; 2015).

For producers of storable goods, supporting regular price promotions can be attractive if stockpiling with forward buying takes purchases away from rivals, but only if this boosts overall quantity sold and does not make consumers more price sensitive (Hendel and Nevo 2013). This may differ across product categories, as indicated by the mixed pattern of whether prices exhibit positive or negative serial correlation (Gangwar *et al*. 2014). Yet, perishable products might exhibit more randomized sales patterns in the absence of stockpiling opportunities that could otherwise favour intertemporal price discrimination (Richards 2006).

Hypothesis 3-2 (Seasonality): Sales promotions of food are more likely at Christmas

Seasonal effects on price reductions may be a feature, such as when there is a glut of supply (particularly on fresh foods that are perishable) or at times of the year at which demand peaks and hence when competition between chains is most intense. Being the most important festival period in the UK, firms are likely to compete more vigorously in terms of promotional frequency and depth at Christmas than at other times of the year (Warner and Barsky 1995; Chevalier *et al*. 2003; Guler *et al*. 2014). In these models, sales are a cyclical feature and thus predictable.

Hypothesis 3-3 (Brand heterogeneity): Price promotions on national brands are more frequent than for private label products

In addition to product characteristics, food processors might also exert influence, especially powerful brand owners (Lal 1990; Gerstner and Hess 1991; 1995; Villas-Boas 1995; Lal and Villas-Boas 1998). Accordingly, we might expect to see regular sales of nationally branded products backed up by trade promotion support, but less so for private label goods that do not have manufacturer promotion support. Lal (1990) and Perloff and Wu (2007) also suggest there will be fewer promotions on private label products in order to keep revenues from loyal consumers, but for which Berck *et al*. (2008), for instance, do not find clear evidence.

Hypothesis 3-4 (Retailer heterogeneity): Sales behaviour varies by retail chain

As well as inherent product characteristics (like shelf life) influencing the timing of sales, the nature and positioning of the firms is likely to be important. Chevalier *et al*. (2003) and Berck *et al*. (2008) find that retailers are not passive but instead actively determine price variations. In particular, in appealing to specific consumer segments, retailers might take different pricing positions. For instance, EDLP retailers (avoiding sales in favour of pricing consistency) and Hi-Lo retailers (reliant on sales with yo-yo pricing) could co-exist if they separately focus on respectively large basket or smaller basket shoppers (Lal and Rao 1997; Bell and Lattin 1998). Lloyd *et al*. (2014) also point to the greater influence of retailer heterogeneity compared to product heterogeneity in influencing sales and attribute this finding to the high concentration and differentiation of modern large supermarket chains. Certainly, the price positioning of retailers, notably between whether they follow an EDLP, Hi-Lo or hybrid position, matters considerably to the chosen pricing strategy (Bell and Lattin 1998; Ellickson and Misra 2008; Fassnacht and El Husseini 2013). While these studies have shown the aggregate influence of retail positioning on price promotions, they have not examined this influence at a highly disaggregated level or considered how the mix of product, retailer and producer effects influences the timing and predictability of sales, which is our intention here, utilizing the capability of duration analysis to discriminate between these dimensions.

Hypothesis 4 (Sale Depth): Deep sales makes sales more likely

Pesendorfer (2002) provides empirical results indicating that the probability of a sale is generally higher the deeper the sale, supporting the notion that deep sales are associated with frequently promoted products.

In line with this finding, cycling frequent deep discounts fits with retailers pursuing Hi-Lo promotional pricing to generate a competitive price image (Rhodes 2014), encourage frequent store visits (Shelegia 2012), and drive impulse purchases (Johnson 2017). Shallower discounts followed by deep discounts may also characterize intertemporal price discrimination, where the former takes out impatient high-value customers, leaving the latter for patient low-value customers (Pesendorfer 2002; Garrett 2016).

When the degree of customer loyalty varies between brands, retailers may prefer to utilize frequent shallow discounts on major brands (to preserve margins) but price more aggressively with less frequent deep discounts on weaker challenger brands (to encourage brand switching) (Agarwal 1996; Allender and Richards 2012).

Even so, there may be an attraction to using deep discounts more widely and frequently across all types of brands if the high pre-sale price signals high product quality and the low sale price provides high transaction value (Thaler 1985), via an anchoring and adjustment process (Kahneman and Tversky 1979). With behavioural consumers, who exhibit reference-dependent preferences, in the sense that they are more likely to buy a product at a given price if they believe that earlier consumers paid a higher price, Armstrong and Chen (2020) provide an explanation for why retailers may wish to exaggerate the level of discount by setting an artificially high pre-sale price to allow for the claim of a deep discount. In our context, regulatory requirements for establishing high pre-sale prices for a minimum period before discounting dictate time limits on “was/now” special offer claims but do not prevent continuous cycling of exaggerated deep discounts with yo-yo pricing, as observed by Lan *et al*. (2015) and CMA (2015), and the possibility of them being used to mask store-wide price increases and obfuscate price comparisons (Chakraborty *et al*. 2015).

Thus, both theory and empirical evidence suggest that deep and shallow discounts play different promotional roles, with deep discounts likely to involve careful planning between the retailer and supplier in view of the large sales bump compared to shallower discounts, and so we expect that the hazard of a sale increases with the depth of the sale.

Summary

In a retail grocery context, theory indicates that competitive pressure to differentiate from rivals might lead to retailers randomizing sales but the type of retailer (EDLP, Hi-Lo or hybrid), type of brand ownership (national brand or private label) or type of product (food category), could all influence the timing and predictability of sales events at the product level. In particular, we anticipate that sales become more regular and more predictable for branded and storable products, especially when sold in Hi-Lo retailers, who also make greater use of deep discounts.

We draw on these theoretical and practical insights to guide our empirical investigation, focusing on two particular aspects. First, we seek to understand time-dependence in the sales pattern at the aggregate level to see how this relates to theoretical insights while controlling for both frequently promoted products and the staggering of sales. Then, we move to a disaggregate-level analysis to examine more specifically the effects of retailer, product, and seasonal heterogeneities, alongside discount depth. We pay particular attention to retailer heterogeneity in terms of the insights provided about the character of supermarket competition.

3. Data

This section outlines the underlying dataset and provides summary statistics on the duration of regular price spells to inform the subsequent analysis of our hypotheses. (See Online Appendix A1 for further details on the data characteristics).

3.1 The dataset

The underlying price data are from Nielsen Scantrack and represent the average weekly price of grocery products sold in the UK’s major supermarket chains over 137 consecutive weeks.[1] While the data are based on 100% of the transactions of the sampled products, with national pricing being the norm in the UK (Dobson and Waterson 2005), the prices represent unit values calculated at the chain (not store) level. This feature of national pricing in the UK is different to other countries, notably the US, where store-level pricing predominates, even though most retail chains exhibit near uniform pricing across their store networks (DellaVigna and Gentzkow 2019). National or near uniform pricing also has a practical dimension in that our dataset of retailer-level prices is considerably more compact in representing supermarket prices across the UK than the vast store-level price datasets used in recent US studies (e.g., Kaplan and Menzio 2015; Anderson *et al*. 2017; DellaVigna and Gentzkow 2019; Hitsch *et al*. 2019). Reassuringly, Bogomolova *et al*. (2015) show that UK and US price promotions exhibit similar patterns.

More specifically, the dataset records these prices at the individual stock keeping unit (SKU) level in each supermarket chain, and assigns a Universal Product Code (UPC) for each retailer-product combination, of which there are 1,704 in the dataset covering both national brands (82%) and private labels (18%). Overall, the dataset covers a panel of 231,069 weekly chain-level prices on 507 food and beverage products in 15 categories. Fresh foods are under-represented (there are no fruit, vegetables and meat products) but the categories do span the spectrum of product formats covering fresh, chilled, frozen, ambient and tinned; the first three of which we classify as perishable and the remainder as shelf-storable.[2]

The price data are from the scanner-based records of the seven largest national retailers, which as a group represented close to two-thirds of all grocery spending in the UK during the sample period. While they are all national retailers, there are noticeable differences in their market positions. Over the period covered, the four largest chains, Tesco (the market leader), Sainsbury, Asda and Safeway, operated large-format one-stop-shop full-range superstores, Waitrose operated as a premium/upmarket large-format retailer, and Somerfield and Kwik Save operated medium-format supermarkets used more for top-up shopping (Competition Commission 2000; 2003; 2008). The remainder of the market consisted of a mix of small

[1] The period, which runs from September 8th 2001 to April 17th 2004, is well-suited to our investigation as it has a very diverse set of retailers, taking a broad spectrum of pricing positions, and operating different store formats. It was also a stable period without mergers and before a subsequent wave of consolidation and more turbulent inflation/deflation cycles.

[2] Perishable product formats (54% of the data) are Fresh (wrapped bread), Chilled (orange juice, yoghurt) and Frozen (fish fingers, frozen peas, frozen chips and frozen pizza). Shelf-storable formats (46%) are Ambient (instant coffee, breakfast cereals, and tea bags) and Tinned (tuna, tomatoes, soup and corned beef). Online Appendix A1 provides further details.

national and regional retail chains and independent retailers, not covered by the Nielsen data.

We define a sale (promotional discount) as a temporary decline in prices of at least 10%.[3] While we cannot distinguish between volume-based discounts (e.g., buy-one, get-one-free) and straight-discount promotions (e.g., 25% off), both are captured in the price data since each observation represents the weekly value-to-volume ratio of purchases of each product by each supermarket chain. Using a 10% sales indicator, we then identify regular price spells, the duration of which measures the number of weeks between two sales events. The duration (in weeks) of each regular price spell is the dependent variable in the econometric analysis. In total, we have 4,303 regular price spells created from 1,704 UPCs in the sample, of which 80% are complete, measuring the exact duration between sales and 20% are right-censored, where the end of the sample period marks the cut-off. It is possible to use both complete and right-censored spells in the analysis of regular spell duration subject to a restriction on the right-censored spells in the parameterization.[4]

Figure 1 illustrates the prices of just one of these UPCs (Del Monte Orange Juice Tetra 1L 3Pack in Safeway from the Chilled Orange Juice category reported in Table 1) to show a typical patterns where prices switch between two states: high regular prices and low sales prices. The shaded areas represent the regular price episodes. According to our definition, six sales punctuate the price series over the sample period. Since sales occur at irregular intervals, the duration of each regular price spell (i.e., the time between each sale) also varies: two of them are short, lasting only one week; others last between 10 and 20 weeks; and one has a relatively long duration of some 63 weeks. Our prime focus in the empirical analysis is this duration of the regular price, and the factors that might account for its length.

[FIGURE 1 - near here]

3.2. Regular Price Spells

As a precursor to the econometric analysis which quantifies the effects of the various product and retail characteristics on the duration of regular price spells, we present a summary

---

[3] The 10% threshold is used commonly in studies that distinguish sale prices from and the generally smaller changes in regular prices (e.g., Nakamura and Steinsson 2008; Berck *et al.* 2008; Seaton and Waterson 2013, Lloyd *et al.* 2014; Kim *et al.* 2021). We also report results in Section 4 using 25% and 35% thresholds.

[4] Left and double censored spells are difficult to accommodate in duration analysis and are typically discarded in empirical work. Re-estimation including left censored spells yields qualitatively similar results to those reported later in the paper and with further details available in Online Appendix A2.

of the regular spell durations in Table 1. This table reports average durations of the individual 4,303 regular price spells in the dataset by retailer, brand type, category, product format and perishability. While the mean duration is 20 weeks overall, there is marked variation across the classifications. Differences by retailer are most apparent. Short-lived regular price spells (frequent sales) are most conspicuous in Safeway (an extreme Hi-Lo retailer, not related to the US chain of the same name), which starkly contrasts with Asda (an EDLP retailer owned by Wal-Mart). Other retailers fit in between with Tesco, Sainsbury and Waitrose (as the other large-format mainstream retailers adopting hybrid Hi-Lo positions) somewhat closer to Asda, compared with Somerfield and Kwik Save (smaller-format price promoters) that are more like Safeway. The duration of regular price spells is also shorter for national brands than private labels, implying brands are promoted more frequently.

[TABLE 1 - near here]

Notable differences exist across product categories, e.g., frozen pizza and yoghurt having short-lived regular price spells (frequent sales) compared with tinned tomatoes. To investigate whether this reflects perishability, we allocate product categories to one of five formats and then into a binary classification according to whether they are shelf-storable or not. Results point to a tendency for more storable formats (such as tinned foods) to have shorter regular price durations, a feature that is apparent in the two-way classification of perishability. While more storable products appear to be promoted more frequently, perishability appears not to be the whole story; tinned soups and tinned tomatoes being among the most and least promoted categories in the data. As far as UK food retailing is concerned, the use of discounts appears principally influenced by the retailer and product category, indicating the importance of the overall pricing strategy alongside category management.

Table 1 also shows that the deeper the discount, the shorter is the regular spell that the sale terminates, a feature of the data that is consistent with Hi-Lo pricing found in some frequently promoted products.[5] With the median duration of regular price spells being around half the mean, some products are frequently on sale. In our sample, only a small fraction (just over 7%) of items have just a single sale, similar to the small fraction (at just under 7%) of items that witnessed no sale. As the distribution of regular price spells by UPC presented in Figure 2 makes clear, the use of sales (which terminate regular price spells) is common throughout the

[5] Online Appendix Table A1-4 shows that deep sales mainly occur in a few categories (Tinned Tuna, Teabags, Oven Chips, Yoghurt and Frozen Pizza) and in two retail chains (Somerfield and Safeway).

dataset. The bar graph (left hand scale) shows that the modal number of regular price spells is four (a feature that around 12% of the UPC-level items have in common) and there are some items that exhibit sales very frequently (e.g., the largest UPC item having 28 regular price spells over the two and half years' time interval, which was a branded wrapped white bread from Somerfield).

[FIGURE 2 – near here]

This feature has a potentially important bearing from an econometric perspective if the regular spells of varying length are unevenly distributed across products, since this will bias the estimates of the duration analysis. This is because the unobserved heterogeneity arising from state dependent characteristics, such as category and brand effects, end up determining the probability of a sale in products of various spell durations, rather than the time that has elapsed since the last sale. With reference to the right-hand scale of Figure 2, the average duration of regular price spells for products with a single spell is 67 weeks while this mean declines to 44 weeks for products with two spells, and for the UPC that had 28 spells, sales occurred on average every three weeks. As this declining trend implies, controlling for such unobserved heterogeneity is likely to play a crucial role in the estimation of whether sales are more or less likely the longer the regular price persists.

Sales may also be connected across retailers either via a competitive response, such as price matching by retailers, or by co-ordination where a manufacturer promotes a sector-wide campaign. Hence, the probability that a product is on sale in one retailer will likely reflect whether it is on sale elsewhere. To consider this aspect, we calculate the synchronization of sales predicted by the binomial distribution and compare this theoretical probability with the actual level that the data reveals.[6] Using this approach, we can determine the degree of synchronization compared to that expected if sales were unrelated. The binomial probability that a product is on sale in two retailers simultaneously is 8.85% compared with its occurrence in the data at 0.38% of the time; for three retailers the binomial probability is 1.28% compared with 0.26% in the data. Overall, we find that products are less likely to be simultaneously promoted than implied by random assignment of sales. This desynchronization (staggering) of

[6] Assuming that sales are independent, the probability that k retailers simultaneously promote a product is given by $r_k = P(r = k) = \frac{k!}{n!(n-k)!} 0.08^k (1 - 0.08)^{n-k}$ where n is the number of retailers stocking the product and 0.08 is the average sales frequency observed in the sample.

sales occurs in both branded products and private labels but is more apparent in national brands suggesting that it is typically in the interests of both manufacturer and retailer to avoid products appearing on sale in more than one retailer at a time.

4. Methodology

Having set out the key features of the regular price spells, we now undertake a formal statistical investigation using duration analysis. (For technical details, see Kalbfleisch and Prentice (2011) and Cleves (2008)). Originating in biomedical science, duration analysis has been applied in economics to investigate a number of topics where the time to the occurrence of an event is a measure of interest (e.g., see Kiefer (1988) and Meyer (1990) on unemployment, and Bunn and Ellis (2012), Fougère *et al.* (2007), and Nakamura and Steinsson (2008) on price changes). Here we propose a duration model to estimate the occurrence rate of sales, taking into account the various product and retailer characteristics identified previously.

At the heart of duration analysis is the *hazard function*, which, in the current application, represents the rate at which sales occur as the duration of the regular price spell increases. To sketch out our empirical approach, let T be a non-negative random variable measuring the duration of a regular price of length t. The hazard rate of regular price spells, $h(t)$, is defined as:

$$h(t) = \lim_{\Delta \to 0} \frac{P(t < T < t + \Delta \mid T > t)}{\Delta} = \frac{f(t)}{1 - F(t)} \tag{1}$$

where $f(t)$ is the density function that defines the probability of a sale terminating regular price spells of length T. $F(t)$ is the cumulative function which defines the probability that regular price spells that have lasted up to t periods will be terminated by a sale. Thus, the hazard rate is the probability that the regular price spell of length t is terminated by a sale, given that it has lasted t periods since the previous sale. In other words, we can interpret the hazard (rate) as the probability that a product goes on sale in the t^{th} week since the last sale. Unlike the density function describing the duration of regular prices, $f(t)$, the hazard function defines the probability of a sale conditional on the regular price spell having lasted for t periods. Hence, while the (unconditional) probability of a sale may be (say) 5%, the probability of a sale occurring immediately after, or a long time after, the previous one may be considerably different from 5%. It is the conditional nature of the hazard function that distinguishes it from the density function and makes it useful for examining the timing of sales. Notice that if the spell is right-censored, the hazard function is simply the survival rate of regular price spells at that duration, such that $h(t) = P(T > t)$.

A flexible yet tractable parameterization of the hazard function is the Weibull proportional hazard (PH) model given by:

$$h_{ik}(t) = h_0(t)\exp(\mathbf{x}'_{ik}\beta)\,\alpha_k = pt^{p-1}\exp\,(\mathbf{x}'_{ik}\beta)\alpha_k \quad (2)$$

where i indexes spells of length t and k indexes UPCs. Of key interest is the term $h_0(t) = pt^{p-1}$, which represents the baseline hazard function in which p measures the time-dependence of the hazard function. If $p > 1$, the hazard is increasing, meaning the probability of a sale rises the longer the regular price persists. If $p = 1$, the hazard is constant and if $p < 1$, the hazard is decreasing, so that sales become less likely the longer the regular price spell lasts. In (2), $\mathbf{x}$ is a vector of covariates used to control for the observed heterogeneity in the duration data and β is a vector of coefficients to be estimated with a sample of regular price spells. The exp(.) function ensures that the hazard is non-negative and thus the covariates have a proportional effect, shifting the baseline hazard function up or down according to the characteristics contained in **x**. These include retailer, brand status (private label =1), seasonal (January =1) and category (and aggregated by format and perishability) dummies. In order to assess whether the hazard of a sale is associated with the depth of sale, in line with Hypothesis 4, we use three different discount thresholds for sales with discounts >10%, >25%, and >35%.

To account for the staggering of sales across retailers by virtue of competitive interaction or strategic co-ordination, **x** is augmented with a [1,0] dummy variable $Rival_{ik}$, indicating that product *i* has been on sale in the four weeks prior to period *t* in at least one rival retailer, zero otherwise.[7] If recent sales of like-products in rival retailers make sales more (less) likely in period *t*, the hazard ratio of $Rival_{ik}$ will be greater (less) than unity. To allow for a potentially large list of factors affecting the likelihood of sales (manufacturer, pack-size, target consumer, *etc*.) equation (2) includes a UPC-specific random effects term, α_k, in which unobserved heterogeneity is distributed as $\alpha_k \sim \text{Gamma}(1, \sigma_\alpha^2)$. Rejection of the null hypothesis $\sigma_\alpha^2 = 0$ underlines the empirical relevance of these factors on the estimation of the hazard rate.

Equation (2) is estimated using maximum likelihood methods. In the estimation, α_k can be integrated out at the UPC level as it is common to regular price spells in each UPC. In this framework the log likelihood function is the sum of the log-likelihood contributions for each UPC so that the log-likelihood contribution for the k^{th} UPC can be written as:

[7] The results reported in the following section relate to sales in the previous four-week period ($t = 4$). Models estimated for sales in the previous week and previous fortnight produce qualitatively similar results.

$$\log L_k = \sum_{i=1}^{n_k} d_{ik}(\log h_0(t) + \mathbf{x}'_{ik}\beta) - \left(\frac{1}{\sigma_\alpha^2} + D_k\right)\log\left\{1 - \sigma_\alpha^2 \sum_{i=1}^{n_k} \log\frac{S_{ik}(t)}{S_{ik}(t_0)}\right\}$$
$$+ D_k \log\sigma_\alpha^2 + \log\Gamma\left(\frac{1}{\sigma_\alpha^2} + D_k\right) - \log\Gamma\left(\frac{1}{\sigma_\alpha^2}\right)$$

where $D_k = \sum_i d_{ik}$ is the number of sales in the k^{th} UPC, $\Gamma(\cdot)$ is from the density function of Gamma distribution and $\frac{S_{ik}(t)}{S_{ik}(t_0)}$ describes the probability of surviving beyond time *t* conditional on the entry time t_0 (see Cleves *et al.* 2008 for details). All analysis is conducted in Stata 13 (Statacorp 2013).

5. Results

Hypothesis 1: Time Dependence

Table 2 reports our findings from the estimation of the proportional hazards model (equation (2)) applied to data on 4,303 regular price spells from 1,703 UPCs.

[TABLE 2 – near here]

To address the question of time dependence in the occurrence of sales, consider initially Models 1 and 2. Both contain retailer, category, brand status (private label = 1) and month dummies and thus provide a baseline set of controls that might otherwise influence the timing of promotions. As such, Model 1 represents a baseline specification that treats each regular price spell as being independent of the promotional activity attached to each UPC. Model 2 additionally accommodates UPC-level idiosyncrasies via a random effects estimator and dummy variables to acknowledge the effect of recent sales of like-products in rivals ($rival$). Comparison of Models 1 and 2 thus indicates the impact of UPC-level heterogeneity bias on the pattern of time dependence of sales.[8]

Models 1 and 2 confirm that the timing of sales is not random. Both are estimated with a baseline hazard function parameter (p) that is significantly different from unity, implying time dependence in the temporal pattern of sales. However, what is striking is the impact that UPC-level factors (excluded from (1) but included in (2)) impart on the hazard rate of sales, which actually changes sign when appropriate UPC-level controls are put in place.

[8] The rejection of the null $H_0\colon \sigma_\alpha^2 = 0$ supports the use of UPC level random effects. Models estimated with UPC-level fixed effects also exhibit positive time dependence. Variables accounting for sales in rival retailers increase the magnitude of the positive dependence that is found. See Online Appendices A4 and A8.

Our results provide supporting evidence for Hypothesis 1, namely that sales are time dependent. With appropriate controls in place (Model 2), the baseline hazard rate of sales that is estimated implies that the probability of a sale rises by (1.13-1=) 13% every week without a sale.[9] This result fits with theories positing cycles of periodic sales (Sobel 1984, *inter alia*) and indicates a more general case for food products beyond the single product category covered by Pesendorfer (2002). Indeed, the fact that the time dependence changes sign (flipping from significantly negative to significantly positive) underlines the decisive effect that UPC-level characteristics have on the baseline hazard of sales.

Hypothesis 2: Sales of the same products in rival retailers

Sobel's sales theory predicts a desynchronized pattern (staggering) of sales whereby different retailers price discriminate between heterogeneous consumers at different times to avoid intense competition. Model 2 assesses the effect of recent sales of the same products in rivals via a dummy variable ($rival$) which is interacted with brand status ($rival \times label$) to evaluate whether private labels exhibit the same response as brands. From Table 2, the hazard ratio on $rival$, which is statistically different from unity at the 1% level, indicates that branded products that have been on sale in the previous month in at least one rival retailer are 87% more likely to be promoted than brands which have not. Interestingly, the same does not apply to private labels. As the table shows, the ($rival \times label$) interaction is statistically insignificant and thus the results provide evidence in support of the staggering of sales across retailers for branded products only, pointing to brand producers' influence on sales timing.

In sum, the findings thus far confirm the importance of a product's sales history both in the retailer in question and its rivals. Previous sales are a powerful indicator of future sales. More strikingly, the data reveal the decisive effect that UPC-level factors have in determining not only the size but sign of the hazard rate of sales, which is found to be positive when UPC level factors are taken in to account. For further insights, we now consider the four different sub-hypotheses relating to different aspects of sales being state dependent (Hypothesis 3).

Hypothesis 3-1: Storability

To explore the extent to which the hazard of sales varies according to the storability of products we report the results from two additional models in Table 2. Like Model 2, these models take account of UPC level heterogeneity but differ in the way that UPCs are classified

[9] The hazard rate of sales using fixed effects is also significantly positive. See Online Appendix A4.

with respect to perishability. Whereas Model 2 classifies UPCs by category, Model 3 and 4 aggregate these categories into (one of five) format types and (the binary classification) 'shelf storable' respectively. Results for Model 2, which are relative to the base category (orange juice) indicate a tendency for storable categories to be promoted more frequently (for example, bread being (0.89-1=) 11% less likely and tinned tuna (1.69-1=) 69% more likely). This feature becomes increasingly apparent as products are grouped in more aggregate classifications, with storable products (Model 4) being (1.32-1=) 32% more likely to be promoted than perishable ones, at least according to our definition. Notwithstanding the caveat regarding the under-representation of fresh product in the sample, our results support Hypothesis 3-1, namely that sales are more likely the more storable is the product.

Hypothesis 3-2: Christmas sales

Previous studies have found that sales are more prevalent around major festivals and results from Model 2 (see online appendix for details) corroborate these findings, with sales being 27% more likely in December than in the base month (January). Thus, we find evidence in support of Hypothesis 3-2, that sales are intensified in periods of peak demand.[10]

Hypothesis 3-3: Retailer heterogeneity

Results by retailer in Table 2 are particularly noteworthy. As noted above, food retailing in the UK is characterized by large national retail chains occupying distinct positions in the pricing spectrum. This feature of the UK market is amply demonstrated by the analysis of sales conducted here.[11] Estimates of the hazard rate of sales reported in Table 2 are relative to Tesco, which as market leader, is selected as the base category in all models. Using point estimates from Model (2) suggests that three retailers – Safeway, Somerfield and Kwik Save – occupy distinctive Hi-Lo discount pricing positions, being much more likely to have a sale than the market leader, with Safeway being more than twice as likely. In contrast, Asda appears as the only clear EDLP grocery retailer in the UK, is (0.19 -1=) 81% less likely to have a sale than Tesco. The other mainstream retailer, Sainsbury, along with the upmarket retailer Waitrose are more similar to the market leader, with these three retailers appearing to occupy hybrid Hi-Lo/EDLP positions. Thus, the results support Hypothesis 3-3.

To explore the retailer heterogeneity issue further, we estimate hazard models by retailer

[10] While this result holds for shallow and moderate sales, deep (>35%) sales are less likely. See Table 4.

[11] For analysis by category, perishability and format, see Online Appendix A6 and A7. Differences in the hazard functions within each categorisation are evaluated non-parametrically using the log rank test of Mantel and Haenszel (1959). Results shown in Online Appendix A3 reject the equality of the hazard functions in all classifications at the 1% level. Equality among retailers is rejected particularly strongly.

adopting the specification of Model 4 (shelf storability) to improve the degrees of freedom. Results are reported in Table 3. Of key interest is the baseline hazard, which is significantly positive in all retailers except Asda. To emphasize the differences in pricing behaviour implied by these retailer-specific models, Figure 3 plots the implied hazard function for each retailer. In particular, dynamic pricing all but disappears for the EDLP retailer Asda, confirming the co-existence of Hi-Lo and EDLP pricing in UK food retailing. Note also the high hazard rate for Waitrose, the most upmarket food retailer in the sample, suggesting that Hi-Lo sales strategies are not solely the preserve of retailers with a reputation for discounting.

[TABLE 3 – near here]

[FIGURE 3 – near here]

Hypothesis 3-4: Private Labels

Private labels occupy an important role in UK food retailing, competing more directly with national brands and holding larger market shares than in many other countries (Dobson and Chakraborty 2009). In this light, testing whether national brands are promoted more than private labels (as is typically the case in other countries) has a particular resonance in the UK context. The effect of private labels on the hazard rate of sales is captured by the coefficient on the private label dummy (*label*). Estimates from Table 2 suggest that propensity for sales among private labels is (0.89-1=) 11% lower, but not significantly so.[12] Retailer-specific results reported in Table 3 shed some light on this rather ambivalent market level result. While Asda promotes national brands and its private label products in roughly equal measure (albeit hardly at all) most others chains promote private labels less (although not all significantly so). That Waitrose, the most upmarket retailer among UK chains, is found to promote its own label products twice as frequently as the national brands would indicate that such promotional pricing is the preserve of luxury retail chains only. Accordingly, we find mixed evidence with some but no clear support for Hypothesis 3-4.

Hypothesis 4: Sale depth

[12] With >25% and >35% discount thresholds, the private label dummy effect is statistically significant at the 1% level, indicating private labels tend to have shallower discounts than for national brands. See Table 4 for details.

While our primary interest is in the timing of sales in general, addressing whether the hazard rate is invariant to the magnitude of the sale is clearly also of interest. To investigate the robustness of our findings, Table 4 reports hazard functions for three thresholds representing all sales (>10%), moderate and deep (excluding shallow) sales (>25%), and only deep (>35%) sales. Given the smaller sample for deep sales, Model 4 is used to maintain degrees of freedom. While all sale depths are associated with positive time dependence, increasing the sales depth threshold successively elevates the hazard and amplifies the effect, similar to the findings of Pesendorder's (2002) U.S. ketchup market study. Furthermore, the deeper the sale depth threshold then the more concentrated are sales in nationally branded products sold in Hi-Lo retailers. The results are consistent with the notion of yo-yo pricing in a small number of product categories, such as frozen pizza and tinned tuna (see Appendix Table A1-4). Accordingly, we find support for Hypothesis 4 in keeping with patterns predicted by intertemporal price discrimination models, behavioural economics explanations for rotating exaggerated discounts, and careful retailer-supplier planning for the anticipated sales bump from deeper discounts. Moreover, contemporary evidence by *Which?* (2021) indicates that this is a continuing practice with deep discounts on frequent rotation across UK grocery retailers.

[TABLE 4 – near here]

6. Summary and conclusions

Price promotions are a key ingredient in the marketing mix for supermarkets competing to boost sales and revenue, but with potential knock-on effects for other parts of the food supply chain. For food producers and farmers, this activity is potentially positive so long as price promotions across different stores do not cancel each other out leaving overall market demand unchanged. However, excessive reliance on price promotions by supermarkets could have negative effects on food supply chains when it undermines consumers' trust in the value on offer at regular prices, or leads to increased costs from managing sudden swings in demand as consumers lie in wait for discounts. The latter is more likely if price promotions are predictable rather than random events in the eyes of the consumer, even if supermarkets plan the timing of all price promotions in advance with their suppliers. Yet, random price promotions may also entail supermarkets making sudden or retrospective demands on food suppliers to fund price promotions, which can result in economic harm to producers (CC 2008; GSCOP 2009). Accordingly, whether supermarket discounts are random or predictable has practical implications for food supply chains beyond academic curiosity.

The existing literature on the timing of sales discounts, focusing mostly on individual product categories or individual retailers, has produced conflicting findings. Using duration analysis for a wide range of food products, we estimated the hazard function of discounts, accounting for a number of important micro-level market heterogeneities, which appears to be a critical gap in the current theoretical and empirical literature. We find that the probability of a discount is, in the main, time dependent, so that the longer a product remains without a discount then the greater the likelihood of it going on promotion; a result that is consistent with Sobel (1984), Pesendorfer (2002) and others in viewing periodic discounts as a means for intertemporal price discrimination.

We also find synchronized patterns of discounts across the retailers for branded products but not private labels. This key difference highlights the role of branded manufacturers in setting the timing of promotions. In addition, our analysis also addresses the issue of heterogeneity in terms of type of retailer, product category, and brand status (national brand vs. private label). Above all, discounting strategies appear heterogeneous across the UK retailers and influenced by their market positioning and oligopolistic interaction. The timing and frequency of discounts varies significantly across retailers and product categories, with brands promoted more than private labels. Most importantly, retailers appear to occupy niches in the market whereby variants of Hi-Lo and EDLP sales strategies co-exist.

Our central finding that the likelihood of a sale for a product is increasing in the time since the last sale appears inconsistent with Varian (1980) and related models predicting randomized sales. Nevertheless, we need to add an important qualification and emphasize that our analysis relates to the predictability of pricing patterns at product level rather than at the store level where a vast array of price promotions can simultaneously operate, with varying compositions of products on sale along with varying discounts depths. Thus, while the individual products may not exhibit the pricing pattern predicted by a Varian style model, it is possible that the price of the bundle of products purchased by consumers may follow this pattern in a store-wide context and thus characterize broader retail pricing competition. Accordingly, we do not claim that our findings refute such models in describing retailer behaviour more generally.

For keen shoppers, our findings suggest opportunities exist for cherry picking across retailers for products on sale, while also using their temporal predictability to reduce purchases when the price is high and then stock up when the price is low. Empirical evidence supports such strategic behaviour by consumers adopting rational expectations (Liu and Balachander 2014; Février and Wilner 2016). While segmenting consumers based on intertemporal price discrimination can significantly raise profits (e.g., Hendel and Nevo 2013), there is the risk that if consumers become too "savvy" and demand is not expandable then all that happens is consumers buy goods when they are on offer and avoid buying them otherwise. However, the savviness of consumers will always be tested when supermarkets run with thousands of offers at any one time and retailers have the opportunity to confuse consumers and hide misleading offers in amongst genuine ones (e.g., Chakraborty *et al.* 2015; CMA 2015; *Which?* 2021). In this sense, even if the timing of a sale is predictable, the value on offer might not be: *caveat emptor*.

Acknowledgements

We are extremely grateful for the helpful comments from three anonymous reviewers and the editor, David Harvey. Please contact Paul Dobson (p.dobson@uea.ac.uk) for correspondence.

References

Agarwal, D. (1996) 'Effect of brand loyalty on advertising and trade promotions: a game-theoretic analysis with empirical evidence'. *Marketing Science,* **15** (1), 86-108.

Albrecht, J., Postel-Vinay, F. and Vroman, S. (2013) 'An Equilibrium Search Model of Synchronized Sales'. *International Economic Review,* **54** (2), 472-493.

Allender, W.J., and Richards, T. (2012) 'Brand loyalty and price promotion strategies: an empirical analysis'. *Journal of Retailing,* **88** (3), 323–342.

Anderson, E., B.A. Malin, B.A., Nakamura, E., Simester, D. and Steinsson, J. (2017) 'Informational rigidities and the stickiness of temporary sales'. *Journal of Monetary Economics,* **90**, 64–83.

Anderson, E.T. and Fox, E.J. (2019) 'How price promotions work: A review of practice and theory'. In Dubé, J.-P.H. and Rossi, P.E., editors, *Handbook of the Economics of Marketing,* **1**, Ch.9, 497-552.

Anderson, E.T. and Kumar, N. (2007) 'Price competition with repeat, loyal buyers'. *Quantitative Marketing and Economics,* **5** (4), 333–359.

Armstrong, M. and Chen, Y. (2020) 'Discount Pricing'. *Economic Inquiry,* **58** (4), 1614–1627.

Bakucs, Z. and Ferto, I. (2015) 'Empirical tests of sales theories: Hungarian milk prices'. *Agricultural Economics Czech,* **61** (11), 511–521.

Bass, F.M. (1980) 'The Relationship between Diffusion Rates, Experience Curves, and Demand Elasticities for Consumer Durable Technological Innovations'. *Journal of Business,* **53** (3-2), S51-S67.

Bell, D.R. and Lattin, L.M. (1998) 'Shopping behaviour and consumer preference for store price format: Why 'large basket' shoppers prefer EDLP'. *Marketing Science,* 17(1), 66-88.

Berck, P., Brown, J., Perloff, J.M. and Villas-Boas, S.B. (2008) 'Sales: tests of theories on causality and timing'. *International Journal of Industrial Organization,* **26** (6), 1257-1273.

Bogomolova, S., Dunn, S., Trinha, G., Taylor, J. and Volpe, R.J. (2015) 'Price promotion landscape in the US and UK: Depicting retail practice to inform future research agenda'. *Journal of Retailing and Consumer Services,* **25** (C). 1–11.

Bunn, P. and Ellis, C. (2012) 'Examining the behaviour of individual UK consumer prices'. *Economic Journal,* **122** (558), F35–F55.

Chakraborty, R., Dobson, P.W., Seaton, J.S. and Waterson, M. (2014) 'Market Consolidation and Pricing Developments in Grocery Retailing: A Case Study,' in *Analysis of Competition Policy and Sectoral Regulation,* Martin Pietz and Yossi Spiegel (ed.), Now Publishers, 3-29.

Chakraborty, R., Dobson, P.W., Seaton, J.S., and Waterson, M. (2015) 'Pricing in inflationary times: The penny drops'. *Journal of Monetary Economics,* **76**, 71-86.

Chevalier, J.A., Kashyap, A.K. and Rossi, P.E. (2003) 'Why don't prices rise during periods of peak demand? Evidence from scanner data'. *American Economic Review,* **93** (1), 15-37.

Cleves, M. (2008) *An introduction to survival analysis using Stata*. College Station, Texas: Stata Press.

CMA. (2015) *Pricing Practices in the Groceries Market: Response to a super-complaint made by Which? on 21 April 2015*. London: Competition and Markets Authority.

Competition Commission (2000) *Supermarkets: A Report on the Supply of Groceries from Multiple Stores in the United Kingdom*. London: HMSO.

Competition Commission (2003) *Safeway plc and Asda Group Limited (owned by Wal-Mart Stores Inc); Wm Morrison Supermarkets PLC; J Sainsbury plc; and Tesco plc: A report on the mergers in contemplation*. London: HMSO.

Competition Commission (2008) *The Supply of Groceries in the UK*, London: HMSO.

Conlisk, J., Gerstner, E. and Sobel, J. (1984) 'Cyclic pricing by a durable goods monopolist'. *Quarterly Journal of Economics*, **99** (3), 489-505.

de Prince, D. (2018) 'Are price hazard functions really decreasing functions in Brazil?' *Journal of Macroeconomics*, **57**, 266-276.

DellaVigna, S. and Gentzkow, M. (2019) 'Uniform Pricing in U.S. Retail Chains'. *Quarterly Journal of Economics*, **34** (4), 2011–2084.

Dobson, P.W. and Chakraborty, R. (2009) 'Private Labels and Branded Goods: Consumers' 'Horrors' and 'Heroes''. In A. Ezrachi and U. Bernitz, eds. *Private Labels, Brands and Competition Policy: The Changing Landscape of Retail Competition*. Oxford: Oxford University Press, pp. 99-124.

Dobson, P.W. and Waterson, M. (2005) 'Chain-Store Pricing Across Local Markets', *Journal of Economics and Management Strategy*, **14** (1), 93-119.

Dobson, P.W., Waterson, M. and Davies, S.W. (2003) 'The patterns and implications of increasing concentration in European food retailing'. *Journal of Agricultural Economics*, **54** (1), 111-125.

Eales, T. (2016) *Price and Promotion in Western Economies. A pause in promotion escalation*. IRI Special Report. Available at: https://www.iriworldwide.com/IRI/media/IRI-Clients/International/Price-Promotion-in-Western-Economies-a-Pause-in-Promotion-Escalation.pdf. (Accessed 10 December 2020).

Ellickson, P.B. and Misra, S. (2008) 'Supermarket pricing strategies'. *Marketing Science*, **27** (5), 811-828.

Fassnacht, M. and El Husseini, S. (2013) 'EDLP versus Hi–Lo pricing strategies in retailing—a state of the art article'. *Journal of Business Economics*, **83** (3), 259-289.

Février, P. and Wilner, L. (2016) 'Do consumers correctly expect price reductions? Testing dynamic behaviour'. *International Journal of Industrial Organization*, **44** (C), 25-40.

Fougère, D., Le Bihan, H. and Sevestre, P. (2007) 'Heterogeneity in consumer price stickiness: a microeconometric investigation'. *Journal of Business & Economic Statistics*, **25** (3), 247-264.

Gangwar, M., Kumar, N. and Rao, R.C. (2014) 'Consumer Stockpiling and Competitive Promotional Strategies'. *Marketing Science*, **33** (1), 94–113.

Garrett, D.F. (2016) 'Intertemporal Price Discrimination: Dynamic Arrivals and Changing Values'. *American Economic Review*, **106** (11), 3275-3299.

Gerstner, E., and Hess, J.D. (1991) 'A theory of channel price promotions'. *American Economic Review*, **81** (4), 872-886.

Gerstner, E., and Hess, J.D. (1995) 'Pull promotions and channel coordination'. *Marketing Science*, **14** (1), 43-60.

GSCOP. (2009) *Groceries Supply Code of Practice*, Department of Business, Energy and Industrial Strategy, HMSO.

Guler, A.U., Misra, K. and Vilcassim, N. (2014) 'Countercyclical pricing: A consumer heterogeneity explanation'. *Economics Letters*, **122** (2), 343-347.

Hendel, I. and Nevo, A. (2013). Intertemporal price discrimination in storable goods markets. *American Economic Review*, **103** (7), 2722-2751.

Hitsch, G.J., Hortaçsu, A. and Xiliang, L. (2019) 'Prices and Promotions in U.S. Retail Markets:

Evidence from Big Data'. NBER Working Paper 26306.
Hosken, D. and Reiffen, D. (2004) 'Patterns of retail price variation'. *RAND Journal of Economics*, **35** (1), 128-146.
Hosken, D. and Reiffen, D. (2007) 'Pricing Behavior of Multiproduct Retailers'. *BE Journal of Theoretical Economics*, **7** (1), Art. 39.
Jing, B. and Zhang, Z.J. (2011) 'Product line competition and price promotions'. *Quantitative Marketing and Economics*, **9** (3), 275-299.
Johnson, J.P. (2017) 'Unplanned Purchases and Retail Competition'. *American Economic Review*, **107** (3), 931–965.
Kahneman, D., and Tversky, A. (1979) 'Prospect theory: An analysis of decision under risk'. *Econometrica*, **47** (2), 263-291.
Kalbfleisch, J.D. and Prentice, R.L. (2011) *The statistical analysis of failure time data*. Hoboken, NJ: John Wiley & Sons.
Kaplan, G. and Menzio, G. (2015) 'The morphology of price dispersion'. *International Economic Review*, **56** (4), 1165-1206.
Kiefer, N.M. (1988) 'Economic duration data and hazard functions'. *Journal of Economic Literature*, **26** (2), 646-679.
Kim, S.-H., Lan, H. and Dobson, P.W. (2021) 'Identifying price-leadership structures in oligopoly'. *Oxford Economic Papers*, 73 (1), 350–370.
Klenow, P. and Malin, B. (2011) Microeconomic evidence on price-setting. In: Friedman, B., Woodford, M. (Eds.), *Handbook of Monetary Economics* 3A. Elsevier, 231–284.
Lach, S., and Tsiddon, D. (1996) 'Staggering and synchronization in price-setting: evidence from multiproduct firms'. *American Economic Review*, **86** (5), 1175-1196.
Lal, R. (1990) 'Manufacturer trade deals and retail price promotions'. *Journal of Marketing Research*, **27** (4), 428-444.
Lal, R. and Matutes, C. (1989) 'Price competition in multimarket duopolies'. *RAND Journal of Economics*, **20** (4), 516-537.
Lal, R. and Rao, R. (1997) 'Supermarket competition: The case of every day low pricing'. *Marketing science*, **16** (1), 60-80.
Lal, R. and Villas-Boas, J.M. (1998) 'Price promotions and trade deals with multiproduct retailers'. *Management Science*, **44** (7), 935-949.
Lan, H. and Dobson, P.W. (2017) 'Healthy Competition to Support Healthy Eating? An Investigation of Fruit and Vegetable Pricing in UK Supermarkets'. *Journal of Agricultural Economics*, **68** (3), 881-900.
Lan, H., Lloyd, T.A. and Morgan, C.W. (2015) 'Price Promotions and Food Prices: A Note'. *Journal of Agricultural Economics*, **66** (2), 555-562.
Lazear, E.P. '1986) 'Retail Pricing and Clearance Sales'. *American Economic Review*, **76** (1), 14-32.
Liu, Y. and Balachander, S. (2014) 'How long has it been since the last deal? Consumer promotion timing expectations and promotional response'. *Quantitative Marketing and Economics*, **12** (1), 85-126.
Lloyd, T.A., McCorriston, S., Morgan, C.W., Poen, E. and Zgovu, E. (2014) 'Retail price dynamics and retailer heterogeneity: UK evidence'. *Economics Letters*, **124** (3), 434-438.
Mantel, N. and Haenszel, W. (1959) 'Statistical aspects of the analysis of data from retrospective studies of disease'. *Journal of National Cancer Institute*, **22**, 719–748.
Meyer, B.D. (1990) 'Unemployment Insurance and Unemployment Spells'. *Econometrica*, **58** (4), 757-782.

Nakamura, E., and Steinsson, J. (2008) ‘Five facts about prices: A reevaluation of menu cost models’. *Quarterly Journal of Economics,* **123** (4), 1415-1464.

Narasimhan, C. (1984) ‘A price discrimination theory of coupons’. *Marketing Science,* **3** (2), 128–147.

Nielsen. (2012) *Shopper Promiscuity Increases as Consumers Seek the Best Supermarket Deals*. Nielsen Homescan report.

Pashigian, B.P. and Bowen, B. (1991) ‘Why are products sold on sale? Explanations of pricing regularities’. *Quarterly Journal of Economics*, **106** (4), 1015-1038.

Pesendorfer, M. (2002) ‘Retail sales: A study of pricing behaviour in supermarkets’. *Journal of Business*, **75** (1), 33-66.

Raju, J.S., Srinivasan, V. and Lal, R. (1990) ‘The effects of brand loyalty on competitive price promotional strategies’. *Management Science*, **36** (3), 276–304.

Rao, R.C. (1991), ‘Pricing and promotions in asymmetric duopolies’. *Marketing Science,* **10** (2), 131–144.

Rhodes, A. (2015), ‘Multiproduct retailing’. *Review of Economic Studies*, **82** (1), 360-390.

Richards, T.J. (2006), ‘Sales by multi-product retailers’. *Managerial and Decision Economics,* **27** (4), 261-277.

Seaton, J.S. and Waterson, M. (2013) ‘Identifying and characterising price leadership in British supermarkets’. *International Journal of Industrial Organization,* **31** (5), 392-403.

Shelegia, S. (2012) ‘Multiproduct pricing in oligopoly’. *International Journal of Industrial Organization,* **30** (2), 231-242.

Simester, D. (1997) ‘Optimal promotion strategies: A demand-sided characterization’. *Management Science*, **43** (2), 251-256.

Sinitsyn, M. (2008) ‘Price promotions in asymmetric duopolies with heterogeneous consumers’. *Management Science*, **54** (12), 2081–2087.

Sinitsyn, M. (2012) ‘Coordination of price promotions in complementary categories’. *Management Science*, **58** (11), 2076-2094.

Sinitsyn, M. (2015) ‘Managing Price Promotions Within a Product Line’. *Marketing Science,* **35** (2), 304-318.

Sinitsyn, M. (2017) ‘Pricing with Pre-Scheduled Sales’. *Marketing Science,* **36** (6), 999–1014.

Sobel, J. (1984) ‘The timing of sales’. *Review of Economic Studies,* **51** (3), 353-368.

StataCorp. (2013) *Stata Statistical Software: Release 13*. College Station, TX: StataCorp LP.

Thaler, R. (1985) ‘Mental accounting and consumer choice’. *Marketing Science*, **4** (3), 199-214.

Varian, H.R. (1980) ‘A model of sales’. *American Economic Review,* **70** (4), 651-659.

Villas-Boas, J.M. (1995) ‘Models of competitive price promotions: Some empirical evidence from the coffee and saltine crackers markets’. *Journal of Economics & Management Strategy,* **4** (1), 85-107.

Warner, E.J., and Barsky, R.B. (1995) ‘The timing and magnitude of retail store markdowns: evidence from weekends and holidays’. *Quarterly Journal of Economics,* **110** (2), 321-352.

Which? (2021). ‘*Which?* reveals the groceries that cost three times more depending on when you shop’. Available at: https://www.which.co.uk/news/2021/05/which-reveals-the-groceries-that-cost-three-times-more-depending-on-when-you-shop/ (accessed 21 May 2021).

Figure 1. The price sequence of a single UPC

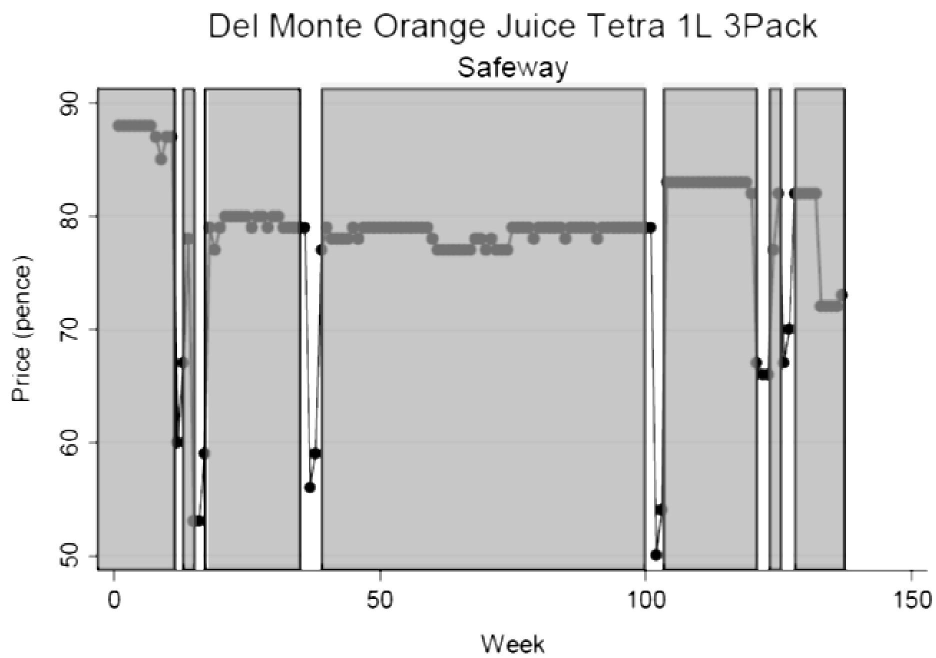

Figure 2. The distribution and duration of regular price spells

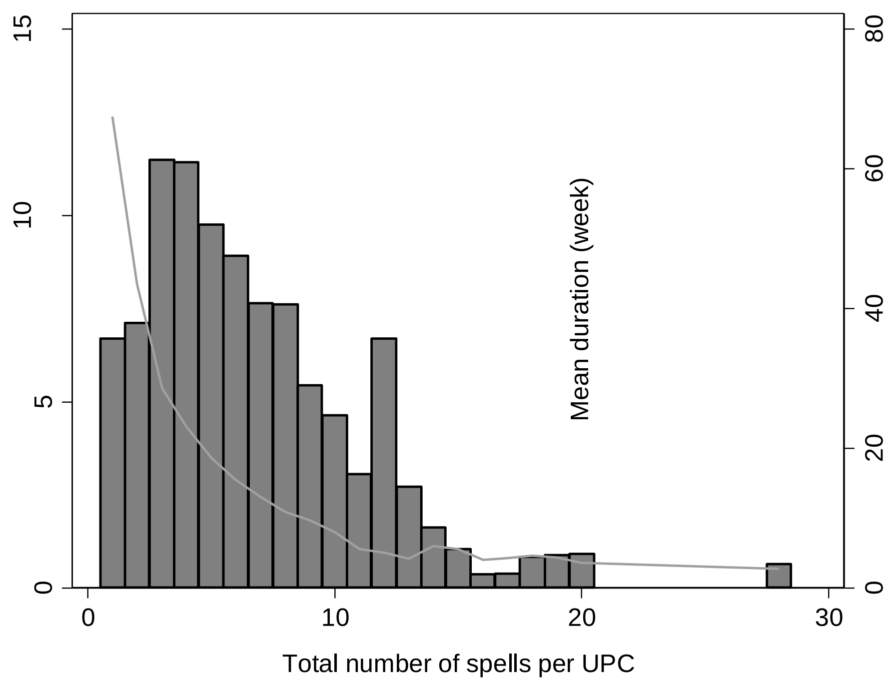

Figure 3. The hazard function of sales for the major UK food retailers

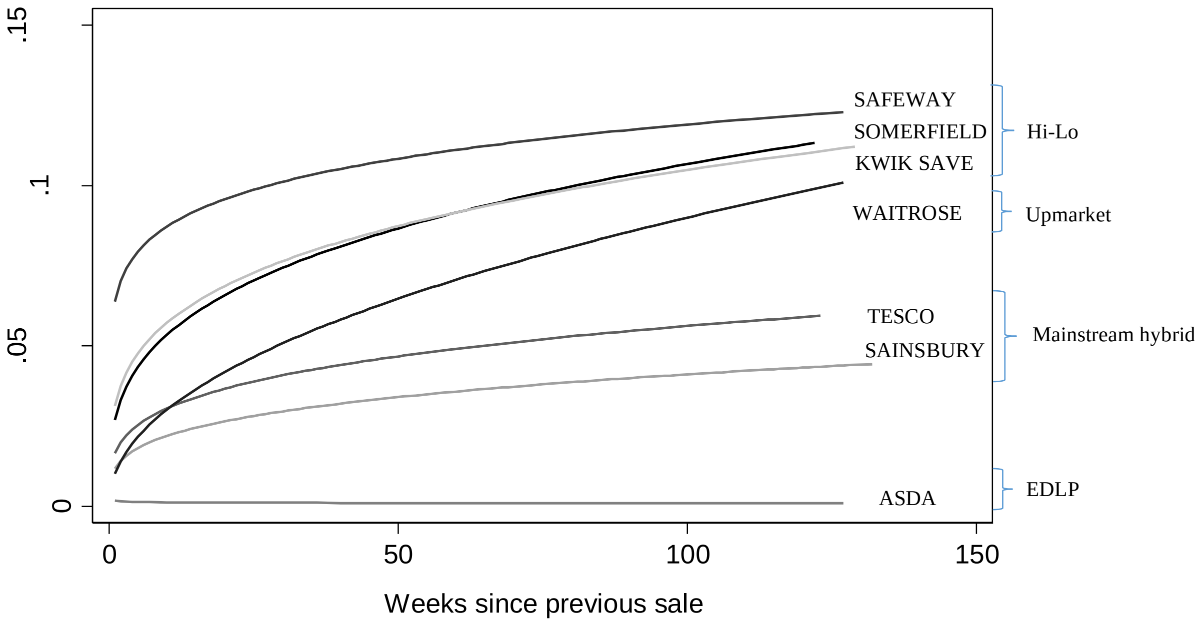

Table 1. The duration of regular price spells (weeks) by classification

	Mean	Median	S.D.	Min	Max
Overall average	20	10	25	1	132
Retailer					
Asda	54	41	39	1	127
Kwik Save	17	10	21	1	129
Safeway	14	5	21	1	127
Sainsbury	29	17	31	1	132
Somerfield	17	9	20	1	122
Tesco	24	15	26	1	123
Waitrose	26	16	26	1	127
Brand Type					
National Brands	20	10	25	1	132
Private Labels	26	14	27	1	132
Product Category					
Corned Beef	23	12	28	1	122
Tinned Soup	17	9	21	1	126
Tinned Tomatoes	51	44	44	1	132
Tinned Tuna	13	7	20	1	127
Breakfast Cereal	18	12	19	1	112
Instant Coffee	20	11	25	1	129
Tea Bags	17	9	21	1	128
Jam	28	17	29	2	111
Fish Fingers	24	12	30	1	116
Frozen Peas	22	17	20	1	87
Frozen Pizza	15	9	18	1	73
Oven Chips	25	16	25	1	115
Chilled Orange Juice	22	10	29	1	132
Yoghurt	20	10	27	1	127
Bread	24	12	29	1	122
Product Format					
Tinned	18	9	23	1	132
Ambient	20	11	23	1	129
Frozen	21	13	23	1	116
Chilled	21	9	29	1	132
Fresh	24	12	27	1	127
Perishability					
Shelf-storable	19	10	23	1	132
Perishable	23	11	27	1	132
Sales Depth					
10-25%	17	10	19	1	114
25-35%	15	9	17	1	109
35-100%	12	7	15	1	79

Table 2. Proportional hazard models of sales in UK food retailing

	Model 1		Model 2		Model 3		Model 4	
	Hazard	S.E.	Hazard	S.E.	Hazard	S.E.	Hazard	S.E.
Baseline (p)	0.87***	(0.01)	1.13***	(0.02)	1.13***	(0.02)	1.13***	(0.02)
Breakfast Cereal	1.27**	(0.15)	1.38	(0.31)				
Corned Beef	0.95	(0.15)	0.98	(0.28)				
Fish Fingers	0.67	(0.26)	0.59	(0.33)				
Frozen Peas	0.73	(0.15)	0.73	(0.25)				
Frozen Pizza	1.39**	(0.20)	1.29	(0.37)				
Instant Coffee	1.20**	(0.11)	1.21	(0.22)				
Jam	0.64***	(0.10)	0.60*	(0.16)				
Oven Chips	0.84	(0.10)	0.77	(0.17)				
Tea Bags	1.29**	(0.13)	1.22	(0.25)				
Tinned Soup	1.46***	(0.12)	1.41**	(0.22)				
Tinned Tomatoes	0.32***	(0.07)	0.34***	(0.11)				
Tinned Tuna	1.57***	(0.18)	1.69**	(0.40)				
Wrapped Bread	0.85**	(0.07)	0.89	(0.14)				
Yoghurt	1.30***	(0.13)	1.26	(0.25)				
Fresh					1.01	(0.13)		
Frozen					0.78**	(0.09)		
Ambient					0.75*	(0.12)		
Tinned					1.15	(0.14)		
Shelf Storable							1.32***	(0.10)
ASDA	0.22***	(0.04)	0.19***	(0.04)	0.19***	(0.04)	0.19***	(0.04)
KWIK SAVE	1.55***	(0.10)	1.70***	(0.22)	1.66***	(0.21)	1.72***	(0.22)
SAFEWAY	2.03***	(0.13)	2.66***	(0.31)	2.58***	(0.30)	2.60***	(0.31)
SAINSBURY	0.86**	(0.06)	0.83	(0.10)	0.80*	(0.10)	0.79*	(0.10)
SOMERFIELD	1.50***	(0.10)	1.71***	(0.210)	1.62***	(0.20)	1.66***	(0.21)
WAITROSE	1.03	(0.09)	1.11	(0.16)	1.05	(0.15)	1.04	(0.15)
Label	0.75***	(0.05)	0.89	(0.11)	0.82	(0.10)	0.86	(0.10)
Rival			1.87***	(0.10)	1.94***	(0.10)	1.94***	(0.10)
Label x Rival			0.93	(0.16)	0.83	(0.14)	0.81	(0.14)
Month dummy	Yes		Yes		Yes		Yes	
UPC Random Effects	No		Yes		Yes		Yes	
Likelihood-ratio test of $H_0\colon \sigma_\alpha^2 = 0$ (*p* value)			0.00		0.00		0.00	
Observations	4303		4303		4303		4303	
UPCs	1703		1703		1703		1703	

Notes: Coefficients minus one represent the proportional change in the occurrence of a sale. Results are relative to the base group, orange juice, branded products stocked by the market leader, Tesco in Model 2 (Chilled in Model 3 and Perishable in Model 3). ***, ** and * denote that the null hypothesis of no effect (i.e. unity in the hazard ratio) is rejected at the 1%, 5% and 10% level respectively.

Table 3: Proportional Hazard models by Retailer (Model 4)

	ASDA	KWIKSAVE	SAFEWAY	SAINSBURY	SOMERFIELD	TESCO	WAITROSE
Baseline (p)	0.86	1.22^{***}	1.12^{***}	1.26^{***}	1.25^{***}	1.26^{***}	1.41^{***}
	(0.13)	(0.04)	(0.03)	(0.05)	(0.04)	(0.06)	(0.07)
Shelf-Storable	0.56	0.67^{**}	2.95^{***}	1.79^{***}	0.73^{**}	2.63^{***}	1.97^{***}
	(0.22)	(0.13)	(0.50)	(0.35)	(0.11)	(0.42)	(0.52)
Label	1.45	1.14	0.72	0.77	0.33^{***}	0.32^{***}	1.89^{*}
	(1.56)	(0.38)	(0.20)	(0.23)	(0.12)	(0.11)	(0.63)
Rival	1.51	1.64^{***}	1.98^{***}	2.00^{***}	1.64^{***}	2.67^{***}	2.47^{***}
	(0.63)	(0.20)	(0.20)	(0.31)	(0.19)	(0.37)	(0.53)
$Rival \times label$		0.63	0.81	0.87	2.04	1.22	0.52
		(0.26)	(0.25)	(0.35)	(1.10)	(0.71)	(0.38)
Month dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
UPC Random Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Likelihood-ratio test of σ_{α}^{2}=0: (P value)		0.00	0.00	0.00	0.00	0.00	0.00
Observations	101	739	1151	600	820	527	365

Notes: Coefficients minus one represent the proportional change in the occurrence of a sale. Results are relative to the base group, perishable branded products. The asterisks ***, ** and * denote that the null hypothesis of no effect (i.e. unity in the hazard ratio) is rejected at the 1%, 5% and 10% level respectively. Standard errors are in brackets. Insufficient observations mean that random effects cannot be applied to the Asda model reported here. Random effects are applied to variants of the Asda model in Online Appendix A5. Results on the nature of time dependence remain unchanged.

Table 4: Hazard functions by sale depth threshold (Model 4)

	>10% discounts		>25% discounts		>35% discounts	
	Hazard	S.E.	Hazard	S.E.	Hazard	S.E.
Baseline (p)	1.13***	(0.02)	1.21***	(0.03)	1.28***	(0.05)
label	0.86	(0.10)	0.55***	(0.11)	0.36***	(0.11)
rival	1.94***	(0.10)	1.61***	(0.12)	2.42***	(0.36)
label×rival	0.81	(0.14)	0.79	(0.28)	4.08	(4.76)
Shelf-Storable	1.32***	(0.10)	1.63***	(0.21)	0.94	(0.20)
SAINSBURY	0.79*	(0.10)	0.52***	(0.13)	0.15***	(0.07)
ASDA	0.19***	(0.04)	0.08***	(0.05)	0.05**	(0.06)
SAFEWAY	2.60***	(0.31)	5.30***	(1.22)	2.40**	(0.87)
SOMERFIELD	1.66***	(0.21)	2.62***	(0.62)	1.13	(0.42)
KWIK SAVE	1.72***	(0.22)	2.70***	(0.69)	0.95	(0.40)
WAITROSE	1.04	(0.15)	1.35	(0.39)	0.27*	(0.19)
February	1.02	(0.10)	1.55***	(0.23)	1.37	(0.45)
March	0.74***	(0.07)	1.05	(0.16)	0.71	(0.19)
April	0.87	(0.09)	1.36*	(0.22)	0.44**	(0.14)
May	0.72***	(0.08)	0.62***	(0.11)	0.60*	(0.17)
June	0.90	(0.10)	1.01	(0.19)	0.88	(0.34)
July	1.32**	(0.16)	1.98***	(0.41)	1.43	(0.49)
August	1.04	(0.11)	1.20	(0.22)	1.19	(0.35)
September	1.14	(0.13)	1.76***	(0.32)	0.90	(0.26)
October	1.23**	(0.12)	1.86***	(0.30)	1.65*	(0.48)
November	1.08	(0.10)	2.04***	(0.30)	1.39	(0.37)
December	1.26**	(0.12)	1.19	(0.20)	0.62*	(0.18)
UPC Random Effects	Yes		Yes		Yes	
LR test of $H_0\!: \sigma_\alpha^2$=0 (p value)	0.00		0.00		0.00	
N	4303		2021		820	

Notes: Coefficients minus one represent the proportional change in the occurrence of a sale. Standard error is reported in brackets. ***, ** and * denote that the null hypothesis of no effect (i.e., unity in the hazard ratio) is rejected at the 1%, 5% and 10% level respectively. LR test refers to likelihood –ratio test.