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Do Sales Matter? Evidence from UK Food Retailing

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Abstract

This paper assesses the role of sales as a feature of price dynamics using scanner data. The study analyses a unique, high frequency panel of supermarket prices consisting of over 230,000 weekly price observations on around 500 products in 15 categories of food stocked by the UK's seven largest retail chains. In all, 1,700 weekly time series are available at the barcode-specific level including branded and own-label products. The data allows the frequency, magnitude and duration of sales to be analysed in greater detail than has hitherto been possible with UK data. The main results are: (i) sales are a key feature of aggregate price variation with around 40 per cent of price variation being accounted for by sales once price differences for each UPC level across the major retailers are accounted for; (ii) much of the price variation that is observed in the UK food retailing sector is accounted for by price differences between retailers; (iii) only a small proportion of price variation that is observed in UK food retailing is common across the major retailers suggesting that cost shocks originating at the manufacturing level is not one of the main sources of price variation in the UK; (iv) own-label products also exhibit considerable sales behaviour though this is less important than sales for branded goods; and (v) there is some evidence of coordination in the timing of sales across retailers insofar as the probability of a sale at the UPC level at a given retailer increases if the product is also on sale at another retailer.

Keywords: Sales, price variation, retail.

JEL Classification: L16; L66; Q13.

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1. Introduction

The relative importance of sales (i.e. temporary reductions in price) in understanding price dynamics has attracted attention in the macroeconomic and industrial organisation literature. Against the background of explaining aggregate price adjustment, recent empirical studies have found that the role of sales to feature significantly. Nakamura and Steinsson (2008) report that 20 per cent of price changes are due to sales which are typically concentrated in relatively few sectors such as food and clothing. Nakamura (2008) reports that a large proportion of price adjustment originates at the store and product levels. Hosken and Rieffen (2004) also focus on the importance of sales in overall price adjustment and provide evidence that sales are a significant feature of retail price dynamics. Specifically, depending on the product category, they report that 20 to 50 per cent of the annual variation in retail (food) prices is due to sales. These recent studies employ US data, the main feature of which being that they are relatively comprehensive in that they cover a large range of products or product groups, use monthly or weekly data and include price data over retailers and/or stores. With reference to European data, comparable studies are relatively sparse, the recent Eurosystem Inflation Persistence Network making only limited reference to the role of sales; Dhyne *et al.* (2006) argue that the relative importance of sales is less significant in the EU than it is likely to be for the US, their assessment being that sales account for only 3 percentage points in the overall frequency of price changes[1].

From an industrial organisation perspective, the main focus in the theoretical literature has been on the role of sales in firm's strategies and where temporary price reductions can arise

[1] Dhyne *et al.* (2006) note that there are methodological issues in identifying sales across the EU. Given that the Inflation Persistence Network was based on data from national statistical agencies, some agencies record sales while others do not. Dhyne *et al.* (2006) provide an overview of the key insights from this project.

endogenously. Most notable contributions that address the issue of sales include Varian (1980), Sobel (1984), Pesendorfer (2002) among others[2]. In terms of matching empirics with theory, Hosken and Rieffen (*op. cit.)* argue that the existing theoretical literature does not sit comfortably with the data. More recently, Berck *et al.* (2008) test the predictions arising from the theoretical literature on sales using weekly data on orange juice in the US. They note that the existing theoretical literature on sales implicitly assumes that sales are determined by manufacturers not retailers while their results suggest that understanding the role of retailers is key in understanding sales behaviour. They also note other disparities between data and theory including the conjecture that own-label goods are less likely to be on sale than branded goods, this distinction not being so apparent in the data they observe. The observation that sales are more likely to be driven by retailers rather than manufacturers is also noted by Nakamura (*op. cit*.), the role of retailers in price behaviour more generally being highlighted by Villas-Boas (2007) and Chevalier *et al.* (2003) among others.

In this paper, we contribute to the empirical literature on sales and the role of sales in price variation using high-frequency data on UK food retailing. Our coverage fills some gaps in this literature while combining several of the advantages that are present in some of the recent empirical research on this issue[3]. Most obviously, it addresses these issues using high-frequency data for an EU country, the more recent empirical sales studies being confined to US data and with the issue of sales not being directly addressed in the EU Inflation Persistence Network. As noted above, there is a perception that sales are a less important

[2] One strand of the theory of sales relates to firms discriminating among different types of consumers or over time. Another strand emphasises the role of store inventories. For an example of the latter, see Aguirregabiria (1999).

[3] Data frequency and how the data are reported is an issue in identifying sales. In Nakamura and Steinsson (2008), the data is monthly and comes from the Bureau of Labor Statistics (BLS) used to construct the consumer price index where a 'sale' is denoted by a sale flag when the data is collected. Nakamura (2008) uses weekly scanner data at the UPC level by retailer and store for one year. Berck *et al*. (2008) use weekly scanner data for two product categories (fresh and concentrated orange juice) across stores and retailers across the US. In the latter, they have to define what will be categorised as a "sale" in the data, which is the approach that is also followed here. Determining a sale in this manner is also the approach followed by Hosken and Rieffen (2004).

feature of price behaviour across the EU and we are able to offer a more detailed assessment of this claim. The paper uses scanner data at the Unique Product Code (UPC) level, covering 500 products in 15 categories of food sold UK's seven largest UK food retail chains over a two and a half year period from September 2001 to April 2004. The data we employ are at weekly intervals rather than monthly (see, in comparison, Hosken and Rieffen (*op. cit.)* and Nakamura and Steinsson (*op. cit*.) who use monthly), which is an advantage in determining sales since promotions may exist for only one or two weeks at a time and hence be missed with monthly data (Hosken and Rieffen, *op. cit.).* In addition, the UPC data is available at the individual retailer-level and our coverage relates to all the major food retailers in the UK, giving 1,704 UPCs in all. Since the UK food retailing sector is relatively concentrated with the retailers reportedly employing national pricing strategies, the data coverage here offers a comprehensive perspective on the significance of sales in the UK food retailing sector with the variation in prices and the relative importance of sales being identified at the retailer-level[4]. Finally, the UPC data we use separates out own-label products from branded products for each of the major retailers, so we are able to offer an assessment of the distinction between these product categories, a distinction that was not possible in the studies by Hosken and Rieffen (*op. cit.)* and Nakamura (*op. cit*.). As noted, this distinction has been highlighted by Berck *et al*. (*op. cit.)* but the data coverage relating to orange juice products only. As such, we offer a more general perspective on the brand/own-label distinction.

Our key results are as follows: (i) sales are a key feature of aggregate price variation with around 40 per cent of price variation being accounted for by sales once price differences for each UPC level across the major retailers are accounted for; (ii) much of the price variation that is observed in the UK food retailing sector is accounted for by price differences between

[4] Concerns about the potential for market power exerted by UK food retailers have attracted the attention of the UK Competition Commission. See Competition Commission (2000) for a comprehensive overview of this sector and assessment relating to concerns about market power.

retailers; (iii) only a small proportion of price variation that is observed in UK food retailing is common across the major retailers suggesting that cost shocks originating at the manufacturing level is not one of the main sources of price variation in the UK (this observation being consistent with Nakamura (*op. cit*) and Hosken and Rieffen (*op. cit.)* for the US but with the evidence reported here being suggesting that the role of 'common' shocks to be less important than in the US); (iv) own-label products also exhibit considerable sales behaviour though this is less important than sales for branded goods; and (v) there is some evidence of coordination in the timing of sales across retailers insofar as the probability of a sale at the UPC level at a given retailer increases if the product is also on sale at another retailer.

The paper is organised as follows. In Section 2, we describe the data that forms the basis for the analysis of sales. In Section 3, we present a discussion of the methodological issues in identifying sales periods and, in Section 4, we provide a summary of the principal features of sales in the UK food retailing sector. In Section 5, we provide an overall assessment of the relative importance of sales in price variation and gauge the role of sales against 'common' price changes originating from the manufacturing sector and retailer-specific price variation. We address the timing of sales across retailers in Section 6 and, in Section 7, we summarise and conclude.

2. Price Data

In the empirical analysis we utilise a unique, extensive and high-frequency panel of supermarket food prices derived from electronic point of sale (EPOS) data obtained from A.C. Nielsen (UK), a leading market research company to whom all major UK supermarket chains submit data relating to in-store transactions. Our data derives from the records of the seven largest of these supermarkets, which as a group represented around three-quarters of all food sales in the UK during the sample period. The supermarkets include all mainstream and one prestige grocery retailer. [5]

The price information contained in the dataset is based on the details recorded by laser bar-code scanners as products pass through supermarket check-outs. As a result, prices are based on 100% of transactions of the sampled products rather than derived from consumer surveys. Overall, the sample consists of 231,069 weekly price observations on 507 products in 15 categories of food.[6] They relate to a (137 observation) sample frame running from 8th September 2001 to 17th April 2004. Some 90% of products are available throughout this period, the minimum number of observations for any product being 103 weeks. [7]

Each price observation in the sample represents the simple average of the prices posted in each of the retailers' stores on the Saturday of each week. Price observations are thus retailer-based national (Great Britain) averages. For a retailer such as Tesco, (the largest in the UK) prices are averaged over those posted in several hundred of its stores nation-wide. While store managers may have some flexibility over pricing, particularly for perishable items, the large number of products stocked in most stores (which typically exceeds 25,000) mitigates against widespread differences between stores. Also, major UK grocery retail chains claim that national pricing strategies are the norm for the bar-coded food products (Competition Commission, 2000).

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[5] The seven supermarkets included in the sample are Tesco, Sainsbury, ASDA, Safeway, Somerfield, Kwik Save and Waitrose. The remaining 25% of sales are accounted for by small national and regional supermarket chains and independent retailers. Discounters such as Lidl, Netto and Aldi did not submit data to Neilsen at the time of the sample, but together accounted for less than 3% of market share. Marks and Spencer did not sell branded goods and are excluded for this reason.

[6] The 15 categories are orange juice, instant coffee, breakfast cereals, teabags, yoghurt, wrapped bread, tinned tuna, tinned tomatoes, tinned soup, corned beef, fish fingers, frozen peas, frozen chips, Jam and frozen pizza.

[7] Time series are contiguous (in that there are no missing observations once the time series has begun) in 100% of cases, although some (10%) start later than 8th September. All time series finish in the week ending 17th April 2004.

One key feature of the prices is that they incorporate the effect of promotional activity. The price data used in this study include all promotional activity, whether in the form of price (e.g. '50% off') or quantity ('buy-one-get-one-free') discounts. Discounts relating to store 'loyalty' cards are not included since they apply to the consumer's total spend rather than the prices of specific products.

The data set identifies products at a highly detailed level. In general, two products are distinct if they have different bar-codes, so that 100 gram and 200 gram jars of the same brand of instant coffee are different products for which separate prices are recorded. Furthermore, many of the products are national brands that are sold by all retail chains, so the data set contains retailer-specific prices of such products. We identify each retailer-product combination with a Unique Product Code (UPC), so that, for example, a 100 gram jar of Nescafe 'Gold Blend' instant coffee stocked by Tesco and Sainsbury are two separate UPCs each with their own time series of weekly prices. In all there are 1,704 such UPC prices series, the distribution of which is summarised in Table 1.[8] Data (percentage of data set) are most prevalent in the bread (34%), soup (18%), coffee (8%) and orange juice (6%) categories, each of which contain in excess 100 UPCs. The least populated categories, such as frozen fish fingers (1%) and frozen pizza 1(%), contain 20 UPCs each. As is evident from these figures, the dataset is by no means a representative sample of consumer spending on food (fresh fruit and vegetables are not part of the dataset since they do not carry unique barcode indicators) but the range of categories is relatively broad, spanning beverages and foods across a range of formats (fresh, chilled ambient and frozen).

[8] Each price observation is uniquely identified by its UPC and the (week ending) date but because the data set is an unbalanced panel (in that not all products are sold in all supermarket chains in all weeks) summary statistics vary slightly depending on the standardisation that is used. For example, orange juice accounts for 5.33% of the product codes, 6.34% of the UPCs (product code × retailers stocking the product) and 6.40% of the observations (product code × retailers × weeks). Unless specifically stated, UPC (i.e. the product code-retailer combination) will be taken to represent the principal unit of analysis when describing the dataset.

As Table 1 also shows, seven categories contain products in both branded (sold with the manufacturer's name) and own-label (sold under the retailer's name) forms. Own-label products with the same product profile (e.g. an 800 gram standard medium sliced white loaf) are treated as one product and have the same product code in the data base. Retailer-specific prices of these products (i.e. UPCs) represent the Tesco own-label 800 gram standard medium sliced white loaf, or the Sainsbury own label 800 gram standard medium sliced white loaf, for example. Hence, own-label versions of the same product are treated analogously to the branded products stocked by multiple retailers in the Neilsen data set. In the UK, where sales of own-label products account for a significant minority of the total consumer spend, this dimension of the data set offers potentially insights in to any differences between the pricing of manufacturer- and retailer- branded products. Own-label products account for nearly one-fifth of the products listed in the dataset.

Table 1: Distribution of Unique Product Codes (UPCs) by Category

Category	**Brands**	**Own Label**	**All**	**% of total**
Orange Juice	57	51	108	6.34
Instant Coffee	111	27	138	8.10
Tinned Tuna	51	0	51	2.99
Tinned Tomatoes	50	0	50	2.93
Tinned Soup	237	71	308	18.08
Oven Chips	83	0	83	4.87
Corned Beef	25	5	30	1.76
Frozen Peas	34	0	34	2.00
Fish Fingers	20	0	20	1.17
Breakfast Cereal	66	0	66	3.87
Tea Bags	59	8	67	3.93
Yoghurt	65	4	69	4.05
Wrapped Bread	488	95	583	34.21
Jam	33	44	77	4.52
Frozen Pizza	20	0	20	1.17
Total	**1,399**	**305**	**1,704**	**100.00**

One of the most interesting aspects of the data set is that prices are available by retail chain, facilitating comparison of price and sales behaviour for identically bar-coded products across retailers. The 1,704 UPCs belong to 507 bar-coded products, and Table 2 drills down through the data set to see how these products are distributed across retailers, broken down by label. [9] As is clear, not every product is stocked by all retailers but two-thirds (64%=325/507) are sold in at least 2 retailers, and 18% sold in all seven. In terms of the distribution of products by label, some 71% (=267/375) of branded products are sold in at least 2 retailers with 21% sold in all seven. For own-label products comparable statistics are 43% and 11% suggesting that coverage is reasonably broad across the market as a whole, particularly for branded goods.

Table 2: The Distribution of Products (by label) Stocked by the Supermarkets

	Number of Supermarkets							
	1	2	3	4	5	6	7	**Total**
Branded	**107**	**46**	**36**	**37**	**28**	**43**	**78**	**375**
	28%	12%	10%	10%	7%	11%	21%	100%
	59%	68%	92%	76%	85%	98%	85%	74%
Own Label	**75**	**22**	**3**	**12**	**5**	**1**	**14**	**132**
	57%	17%	2%	9%	4%	1%	11%	100%
	41%	32%	8%	24%	15%	2%	15%	26%
Total	**182**	**68**	**39**	**49**	**33**	**44**	**92**	**507**
	36%	13%	8%	10%	6%	9%	18%	100%
	100%	100%	100%	100%	100%	100%	100%	100%

Note: Cell entries in bold represent the number of series in each classification, with this number expressed as a percentage of the row (label) and column (sold in) totals respectively in the cell entries beneath.

[9] Note that the entries in Table 2 refer to products (e.g. 100g jar of Nescafe 'Gold Blend' instant coffee) rather than UPCs (100g jar of Nescafe 'Gold Blend' instant coffee in Tesco) and thus proportions in the table need not correspond to those in Table 1. See previous footnote for clarification.

Finally, Table 3 shows how the UPCs are distributed by retailer. The figures suggest that all seven supermarkets are well-represented in the sample, Tesco having the largest number of observations at 17%, Waitrose the fewest at 11%.

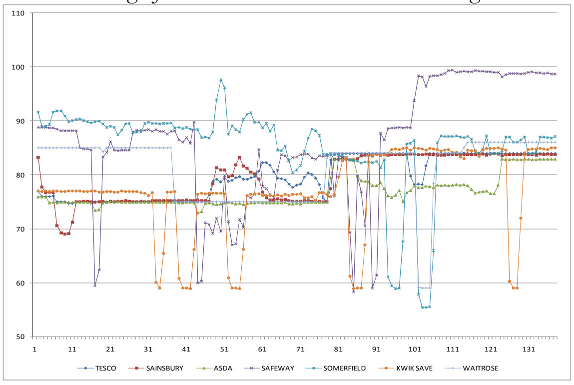
Table 3: Distribution of Unique Product Codes by Retailer

Chain	**UPCs**	**% of total**
Tesco	292	17.14
Sainsbury	275	16.14
Asda	228	13.38
Safeway	263	15.43
Somerfield	242	14.20
Kwik save	221	12.97
Waitrose	183	10.74
Total	**1,704**	**100.00**

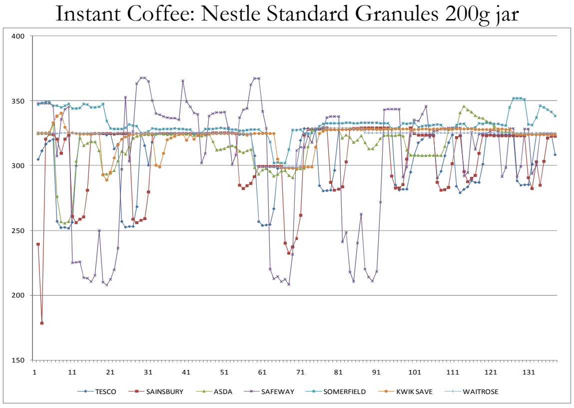
To give a flavour of the data, Figure 1 presents the prices of eight well-known branded products selected from the data set on the basis that they are sold in most if not all of the retail chains. Hence, for each product there are seven UPCs representing the national average prices in each of the retailers at weekly intervals. Although accounting for a small fraction of the prices in the data set, they display a number of interesting features, in particular is the way that sales punctuate the time series, albeit with as frequency and intensity that varies by product and retailer. When not on sale, prices tend to coalesce around particular levels, although this regular (i.e. non-sale) price changes at discrete points in the sample. It is also apparent that, despite representing the prices of identically bar-coded products, there are persistent and substantial differences in the prices charged by retail chains.

Figure 1: Weekly Prices (pence) of a Selection of Products sold by UK Retail Chains

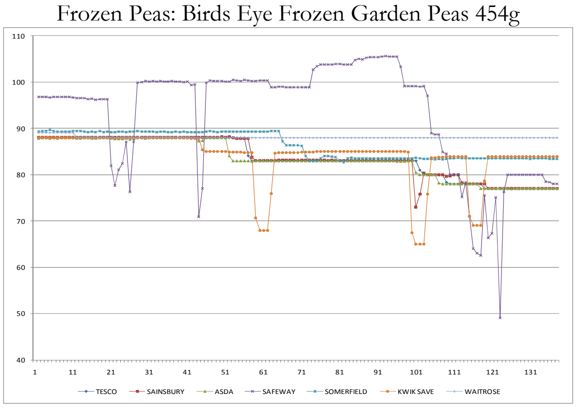
Orange Juice: Del Monte 1 Litre Tetra Single



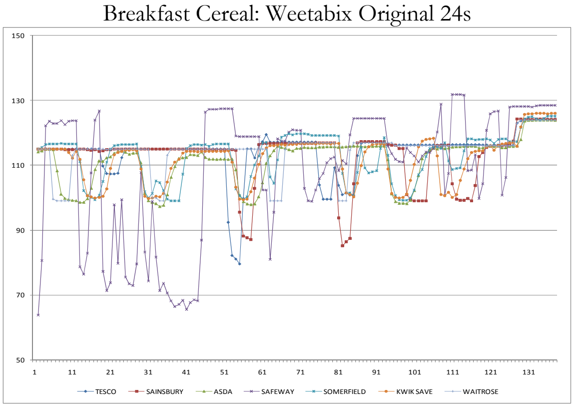
Instant Coffee: Nestle Standard Granules 200g jar



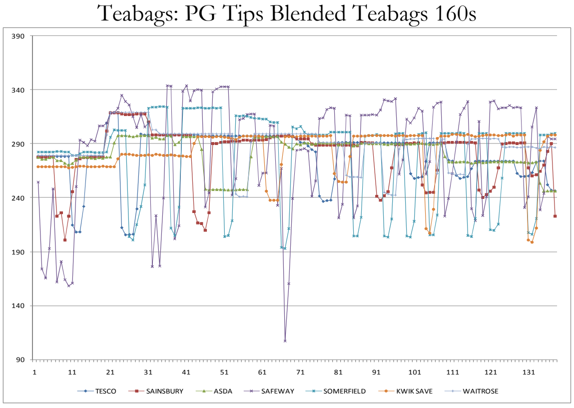
Frozen Peas: Birds Eye Frozen Garden Peas 454g



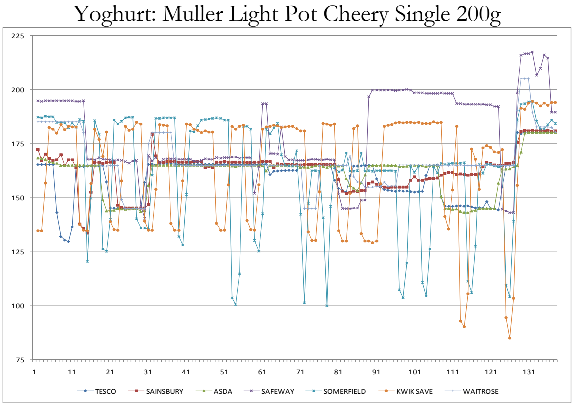
Breakfast Cereal: Weetabix Original 24s



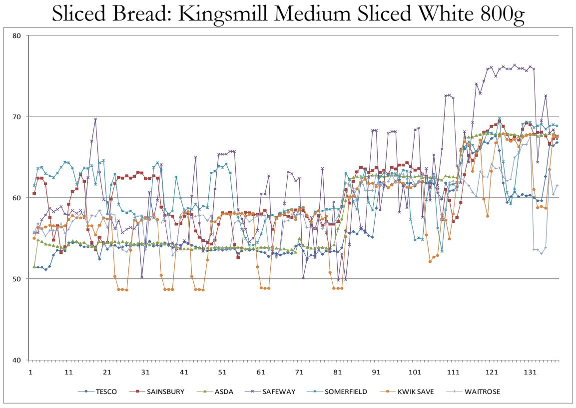
Teabags: PG Tips Blended Teabags 160s



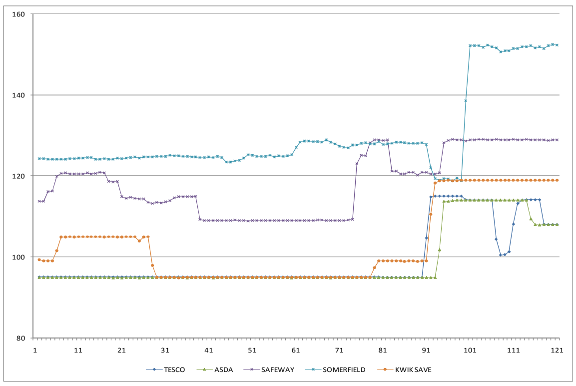
Yoghurt: Muller Light Pot Cheery Single 200g



Sliced Bread: Kingsmill Medium Sliced White 800g



Jam: Streamline Strawberry 400g Jar



Using the entire data set the average difference between the highest and lowest weekly prices paid for products with the same barcode is 30%. For branded products this dispersion is 27% and for own-label products 45%. While this figures underline the fact that price dispersion is pervasive and significant, it seems likely that such dispersions arises from not only from persistent price differentials across retailers but also the compounding effect of sales.

Before we attempt to disentangle the contribution of these effects to overall price variation, it is useful to investigate the dispersion of average prices charged by each retailer over the sample. To do so, consider Table 4 which details the average prices of products in each retailer for branded, own-label and all products (i.e. branded and own-label combined). As alluded to above, not every product is stocked by all retailers so the table reports prices based on two classifications of products: (a) those products stocked in each retailer and (b) the subset of 92 products (comprising 78 branded 14 own label) and that are stocked by all seven retailers. Being common to all the retailers these products typically represent market leaders, major national brands and everyday own label products such as standard white loaf and tinned tomatoes. The table also lists the rank order of average prices by supermarket (1 denoting the cheapest) and the number of price observations upon which the averages are based.

With differences according to the product grouping and label status, the picture is somewhat of a complex one, but a few features are particularly noteworthy. In terms of the classification given by (a) namely, the products that each supermarket stocks, there appears to be a cluster of budget supermarkets (Asda, Somerfield and Kwik Save) selling branded products at low cost and another largely separate cluster of mainstream retailers (comprising Asda, Tesco and Sainsbury) selling own-label products at low cost. This pattern may reflect the preponderance of cheaper brands sold in the budget supermarkets on the one hand and the ability of mainstream retailers to negotiate low prices with the manufacturers of their own-label products on the other. The luxury retailer Waitrose, is among the highest priced retailers for both branded and own-label products.

While offering a useful summary of pricing across retailers, it is price comparisons based on a common basket of products that typically generates the keenest interest. Using the prices of the 92 products stocked in all seven retailers we find that a single cluster of supermarkets (Asda, Tesco, Sainsbury and Kwik Save) offers low prices in both branded and own label product categories. One retailer appears in all such clusters and leads the rankings whichever way the data are classified and thus it would appear that on the sample used here Asda is most justified in staking a claim as the lowest cost retailer. While it offers the same average price for the set of branded products as the UK’s largest retailer, Tesco, it is prices of like-for-like own-label products are markedly lower than its rivals.

Overall, the following stylised facts emerge from this simple analysis of average prices, namely:

(i) The average prices for national brands and brand leaders are remarkably similar, particularly among the four retailers with the lowest average prices;

(ii) There is a significant premium for branded products, which across all retailers is 50% under (a) and 15% under (b);

(iii) When comparing the like-for-like products in our sample, it is the mainstream retailers that offer the lowest prices for both branded and own-label products.

Table 4: Average Prices by Retailer

	Branded Products				Own-Label Products				All Products			
	(a) stocked by retailer		(b) stocked by all		(a) stocked by retailer		(b) stocked by all		(a) stocked by retailer		(b) stocked by all	
	Price	Rank	Price	Rank	Price	Rank	Price	Rank	Price	Rank	Price	Rank
TESCO	142	4	132	1	79	2	109	2	128	4	128	2
SAINSBURY	143	5	134	2	90	3	118	4	132	5	131	4
ASDA	128	2	132	1	64	1	102	1	117	1	127	1
SAFEWAY	149	6	142	7	102	5	125	5	142	7	140	7
SOMERFIELD	129	3	141	6	109	7	130	7	127	3	140	6
KWIK SAVE	124	1	134	2	98	4	113	3	121	2	131	3
WAITROSE	155	7	138	5	103	6	128	6	140	6	137	5
Average	**138**		**136**		**92**		**118**		**130**		**133**	

3. Creating Sales Data

In order to investigate the impact of sales, an indicator variable is created to identify sale periods. Prices are generally not declared as ‘sale’ or ‘regular’ by manufacturers or retailers in the datasets constructed by government departments or commercial organisations, with the result that the identification of sale periods is based upon the prices themselves. Broadly speaking, sales are simply periods of temporary price reduction, although the precise definition employed in empirical work varies. For example, prices supplied by the Bureau of Labour Statistics (BLS) for the construction of the U.S. Consumer Price Index is identified as ‘on sale’ if the product is sold below its ‘regular selling price’, as assessed by the Bureau’s field agents in the monthly survey. Nakamura and Steinsson (*op. cit.)* use this sales flag to identify sale periods. Hosken and Reiffen (*op. cit.)* also use BLS data but define a sale with reference to the actual behaviour of prices, rather than the field agents' assessment. Specifically, if a price falls by more than some fixed percentage (they consider 10% and 20%) between two adjacent months (*m*-1 and *m*) but is then reversed in the following month (i.e. between *m* and *m*+1), the product is treated as being on sale in month *m*. In other words, a product is recorded as being 'on sale' in month *m* if the prices in months *m*-1 and *m*+1 are markedly (i.e. 10% or 20%) higher. Unlike Nakamura and Steinsson's (*op. cit.)* measure, this definition implicitly restricts sales to last one month, although this is probably not an unreasonable assumption in the majority of cases. Nevertheless, because price setting typically occurs on a weekly basis, some of the finer detail of price adjustment is inevitably obscured by the use of monthly data.

In those studies analysing weekly price data, definitions of sale prices are modified to reflect the data's higher frequency. For example, Campbell and Eden (2005) define a sale to have occurred if a price decline of 10% or more between weeks *w*-1 and *w* is then completely reversed within two weeks (i.e. in *w* +1 or *w*+2). Using this definition, a sale lasts for a minimum of one and a maximum of three weeks. Berck *et al.* (*op.cit.*) consider price falls of 25%, 35% and 50%, but use the store's modal price ($\tilde{p}$) over a two year period as the basis for comparison rather than the price in the week preceding the decline. Using this definition, sales are recorded for all weeks *w* in which the price falls below $\tilde{p}$. While this approach leaves the length of sales unconstrained, it relies upon the mode being representative of the non-sale (or regular) price. Where the regular prices changes over time (reflecting general inflation or specific changes in production costs, for example) use of the mode to identify sales is arguably less than ideal (see below).[10]

The foregoing discussion serves to highlight some of the practical difficulties in identifying sales - 'periods of temporary low prices' -, from price data alone, namely the duration of 'temporary', the magnitude of 'low' and the reference price used in the assessment of each. Mindful of these considerations we define a sale as a period during which price falls by at least *x*% of the observation immediately preceding the decline in prices, and then which is reversed within 12 weeks. In this definition notice that:

(i) sales of long duration (i.e. less than 3 months) are allowed for. While sales of 2-4 weeks are typically believed to be the norm and sales of longer than 6 weeks rare in UK food retailing (Competition Commission, 2000 p.116) this measure does allow for the (albeit infrequently observed) longer sale durations;

(ii) it is the cumulative price drop (i.e. the peak-to-trough difference) that it used rather than any week-on-week change in price that is used to define the magnitude of price change. This allows for price changes that are staggered over more than a single week at the start of or end of a sale period. This may be important in our data if a national price promotion is implemented over adjacent weeks;

(iii) it is actual prices that act as the reference price. This is likely to be useful in cases where there is no single non-sale price (e.g. 99p) that applies over the entire sample. Hence, the *regular price*, refers to a state of nature (paralleling the status of the term *sale price*) rather than a fixed value such as the mode;

[10] It is noteworthy that in their study of refrigerated and frozen orange juice, Berck *et al.* (2008) find evidence of a clear mode in fewer than half the refrigerated products and in two-thirds of frozen products they analyse.

(iv) in recognition of the fact that results inevitably depend on the price decline that is chosen, we consider three thresholds, namely x = 10%, 25%, and 35%;

(v) the sale period ends when prices return to a new regular price. With this condition, prices do not need to return to their pre-sale level.

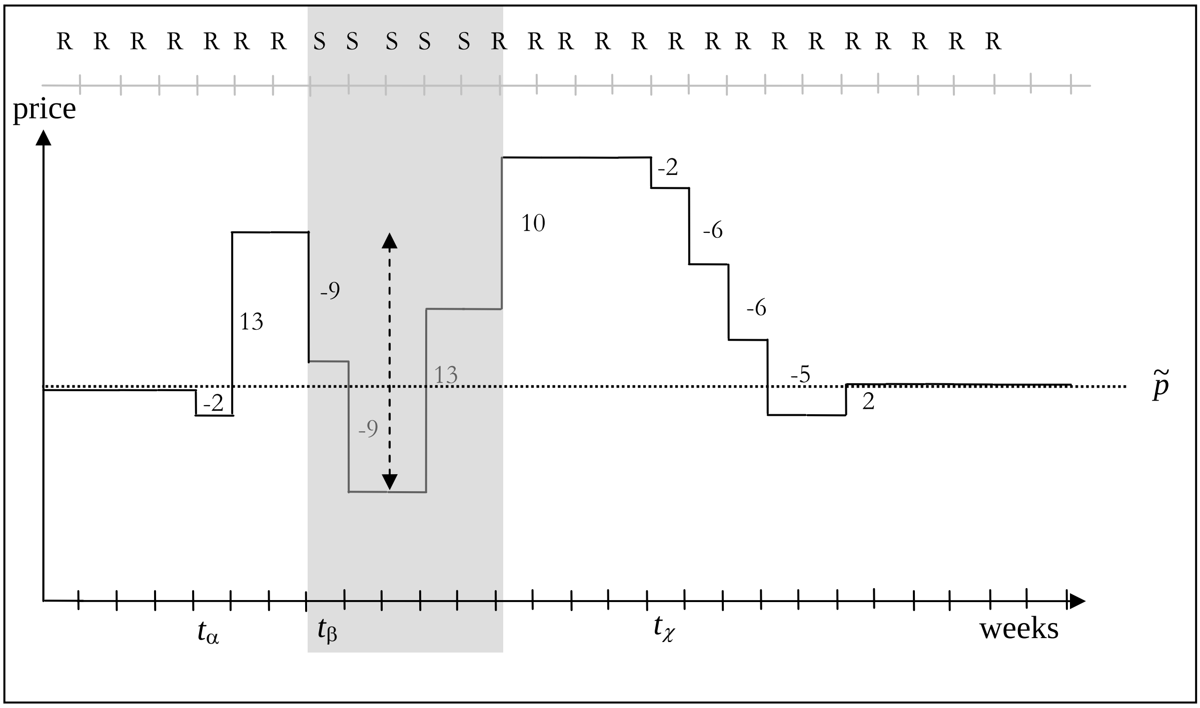
(vi) all prices between the initial decline and the subsequent reversal are counted as sale prices. Where the start (end) of a sale occurs in adjacent weeks in different regions, the fall (rise) in the national average price will be staggered and tend to overstate the duration of the sale slightly.

In order to illustrate the effect of these conditions in the creation of a sale indicator, consider the stylised weekly time series of prices depicted in Figure 2. While the figure is by no means representative of the price series in the dataset, it exhibits some of the more problematic features that characterise some series, most notably changes in the regular price and staggered sale prices. At the top of the figure are labels (R and S denoting regular and sales prices respectively) generated by application of our sales algorithm with a 10% threshold to the stylised data. Numbers adjacent to the price levels denote the (non-zero) week-on-week percentage price changes.

In the figure there are three episodes of lower prices, commencing at weeks t_α, t_β and t_χ, although only one (at time t_β and shaded grey)) is recorded as a 'sale' by our definition. This owes to the fact this is the only one of the three periods which satisfies the conditions that (a) the peak-to-trough price drop exceeds 10% and (b) the price returns to a level similar to the pre-sale level within 12 weeks. Note that neither of the (9%) falls that make up the 18% cumulative decline would trigger a sale using a 10% week-on-week criterion. The two other periods of price decline shown (at t_α and t_χ)

do not qualify as sales by our definition because in the first case the price decline (of 2%) is too small; and in the second case, the decline is not reversed. The ability to discriminate between sale episodes and periods in which the regular price falls is useful since both behaviours are apparent in some of the price series over the sample period. The hypothetical data also illustrate the limitations of using the sample mode (denoted by $\tilde{p}$ in Figure 2) as a measure of the regular price or indeed monthly (rather than weekly) prices, to detect sales. Whereas changes (or trends) in the regular price undermine the former, aggregation confounds the latter; neither identifies the sale in Figure 2.

Figure 2: Sales Identification in a Stylised Weekly Time Series of Prices



While the flexibility of the sales definition we have adopted in this paper seeks to overcome some of the key issues in data of this sort, it should not be overlooked that any set of criteria designed to distinguish sales from changes in the regular price using prices alone are to some extent arbitrary. As a guiding principle, it seems reasonable that the larger the transitory price decline is, the more likely it is that the observations represent a sale. For this reason we in initially consider (peak-to-trough) price drops of 10%, 25% and 35% in sales identification, a description of which is presented in the following section.

4. Sales Data

Table 4 reports summary statistics of the sales defined according to 10, 25 and 35 percent thresholds. It shows that nearly 8% of prices are classed as 'on sale' using the 10% threshold, a figure that drops to 3.5% and 1.4% using the larger discounts. Thus while sales are clearly the exception to the normal rule of pricing, only very deep sales are rare. Table 4 also reports the proportion of time series that contain at least one sale episode and here the incidence of sales is more evenly distributed. Specifically, two-thirds of all time series have been on a 10% sale, one-fifth experiencing a deep (35%) sale. Taken together, the statistics suggest that sales are unusual but commonly applied across products. Of course, this characteristic is a familiar one, reflecting the role of sales in encouraging consumers to try new products. Interestingly though, around one-third of the series are never discounted (using the 10% measure) during the three years they are observed.. The figures in Table 4 also suggest that sales tend to be around four weeks long, irrespective of their depth, a degree of consistency that suggests that the sales definition is indeed able to discriminate between sales and changes in the regular price.[11]

[11] Had the duration of 10% sales differed substantially from that using other sales depths, it may have suggested that a significant proportion of 10% sales were merely changes in the regular price.

Table 4: Summary Statistics of the Sales Data

	Sale Threshold								
	10%			25%			35%		
	All	Brands	Own Label	**All**	Brands	Own Label	**All**	Brands	Own Label
Frequency (%)	**7.8**	8.5	4.6	**3.5**	3.8	1.9	**1.4**	1.5	0.9
Products (%)	**63.0**	66.9	44.9	**36.8**	49.6	23.9	**20.1**	21.4	13.8
Duration (weeks)	**4.5**	4.5	4.4	**4.4**	4.4	4.5	**4.2**	4.1	4.7
Sale episodes	**4,309**	3,848	461	**2024**	1,824	200	**822**	740	82
Sales per UPC	**2.5**	2.8	1.5	**1.2**	1.3	0.7	**0.5**	0.5	0.3
Sales per UPC (sale products only)	**4.0**	4.1	3.4	**3.2**	3.3	2.7	**2.4**	2.5	2.0

In terms of the number of sale episodes (rather than the number of observations) the dataset contains 4,309 10% sales, of which around half (2,024) are sales of >25% and one-fifth being sales of >35%. These figures imply that on average a UPC will experience a 10% sale around 2.5 times during the sample (a little under once per year), a figure that rises to four (just over 1.5 per year) if we consider only those UPC that have ever been discounted. These averages mask notable differences between branded and own-label products. While the duration of sales is similar, brands tend to be discounted both more frequently and more deeply than own labels.

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As is clear from the distribution of sale episodes per UPC displayed in Figure 2, most products that have been on sale, have only ever been discounted once during the sample frame, although there are a small number of frequently discounted products.

For a more complete picture the distribution of sales depth consider Figure 3. While sales in excess of 80% have occurred in a handful of cases, discounts in excess of 50%

are rare, accounting for less than 5% of all sales. The majority of sales represent discounts of between 10 and 30%, the median discount being 24%.

Figure 2: The Frequency of Sales

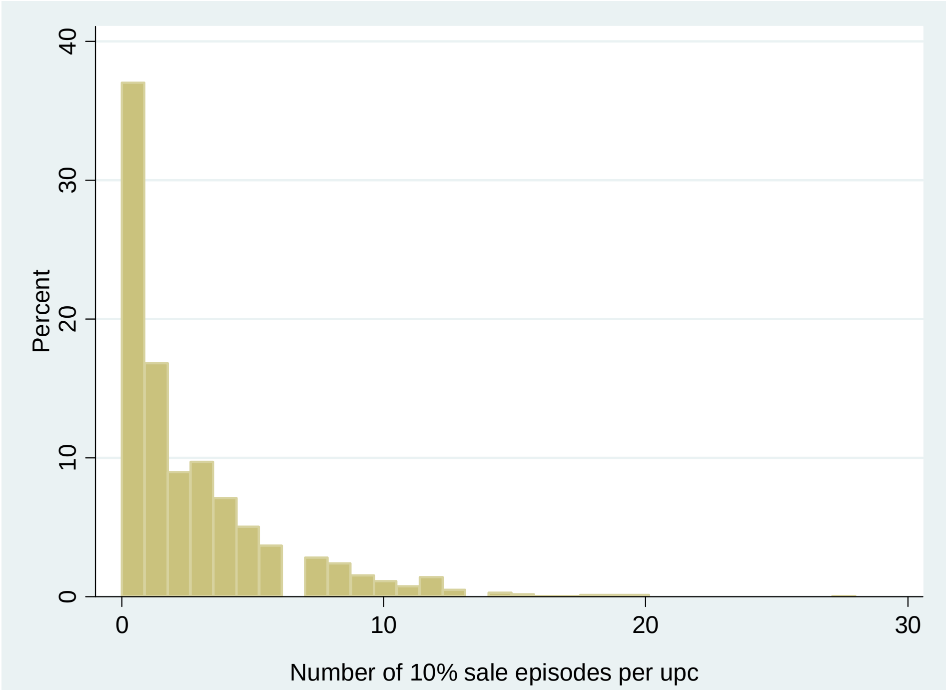
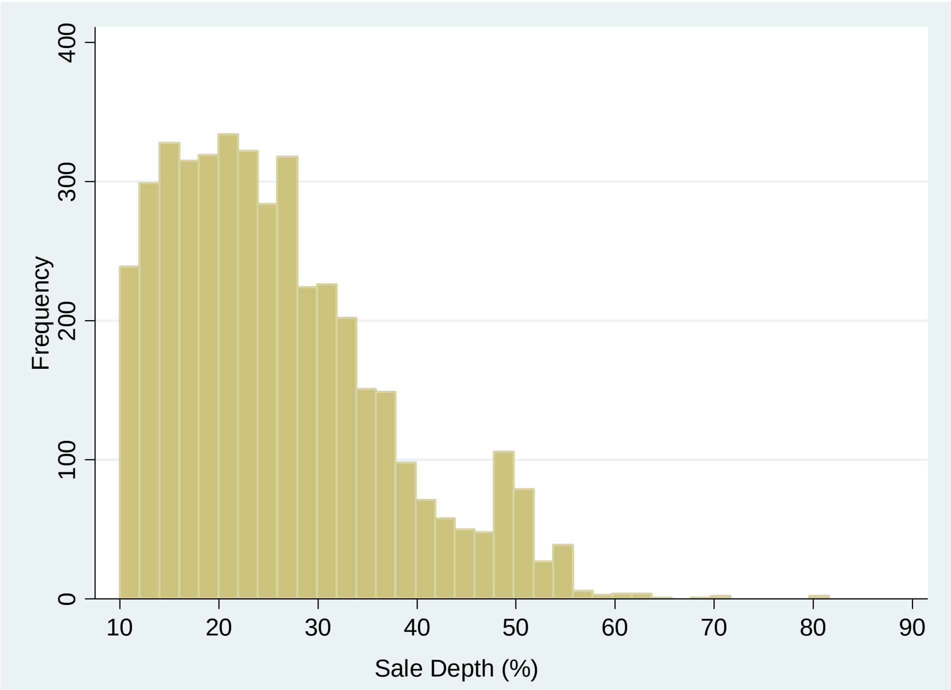
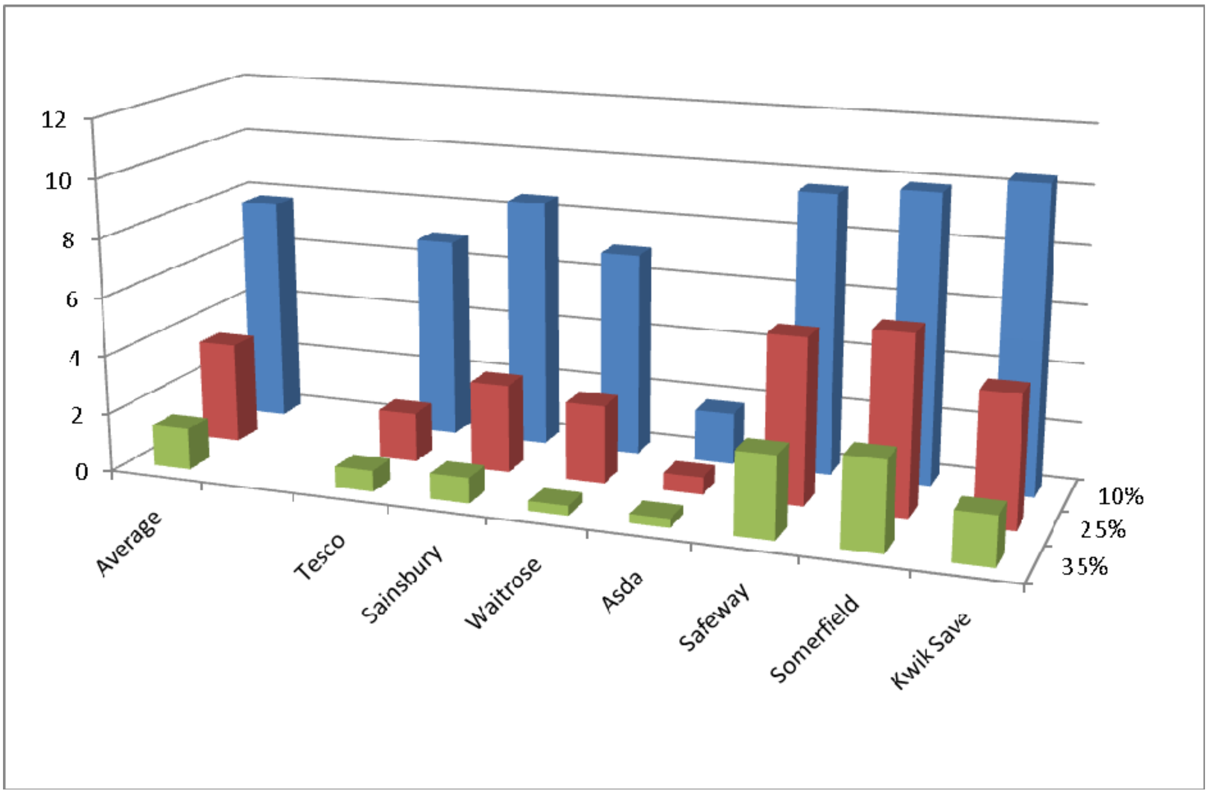


Figure 3: Size Distribution of Sales



Finally, to gain an impression of the use of sales by each of the national retailers consider Figure 4 which shows the proportion of each retailer's prices that are sales under the three thresholds. Differences in marketing strategy are clearly apparent: Consistent with an EDLP pricing strategy, Asda uses sales rarely (almost one-tenth of the average); Safeway, Somerfield and Kwik-Save form a group of 'discounters'; Tesco, Sainsbury and Waitrose forming a group of mainstream retailers lying somewhere in between. This classification is consistent across the depth of sales but becomes increasingly apparent the deeper the sale. All use deep sales rarely, although Waitrose, the only up-market retailer in the sample, uses deep sales -like Asda -very sparingly indeed.

Figure 4: The Prevalence of Sale Prices by Retailer (%)



The statistical description of sales presented above suggests a number of stylised facts, which are summarised as follows:

- Sales are unusual, occurring less than 10% of the time;
- Marketing strategies differ markedly, even among mainstream retailers
- Most UPCs experience a sale, although around one-third do not;
- Brands are discounted twice as frequently as own-labels
- A small number of products are discounted frequently
- Sales last around four weeks;
- Sales typically represent discount of 25%.

5. The Importance of Costs and Sales in Price Variation

Previous sections have highlighted that at the UPC level, prices change in response to both movements in underlying costs and promotional activity. While the former gives rise to step changes in prices across all UPCs in the product category, the latter are more UPC-specific. In this section, we use some simple regression models in an attempt to gauge the relative importance of these in price variation. To do so, we estimate simple price regressions containing increasingly rich sets of dummy variables: in Model 1, the baseline specification, we fit a set of UPC-based dummy variables to the price data (i.e. one dummy for each UPC), around which variation can be assessed. In this model, the coefficient attached to each UPC dummy represents the average weekly price of a bar-coded product (such as a 200g jar of Nescafe standard blend instant coffee) at each retailer stocking the product over the sample period. In Model 2, the UPC-based dummies are augmented with a set of product-level variables that represent the market (i.e. across all supermarkets) average regular price for each product (such as a 200g jar of Nescafe standard blend instant coffee) in which all sale prices have been replaced by the last regular price preceding each sale. Purged of promotional prices, this variable offers a means by which we can capture underlying movements in the regular prices, of which changes in production costs (such as the price of coffee beans) are likely to figure[12]. In Model 3, a set of sales dummies is also included, each dummy representing a unique sale episode. With prices in all models being expressed in natural logarithms, the regression standard errors represent the standard deviation of UPC prices as a proportion of the mean level during the sample, and it is this that we use to evaluate the impact of 'costs' and sales in UPC level price variation.

To facilitate comparison across the models, we use price data from the 967 UPCs that are sold in at least two supermarkets and have experienced a sale of at least 10% during the sample period. The parameters of Models 1, 2 and 3 are estimated by ordinary least squares using 132,280 price observations and the regression standard errors (rse) reported in Table 6. Results for the 'All' regressions head the table with results by label and retailer appended beneath. The results suggest that the standard deviation of prices at the UPC level is around 12%, a figure that changes little we confine the analysis to brands or own-label. Allowing for our cost proxy- the movement in the industry average regular prices- (Model 2) reduces the standard deviation by a little over one percentage point, a result that holds irrespective of the brand/own-label distinction. Accounting for sales (Model 3) has a more marked effect, reducing the variation by over four percentage points but here the effect of sales is larger for brands (4.6%) than own label products (3.1%).

[12] Nakamura (2008) and Hosken and Rieffen (2004) offer similar tests on US data.

These results are comparable with those of Hosken and Rieffen (*op.cit.)* and Nakamura (*op.cit.)*. They also conclude that sales account for a high proportion of price variability though the extent of price stickiness is lower for the data used here than Nakamura (*op. cit.*) finds for the US. In her study, she reports that only 16 per cent of price variation is common across all stores selling an identical product. The reduction in the rse as we move from Model 1 to Model 2 suggests that around 9 per cent of price variation is common across the UK food retailing sector.

Turning to price variation by retailer, Table 6 suggest a group of retailers headed by Safeway (at 15%) with relatively high price variation, and a group of retailers lead by Asda at 9% with the lowest variation. Interestingly, while Asda uses sales infrequently (see Figure 4) it's price variation is only marginally lower than other mainstream retailers, suggesting that Asda regular prices have a tendency to change more than other similar retailers. The effect of our costs measure is broadly the same across retailers with the result that patterns in overall price variation are driven by promotional behaviour, where a triplet of discounters (Safeway, Somerfield and Kwik Save) emerges along with a triplet of mainstream retailers (Tesco, Sainsbury and Waitrose), the outlier being Asda, in keeping with its everyday-low-pricing marketing strategy.

Comparison of the variation between the models in Table 6, delivers estimates of the contribution of costs and sales in UPC price variation. Using the 'All Products' classification costs account for 11% of the price variation, a figure which changes little by label. Of primary interest is the contribution of sales, which turns out to be 37% overall, with a marked difference between brands and own label products (39% and

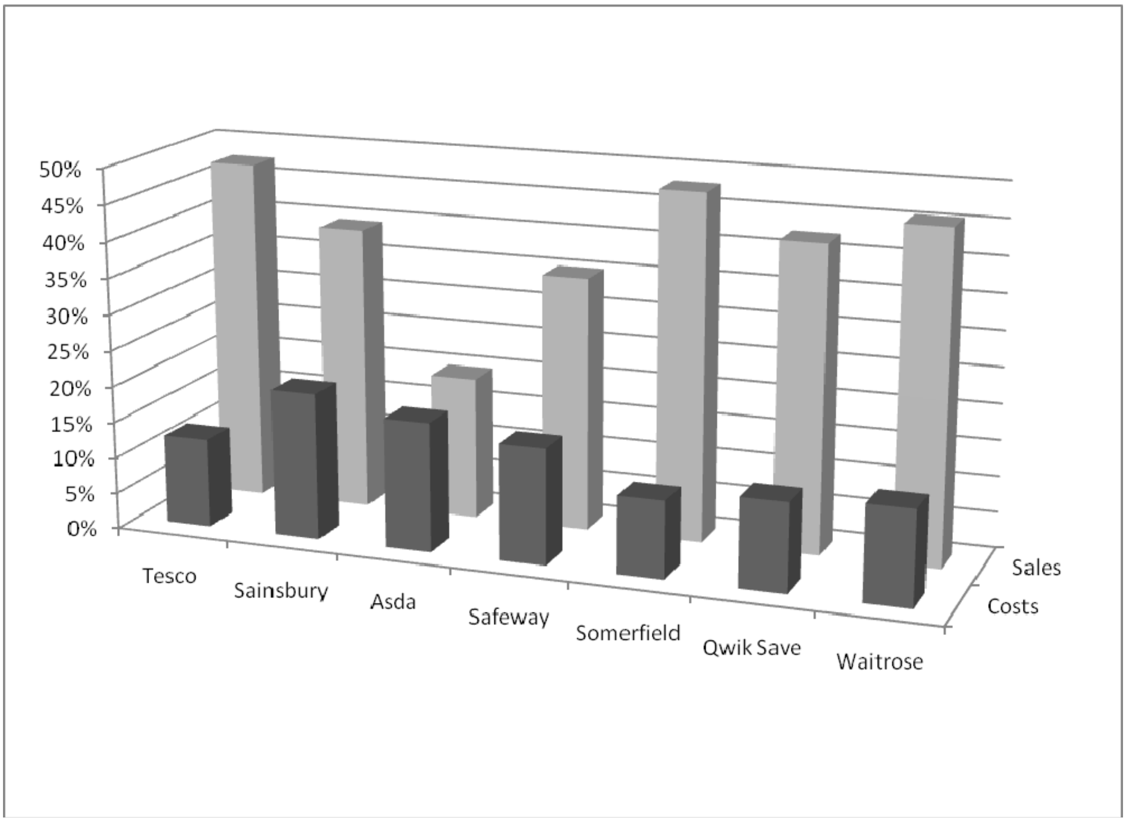
26% respectively). The corresponding proportions by retailer are shown in Figure 5, where the patterns in the absolute levels of price variation are reflected in the relative measures, namely that, while industry costs have broadly relatively small and broadly similar effects across retailers, the contribution of sales is around 40% of UPC price variation in all but the retailer with the everyday-low-pricing policy, Asda.

Table 6: Regression Standard Error (standard deviation) of Food Product Prices

	Model 1 UPC	Model 2 UPC + Costs	Model 3 UPC+ Costs+Sales
All Products	0.1185	.1052	.0609
Label			
Brand	0.1182	.1052	.0592
Own Label	0.1207	.1050	.0737
Retailer			
Tesco	0.0949	0.0832	0.0382
Sainsbury	0.1122	0.0894	0.0452
Asda	0.0912	0.0749	0.0569
Safeway	0.1461	0.1227	0.0713
Somerfield	0.1232	0.1100	0.0509
Kwik Save	0.1298	0.1138	0.0589
Waitrose	0.0943	0.0819	0.0388

Taken together, the picture that emerges from this analysis is one in which sales dominate the effect of costs (as proxied by industry average regular prices, at least) in price variation and combined they account for nearly two-thirds of price variation at the UPC level. Furthermore, sales are more important for branded products so that by our measures, idiosyncratic shocks are relatively more important for own label products than brands, possibly reflecting their less uniform composition within the product definition. While the market segments by sales behaviour to some extent it is also remarkable how important sales are for all retailers; even with and EDLP strategy, sales are a more important source of price variation than costs by our measures[13].

Figure 5: Importance of Sales and Costs in UPC Price Variation by Retailer



6. Are Sales Across Retailers Related?

Since we have prices by retailer, we can address whether sales behaviour is related across retailers. Recall, first of all, that the use of sales by retailer varies (see Figure 5). Taking sales >25% as the benchmark, three retailers are higher employ sales than

[13] As a final step, we carried out the same analysis by UPC. As Hosken and Rieefen (2004) note, the relative role of costs and sales can vary across products. The results do not differ significantly from the above: prices are relatively sticky across for UPCs that constitute a product group and the role of costs is fairly marginal in each case. Sales account for a higher than average proportion of price variation some frozen UPCs (e.g. peas, pizzas) and a lower than average proportion of price variation for bread. Since the results do not provide additional insights beyond those made above, we do not report them in the text. Detailed results are available upon request.

average, Tesco (the market leader) is a below average user of sales, while Asda hardly ever employed sales over the sample period. Taken from a general perspective, the raw data therefore indicates that sales are unlikely to be a common experience across retailers. However, to address the issue more directly, we address whether the probability of a sale in one retailer is influenced by a sale in another retailer using the data available at the UPC level. The central idea here is to determine whether a sale in a specific UPC introduced by a given retailer is a random event or may be related to the presence of a sale in one or more rival retailers.

To address this issue, we employ a fixed effects conditional logit model. Specifically, Let s_{ijt} be a binary categorical (dummy) variable with 1 denoting a sale price and zero for a non-sale price for product $i = 1,\ldots,I$, retailer $j = 1,\ldots,J$ at time $t = 1,\ldots T$. In order to evaluate whether sales of like products in rival retailers affects the probability that the product will be on sale (i.e. discounted) elsewhere we create a $K \times 1$ vector of dummy variables, $\mathbf{r}_{it}$, $[\mathbf{r}_{it} = r1_{it}, r2_{it}, \ldots, rK_{it}]$ that indicates whether product *i* is on sale in a rival retailer *k*. Because each of the variables in $\mathbf{r}_{it}$ refers to each retailer as a rival they are matched with the retailers in s_{ijt} such that $rk_{it} = 0$ for $k = j$ (as j cannot be a rival for itself)[14]. Note also that $rk_{it} = 0$ when the product is either not stocked by retailer *k* or stocked but not on sale. Observations where rk_{it} equals unity signal that product *i* is stocked in retailer *j* and *k* and on sale in retailer *j* ($k \neq j$). For example, when considering sales in supermarket 1, i.e. s_{i1t}, $r1_{it}$ is zero since those observations refer to itself and thus not a rival. Hence $r1_{it}$ equals one when considering a product *i* in at time *t* that is on sale in supermarket 1 and stocked by retailer $k = 2,\ldots,J$.

[14] The focus on a "like" product here refers to the identical UPC that is sold across one or more other retailers (e.g. a 200g jar of Nescafe). This raises the issue of closely related products. For example, whether the sale of a 200g jar of Nescafe is related to a 350g jar of Nescafe or a 200g jar of Nescafe is related to the sale of a 200g jar of another brand of coffee. One difficulty in posing the issue in this way is that the bounds of defining the product space become unlimited. Therefore, to keep the issue manageable, we stick with the sale at the identical UPC level across retailers.

Finally, let M_{ikt} be a dummy variable indicating whether product i is on sale in period t in at least one other retailer in the market, zero otherwise. In other words we have an indicator variable:

$$M_{ijt} = 1 \text{ if } \sum_{k=1}^{J} rk_{it} > 0 \text{ for } j \neq k$$
$$M_{ijt} = 0 \text{ otherwise}$$

If product *i* is only stocked by one supermarket the set of *J* dummy variables rk_{it} will each be zero and hence M_{ijt} will be zero. Where this happens (about one-third of the products are only sold in one supermarket) product *i* drops out of the regression analysis. To investigate whether sales are affected by presence of a sale elsewhere in the market we estimate:

$$s_{ijt} = \alpha_i + \beta M_{ijt} + \varepsilon_{ijt} \qquad (1)$$

where the α_i represent the UPC-based heterogeneity (fixed effects) and ε_{ijt} are disturbances with constant mean and variance. Assuming that ε_{ijt} are uncorrelated with the timing of sales in supermarkets, i.e. $\mathrm{E}[\varepsilon_{ijt} \mid M_{ijt}] = 0$ then, given that s_{ijt} is a binary variable, $\mathrm{E}[s_{ijt} \mid M_{ijt}] = \mathrm{P}[s_{ijt} = 1 \mid M_{ijt}]$ implies that β is the predicted partial marginal probability of a sale on a product given a sale of the same product in at least one other supermarket at time period *t*. Clearly, if a sale of a product at one retailer is independent of the identical product being on sale at any other retailer, $\beta = 0$. Where $\beta > 0$ ($\beta < 0$) this indicates that a sale in a given retailer for a specific UPC is more (less) likely given the existence of a sale elsewhere in period *t*.

We further amend the test by identifying separately whether the sale of the product is related across retailers for own-label products. In this case, the own-label definition relates to the "same" own-label product sold across retailers. For example, we are relating the sale of Tesco 1 litre orange juice with Sainsbury's 1 litre orange juice. *A priori*, we may expect less relatedness in the sale of products across retailers when it applies to own-label goods.

Table 7 reports the estimated probability that a product will be on sale given that it is on sale in at least one other retailer using the marginal effects of the conditional logit model. The results, which are reported for both branded and own-label products, reject the hypothesis that a sale by a retailer is unrelated to the existence of a sale in the same UPC elsewhere for branded products but not in the case of own-labels. Specifically, (10%) sales in branded products increase the likelihood of sales in rivals stocking the product by some 14.3%, a probability that rises slightly for deeper sales. Thus, sales on branded products are not random events, but are to some extent co-ordinated, suggesting a tendency for promotions to be uniformly offered across retailers. However, the probability is not 'high' in the sense that the results do not indicate that there is perfect coordination in the use of sales. Own-label products present a contrasting picture: namely, for 10% and 25% sales, the results indicate that sales are independent across retailers though, for the 35% sale category, sales are not independent. Given that sales with the 35% benchmark are considerably less common, we can conclude that in most cases, sales of own-label goods by retailers are independent[15].

Table 7: Marginal Effect of a Sale in at Least One Other Retailer on the Probability of a Sale Elsewhere

	Extent of Sale		
	10% Sale	25% Sale	35% Sale
Branded	0.143* (.0084)	0.178* (0.0118)	0.172* (0.0274)
Own-label Dummy	-.0148 (.0401)	0.0138 (0.0630)	0.342* (0.0572)

Note: Stars denote significance at the five per cent level. Models estimated using robust standard errors.

[15] We also investigated whether sales behaviour by retailer related to the intensity of sales behaviour across other retailers. Specifically, the discussion in the text relates to whether the sale by one retailer related to the product being on sale at any one of the other retailer. We further investigated the issue in terms of whether the probability of a sale by one retailer depended on how many other retailers the product was on sale at. The results indicate that the probability of a sale increases depending on the number of retailer which also had the product on sale. For example, for the >25% sale benchmark, the probability that the product was on sale at one other retailer was 16.2%; if the product was on sale at two or more retailer, the probability increased to 24.7% with estimates statistically significant at the 5% level. Results are available on request.

7. Conclusions

This paper presents an analysis of promotional sales in an extensive high frequency micro-economic database of supermarket prices in the UK. Given that the timing of sales is not recorded, it must be inferred from the prices themselves and the method that we have adopted for the identification of sales is described (and is consistent with other recent research on sales). Using a 10% peak-to-trough measure we find that 92% of prices are regular, the remainder represent sales. So although sales are unusual, the majority of products experience a sale, the norm being around one sale per year. While there are marked differences in the number of times products are on sale (one-third of the 1,700 UPCs considered were never on sale in the sample period) promotional activity generally lasts 4 weeks and represents discounts that average 25%.

The paper also offers an assessment of the importance of sales in overall price variability. In general, retail prices are relatively sticky with ‘common’ cost changes originating from the manufacturing sector accounting for only a small proportion of overall price variability. This general result is consistent with results using data from the US though the evidence presented here suggests that common cost changes account for a smaller proportion of overall price variability than reported in the US studies. Against this background of relative price stickiness, sales are relatively important accounting for around 40 per cent of overall price variability over the data period. However, prices and sales activity vary considerably across the major UK food retailers and this dispersion is a particularly notable dimension of the data. Further results indicate the retailer sales’ activity is not independent and that own-label products are also as likely to be on sale as branded products. Taking together, the results suggest two broad conclusions that relate to both the macroeconomic and industrial organisation literature: first, sales are an important feature of price dynamics; second, the role played by retailers is key to understanding price dynamics.

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