Retail Price Dynamics and Retailer Heterogeneity: UK Evidence

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1. Introduction

This paper contributes to recent research on price dynamics using scanner data, much of which has focussed on the micro-foundations of inflation, highlighting the extent to which prices are sticky[1]. While most studies that have addressed this issue employ data for a single retail chain, typically focusing on the US, we use scanner data for the seven main retail chains in UK food retailing.[2] Further, since private label penetration varies by retail chain, we separate national branded items from private labels as control of the supply chain may also have a bearing on the nature of price adjustment (Li and Hong, 2013). Taken together, the evidence reported here highlights that there is heterogeneity in the frequency of adjustment of actual, reference and regular prices, across retail chains within a single sector, as well as the use of sales, even for identical products.

In general, heterogeneity has been known to matter since it can magnify the effects of monetary shocks as highlighted by Carvalho (2006) and Nakamura and Steinsson (2010).[3] Thus the evidence of retail chain heterogeneity that is explored here adds a further dimension to the nature of heterogeneity which is relevant for macro-based studies. It also complements the heterogeneity found by Baudry *et al*. (2007) who report that price adjustment is likely to vary across outlets. Specifically, we find that the retailer dimension of heterogeneity is more pervasive than the product dimension that has been highlighted in recent studies.

2. Description of Price Data

Our data set is a weekly panel of scanner food prices obtained from Nielsen Scantrack. It covers the seven largest UK supermarket chains (ASDA, Kwik Save, Safeway, Sainsbury, Somerfield, Tesco and Waitrose). The data set contains 231,069 weekly price observations, covering 507

[1] Recent reviews of this literature can be found in Klenow and Malin (2010), Maćkowiak and Smets (2008) and Nakamura and Steinsson (2013).
[2] Exceptions being Nakamura (2008) and Nakamura and Steinsson (2011) who show that price adjustment varies across US retailer chains.
[3] Maćkowiak and Smets (2008) draw comparisons in the extent of price heterogeneity across Euro countries and provide a comparison with the US studies

products in 15 categories of food running from 8th September 2001 to 17th April 2004 (137 weeks). Products are identified at a highly detailed (barcode) level, meaning that 100 gram and 200 gram jars of the same brand of instant coffee are different products. Since the same product may be sold in more than one retailer, we identify each retailer-product combination with a Unique Item Code (UIC). There are 1,704 items in all belonging to 507 bar-coded products 80% of which are branded, the remainder being private labels.[4]

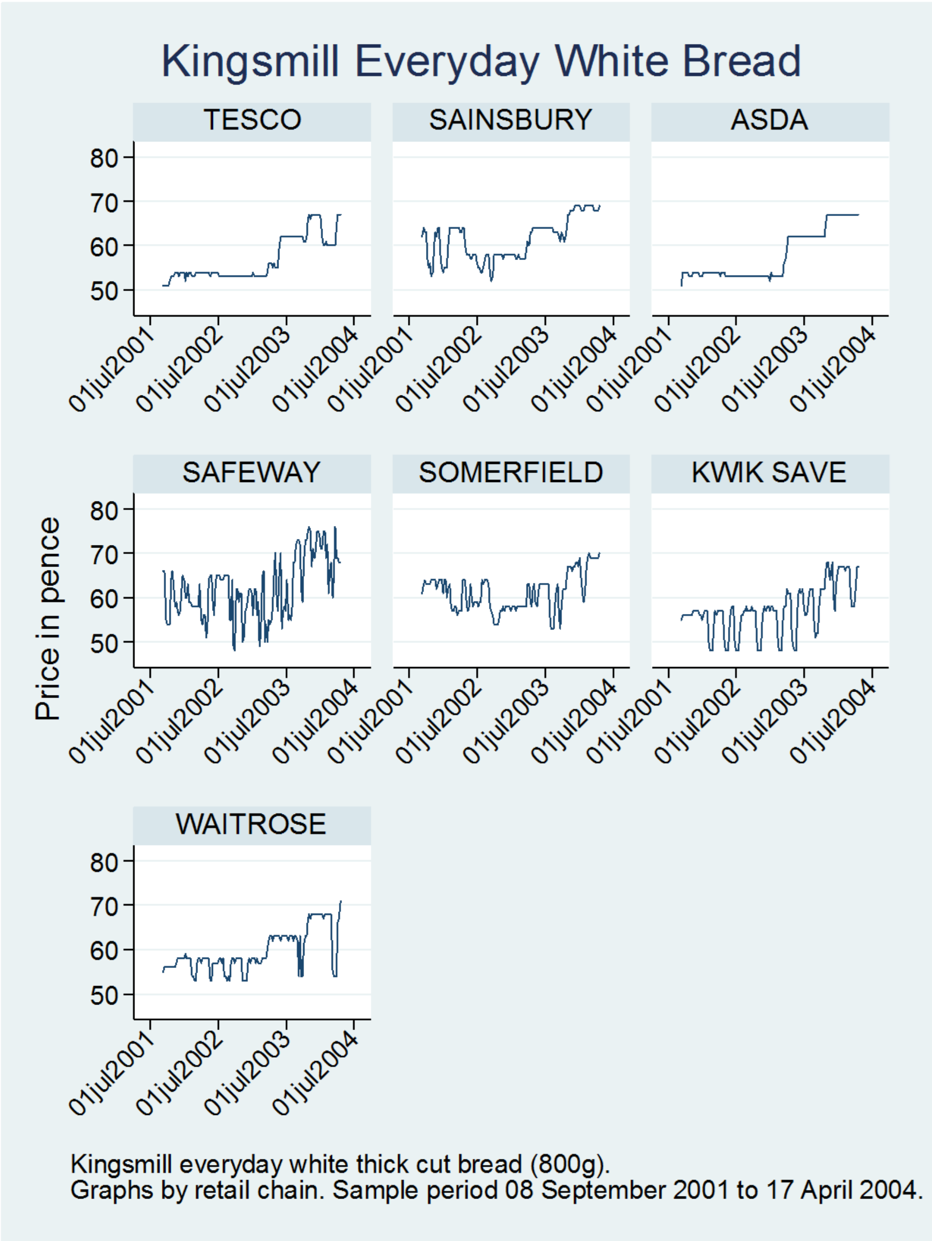
Prices are weekly national average unit revenues at the barcode level by retail chain. Though this national average may hide some variation in prices within specific retail chains, national pricing strategies are the norm in UK retailing (Competition Commission, 2000) a result that is consistent with US evidence reported by Gagnon and Lopez-Salido (2014). Defining prices in this way induces 'noise' in the data (see Eichenbaum *et al*., 2014) and about half of the price changes observed in the raw data are less than one penny. Also of note is that Scantrack prices incorporate the effect of all promotional activity (sales) whether these are price reductions or quantity promotions. Both of these aspects of price dynamics are circumvented by the use of reference prices.

3. Constructing Reference Prices and Sales Prices

Figure 1 shows how prices vary for one branded product (*Kingsmill Everyday* white bread) that is sold by all seven UK chains. As the seven UIC price series reveal, average unit revenue prices are 'noisy' but more importantly there are clear differences in the pricing of this product across the major retailers. One possible explanation for this is their use of sales. Aside from the specific issue of identifying sales in scanner data, sales may not matter in assessing aggregate price adjustment, particularly in the context of menu cost models. Kehoe

[4] Private label versions of a specific product share the same product code but have separate UICs and are thus recorded in Nielsen Scantrack data in the same way that a branded product sold by different retailers are.

Figure 1: Weekly Prices (pence) of Kingsmill Everyday White Bread across All Major Food Retailers



and Midrigan (2012), Guimaraes and Sheedy (2011) and Coibion *et al*. (2013) address these issues. To account for this, recent empirical studies employing high-frequency price data seek to remove sales from price series.

3.1 Sales Filter

As with other micro-pricing studies (for example, Hosken and Rieffen, 2004; Campbell and Eden, 2005; Berck *et al.*, 2011), a simple algorithm is applied to the price data that exploits the depth and duration of price declines to identify sale episodes. We define a sale as a period lasting no more than 12 weeks in which prices fall by at least 10% but return to the pre-sale level. Statistics on the incidence of sales are presented in Table 1. Using the 10% sales definition, around 8% of prices are classed as 'on sale', although two-thirds of all items have experienced a sale, which typically lasts for one month.[5] Marked differences in sales behaviour by retail chain are apparent (compare ASDA with Safeway); branded products tend to be discounted twice as frequently as private label products.

Table 1: Summary Statistics of Sales

	Percentage of Prices on Sales	*Mean Duration (weeks)*	*Percentage of Products Experiencing Sales*
Overall	7.8	4.5	63.0
		Retail Chain	
ASDA	1.8	5.6	32.9
Tesco	6.9	5.4	54.5
Sainsbury	8.6	5.2	69.5
Kwik Save	10.4	4.4	67.4
Waitrose	7.0	4.8	65.6
Somerfield	9.9	4.1	72.7
Safeway	9.6	3.1	77.2
		Brand Status	
Private Label	4.6	4.4	44.9
Brand	8.5	4.5	66.9

3.2 Reference Price Filter

Eichenbaum *et al.* (2011) (hereafter EJR) argue that in terms of firms' pricing schedules, it is useful to think in terms of a reference price and it is this concept that matters for assessing menu cost models and the non-neutrality of monetary shocks. They define the reference price as the modal price in each full quarter. Defining the reference price in this way means that

[5] The proportion falls to 3.5% and 1.4% when considering 25% and 35% sales. Full details are available on request.

changes in the reference price are confined to the start of each quarter irrespective of their actual timing. Moreover, because by construction the quarterly reference price can change at most once per quarter, there is the possibility that the inertia of the quarterly mode may be more apparent than real. We therefore employ two measures of the reference price; the EJR definition and a “rolling” reference price. The rolling reference price is defined as the modal non-sale price six weeks either side of each point in time and, as such, is more flexible with respect to the timing and frequency of reference price changes than the EJR measure.

3.3 Price Stickiness

In Table 2, we report on the degree of price stickiness across retailers using actual data, the EJR reference price and the rolling reference price; we also report the implied duration for the regular non-sale price. Not surprisingly, the actual data have a low implied duration of just over two weeks, highlighting the effect of small price changes which are frequent and the important role of sales in UK food retailing. Since the figures hardly change when non-sale prices are considered, this suggests that it is small price changes that dominate the duration statistics. Reference prices remove this noise. The EJR reference price has an implied duration of 26 weeks, approximately twice that obtained using the rolling reference price measure (14 weeks), suggesting that it may indeed over-emphasize price stickiness. However, irrespective of the measure used, marked differences in price stickiness by retailers are also apparent. Using the rolling reference price measure, prices have an implied duration nearly 2.5 times higher in ASDA and Tesco than in Safeway. It is also noticeable that prices for private label products are also stickier than branded products.[6]

[6] Since this variation across retailers may be due to differences in the product-mix stocked by each retail chain, the analysis was also performed on the common subset of products sold in all seven retail chains. Very similar results were obtained to those reported in the text. Full details are available upon request.

Table 2: Implied Duration Statistics for Actual and Reference Price Data (median item, in weeks)

	Actual Prices	*Regular (non-sale) Prices*	*Rolling Reference Prices*	*EJRReference Prices*
Overall	2.4	2.6	13.9	26.0
		Retail Chain		
ASDA	3.6	3.9	20.8	32.5
Tesco	2.9	3.2	20.8	32.5
Sainsbury	2.5	2.8	15.6	32.5
Kwik Save	2.2	2.5	13.9	26.0
Waitrose	2.0	2.1	15.6	32.5
Somerfield	1.9	2.1	11.4	26.0
Safeway	1.9	2.0	8.9	18.6
		Brand Status		
Private Label	3.0	3.2	17.9	32.5
Brand	2.3	2.5	13.8	26.0

The reciprocal of the implied durations reported in the table gives the median frequency of price change in each classification.

4. Decomposing Price -Variation across Retailers

To what extent do reference prices and sales account for price adjustment in UK food retailing? We address this decomposition issue for the food sector as a whole and also by retailer. To do so, we estimate price regressions in which the deviation in an item's price about its mean $p_{it} = (P_{it} - \overline{P}_i)$ is regressed on two sets of dummy variables, one containing reference price spell dummies, the other containing dummies indicating sales. Dummies switch on and off according to the filters defined in Section 3.1 and 3.2. Since every price observation occurs at either a reference price or during a sale, the two sets of dummies are orthogonal, a feature that we usefully exploit in the attribution of price variation. Specifically, we estimate regressions of the following form:

$$p_{it} = \beta Ref_{it} + \varepsilon_{it} \quad (1)$$

$$p_{it} = \gamma Sales_{it} + \varepsilon_{it} \quad (2)$$

$$p_{it} = \beta Ref_{it} + \gamma Sales_{it} + \varepsilon_{it} \quad (3)$$

where Ref_{it} is a matrix containing reference price spell [0,1] dummies, each of which represents a new reference price spell that switches on for a single reference price spell and is zero elsewhere. $Sales_{it}$ is a matrix containing sales spell [0,1] dummies, with each dummy switching on for a single sale episode, and zero elsewhere. With a separate variable for each and every spell the coefficient matrices β and γ represent estimates of the deviation about each item's mean during each of its spells of reference prices and sales. Our interest is not, however, in these estimates but the explanatory power of the models, for which we use the coefficient of determination, R^2. Owing to the orthogonality of Ref_{it} and $Sales_{it}$, there is a straightforward decomposition of the variation such that $R^2(3) = R^2(1) + R^2(2)$ from which the contribution of reference prices and sales in overall variation can be determined. While equations (1) to (3) are simple enough to estimate in principle, the dimensions of Ref_{it} and $Sales_{it}$ are too unwieldy to use in practice.[7] Our solution is to recover the required R^2 for these aggregate regressions using output from the individual item-based regressions. With N - items, T time periods, and prices expressed in deviation form, the explained sum of squares $[\sum_{t=1}^{T}(\hat{p}_{it})^2]$ and total sum of squares $[\sum_{t=1}^{T}(p_{it})^2]$ from the individual item-based regressions, combine to form the coefficient of determination of the aggregate regressions, given by:

$$R^2 = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}(\hat{p}_{it})^2}{\sum_{i=1}^{N}\sum_{t=1}^{T}(p_{it})^2} \tag{4}$$

It is noteworthy that this differs from the average coefficient of determination of the individual regressions:

$$\frac{1}{N}\sum_{i=1}^{N}\left[\frac{\sum_{t=1}^{T}(\hat{p}_t)^2}{\sum_{t=1}^{T}(p_t)^2}\right]_i \tag{5}$$

since whereas R^2 in (4) is a ratio of sums, (5) is a sum of ratios. Mindful of this, we calculate R^2 as in (4) for Models (1), (2) and (3) using both the rolling and EJR definitions of reference prices in two samples: one for all items and another that includes only those items that have

[7] Stata 12 can handle up to 11,000 regressors, well short of the dimensions of the Ref_{it} and $Sales_{it}$ matrices, which contain 18,805 (9,827) and 4,214 (4,293) dummy variables respectively using the rolling (Eichenbaum *et al*) definition of reference prices and sales.

experienced at least one sale (about two thirds of all items in our sample). The results are summarised in Table 3.

Table 3: Contribution of Reference Prices and Sales in Price Variation (R^2)

	Model (1)	*Model (2)*	*Model (3)*	
	$p_{it} = \beta Ref_{it} + \varepsilon_{it}$	$p_{it} = \gamma Sales_{it} + \varepsilon_{it}$	$p_{it} = \beta Ref_{it} + \gamma Sales_{it} + \varepsilon_{it}$	
	Reference Spell Dummies	**Sales Spell Dummies**	**Reference and Sales Spell Dummies**	**Residual**
		Rolling Reference Prices		
All UICs	0.44	0.43	0.87	0.13
UICs with at least one sale	0.38	0.49	0.87	0.13
		EJR Reference Prices		
All UICs	0.39	0.42	0.82	0.18
UICs with at least one sale	0.34	0.48	0.82	0.18

Note: Since sales and reference prices are orthogonal, the R^2 of Model (3) is the sum of Model (1) and Model (2). See text for details.

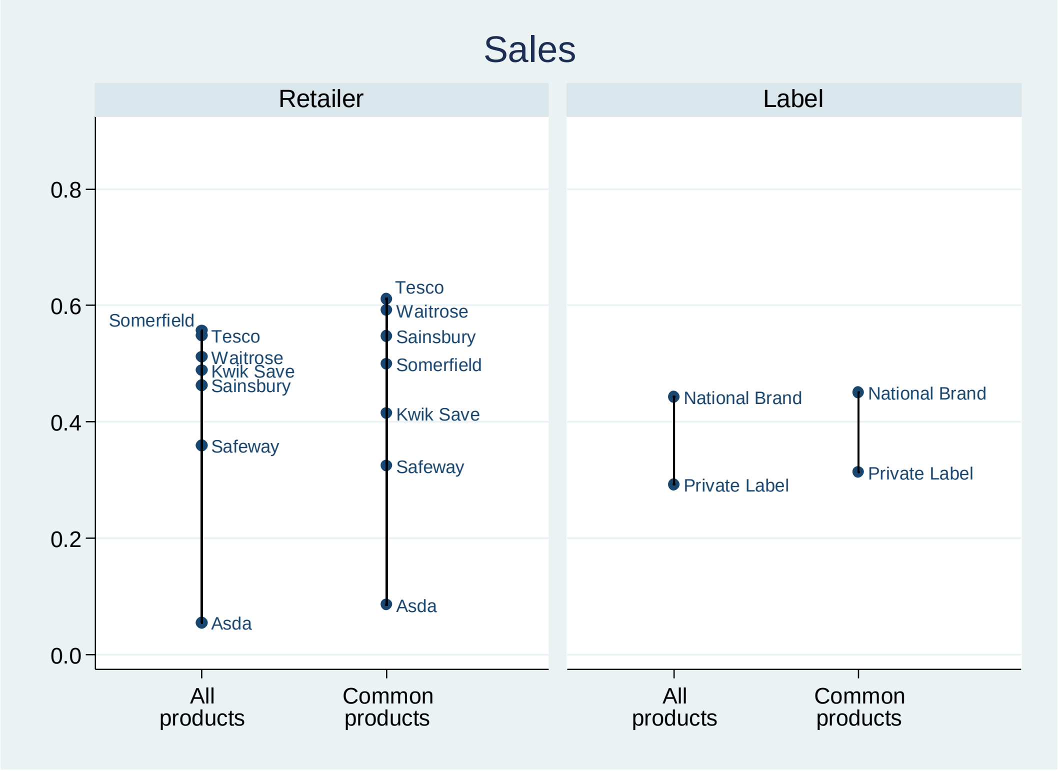
The principal observation is that sales and reference price changes account broadly equally for aggregate price dynamics.[8] Across all items, sales and reference prices together account for 87 per cent of price variation with an almost equal split between reference prices (44 per cent) and sales (43 per cent) using the rolling reference price definition. With the EJR measure, reference price adjustment becomes relatively less important (39 per cent of the aggregate variation) largely due to the fact that the EJR measure is stickier by construction. The findings also highlight the importance of sales in aggregate price variation; despite occupying less than 9 per cent of the dataset, sales are responsible for about 43 per cent of the

[8] *Ceteris paribus*, the relative importance of reference price changes is higher in periods of high inflation as costs are passed through to the retail level. Over the data period, aggregate inflation in the UK was relatively low and stable. However, food inflation was more volatile, varying between 6% and -2% year-on-year.

variation in prices and, when focussing more narrowly on the subset of items that have experienced at least one sale episode, sales emerge as the primary source of variation in prices, accounting for about 49 per cent of the total.

Of equal interest is how the contribution of reference prices and sales to price changes varies across retail chains and by brand status. Applying the same models as above, the results are summarised in Figure 2. Using all products and the rolling mode measure of reference prices, the contribution of reference prices in price variation among UK retail chains varies between 29 per cent (Waitrose) and 82 per cent (ASDA) whereas the sales contribution varies between 6 per cent (ASDA) and 56 per cent (Somerfield). As a check to see if these differences are due to inherent differences in retailer pricing or merely reflect the set of products sold by each retailer, Figure 2 reports results for the 92 products that are sold in each of the seven national retailers (common products). Results remain largely unchanged suggesting that it is the retailer-specific dimension – over and above difference in their product-mix – that gives rise to the observed differences. Figure 2 also reports the breakdown for private label and nationally branded products in both all product and common product groups. The results indicate that retailers are less likely to use sales in the process of adjusting private label prices; however the difference by national brand status is much less marked than by retail chain, emphasising that here too, it is retail chain heterogeneity that imparts the greatest effect.

Figure 2: Contribution of Rolling Reference Prices and Sales in Price Variation (R^2) by Retailer and Label



5. Conclusions

Using weekly scanner data for the seven main food retailers in the UK, we have shown evidence that there is considerable heterogeneity in price dynamics across retail chains. This relates to the use of sales, to the implied duration of reference prices, and the extent to which retailers adjust prices either via sales or reference prices. As such, the heterogeneity we identify here adds another dimension to the issue of heterogeneity in price dynamics that has been observed at more aggregate levels and cautions against the interpretation of price dynamics that arise from studies using single chain data.

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