Retailer Heterogeneity and Price Transmission

H. Lan, T. A. Lloyd, S. McCorriston and C.W. Morgan

Abstract: Differences in price dynamics across retail chains, even for identical products, offer the opportunity to provide new insights into the determinants of price transmission. Specifically, we highlight the role of strategic complementarity and mark-up elasticities as the factors underpinning price transmission. Using supermarket data on a sample of orange juice and coffee products from the seven largest retail chains in the UK, the results show that ignoring strategic complementarity exerts a positive bias the estimation of price transmission and hence overstates the importance of input costs in price setting. In contrast to recent research, private label products are found to exhibit consistently lower levels of price transmission (higher mark-up elasticity) than national brands likely reflecting the context of competition in UK food retailing. The focus on mark-up elasticities points to links between frequency of price adjustment and competition as determinants of price transmission.

Key Words: Mark-up elasticity, price transmission, UK grocery retailing

JEL Codes: D22, L11, L81

Author Information: Hao Lan is Assistant Professor in the International Business School, Suzhou, Xi'an Jiaotong-Liverpool University, China. Tim Lloyd is Professor of Economics in the Business School, Bournemouth University, UK. Steve McCorriston is Professor of Agricultural Economics, in the Business School, University of Exeter, UK and Wyn Morgan is Professor of Economics in the Department of Economics, University of Sheffield, UK. The authors are grateful to Tim Richards and three anonymous reviewers for valuable suggestions and comments. Any errors or omissions that remain are our own.

Empirical analyses of price dynamics using high frequency scanner data has been a growing research area in recent years, much of which has originated in macroeconomics. Klenow and Malin (2011) summarise the main findings of this research, highlighting two key observations. The first is that the micro-dimensions of price adjustment matter for understanding the effectiveness of macroeconomic policy and the impact of cost shocks on retail prices. The second is that the nature of price adjustment is heterogeneous, with price dynamics varying both within and across sectors and product groups and thus having differential impacts on consumers. However, the insights that arise from the use of scanner data have often been based on single retail chains, multi-chain studies being relatively rare. Nakamura (2008) commented that price dynamics may be more heterogeneous across retail chains than across product groups and that this dimension of price dynamics required further investigation. Our aim is to develop this line of research by focussing on the heterogeneity in price dynamics across multiple retail chains and highlight the underlying drivers of price transmission that vary by retail chain, commodity category and product status.

Our primary contribution is to highlight the impact of strategic complementarities (*i.e*. the prices of similar products in competitors) in the price transmission equation and the role of mark-up elasticities (*i.e.* the responsiveness of the mark-up to changes in costs) as the main mechanism underpinning vertical price transmission in modern food retailing. We show the extent to which strategic complementarities impact on estimates of price transmission and how the resulting mark-up elasticities vary across retail food chains and by brand type (*i.e.* national brands and private labels). Like Amiti *et al.* (2019), we estimate the effect of strategic complementarities on cost pass-through and derive mark-up elasticities in a reduced form framework. However, our empirical approach differs from Amiti *et al.* in that it exploits the non-stationarity of prices to obtain the long-run effects directly, thereby circumventing issues of endogeneity that characterise regression with stationary data. Of course, it should be noted that other empirical industrial organisation methods (including those applied to the food retail sector) can also address multi-chain issues as we do here. Most notable in this regard are recent structural modelling approaches by Thomassen *et al*. (2017) and Richards *et al*. (2018)[1]

With a firm base in economic theory, these structural modelling approaches to differentiated product markets such as food retailing necessitate significant data requirements. In circumstances where the data required for the estimation of a structural model is unavailable, or withheld by data providers to preserve commercial confidentiality, our empirical approach offers a way forward in understanding the drivers of price transmission in a general and tractable way.

Our main results are three-fold. First, we show that estimating price transmission without accounting explicitly for the role of strategic complementarities creates an upward bias in the magnitude of price transmission. Second, we find that when strategic complementarities are included, private labels have lower price transmission than national brands. Third, our results show that mark-up elasticities vary significantly across retail chains, by category and by brand status. The results highlight a lack of uniformity as to how retail chains adjust to commodity cost shocks and provide a more granular insight into the functioning of retail food markets. Specifically, we find that the dispersion of price transmission and mark-up elasticities is larger across retail chains than across products or brand status.

Our data are well suited to address these issues. The UK retail food sector is highly concentrated (with a five-firm concentration ratio around 70 per cent) in which private labels proliferate (accounting for 55 per cent of the products on offer). This differentiates the UK from other food retailing environments that have been used to addressed price adjustment with the use of scanner data and, most notably, provides a useful counterpoint to Hong and Li's (2017) assessment of price transmission in US food markets.[2] Aside from differences in context, the data we employ allows us to account for competitor prices for similar products directly as an influence on cost pass-through rather than measures of aggregate market share employed by Hong and Li (2017).

The data we employ are weekly and cover all seven national retail chains in the UK over a two and a half year period. We analyse two product categories, orange juice and coffee, both of which are sold in all retail chains but which offer an interesting contrast; private labels accounting for 63 per cent and 26 per cent in orange juice and coffee categories respectively. The data suggest considerable heterogeneity in price dynamics across retail chains, even for identical products, with the extent of heterogeneity being particularly marked in the orange juice category. Our econometric approach accounts for these heterogeneous price dynamics and identifies not only differences across retail chains and by brand type (national brands and private labels) in the long-run price transmission elasticities but also the sluggishness or otherwise in price adjustment.

As a final contribution, we tie the distribution of price transmission estimates by retail chain, commodity category and product type to characteristics of competition and price-setting by retail food chains in the UK. Specifically, we draw on recent theoretical research that suggests that the frequency of price adjustment is negatively related to mark-up elasticities and, by extension, positively related to price transmission. Moreover, these theoretical developments suggest a more nuanced relationship between market shares and price transmission that reverses the standard notion that less competitive markets are associated with low price transmission. We explore these issues and confirm a positive relationship between the frequency of price adjustment and price transmission and, contingent on the market share data for the UK food retailing sector, find that higher market share is also associated with higher levels of price transmission. These results provide new insights into price-setting behaviour by food retail chains.

The paper is organised as follows. We begin with a brief review of the related literature, and then outline the underlying framework, drawing on Amiti *et al.* (2019) to emphasise the role of mark-up elasticities in price transmission. The data is then presented, highlighting the nature and extent of heterogeneity in price dynamics across retail chains and product types. Following this, details of the econometric approach are provided with our main results and robustness tests. We then consider recent theoretical insights relating to the frequency of price adjustment and market shares that link mark-up elasticities with estimates of price transmission and close with a summary and some concluding remarks.

Related Literature

There is a long-standing body of research addressing the issue of price transmission in agricultural and food markets; Lloyd (2017) provides a review of these issues. Quite commonly, 'low' or imperfect price transmission is associated with a lack of competition in the food chain, although the mechanism linking the two is typically unidentified.[3] However, to the extent that competition impacts on price transmission, the effect manifests itself through changes in firms' mark-ups, which captures the combined effect of the impact of competition interacting with the demand elasticity and the functional form of the demand function (i.e. how the elasticity of demand changes as prices change in response to a cost shock).[4,5]

There are a number of challenges to determining how competition and changes in mark-ups impact on price transmission relating to: data (whether the data relate to single or multiple chains and the frequency of observation); the choice of functional forms; whether the role of intermediate stages in the food chain are accounted for and, related to this; whether private label products are distinguished from national brands. These issues involve trade-offs in any study of price transmission in the food sector. One approach is to estimate a structural model of a specific market, though this still typically involves issues relating to functional forms and how to characterise competition between firms. Examples of this approach include Nakamura and Zerom (2010), Hellerstein and Villas-Boas (2010) and Richards and Hamilton (2015). Multi-retail chain coverage has also focussed on consumer search and variety pass-through (Richards and Hamilton, 2015), asymmetric price transmission and consumer search (Richards *et al*., 2014) and general versus firm-specific shocks (Loy and Weiss, 2019).[6] Competition between retail chains is also addressed by Thomassen *et al*. (2017) and Richards *et al.* (2018) where attention is paid to the cost of 'shopping baskets' rather than individual products in food retailers. Alternative, reduced form approaches have focussed on large data sets and typically involve a one or two-step approach: in the former, price transmission is estimated with interactions accounting for market shares of retailers and manufacturers (c.f. Hong and Li, 2017); in the latter, estimates of price transmission due to cost shocks are first derived and then regressed on characteristics of the retail food market in a second stage (c.f. Durevall, 2018 and Antioniades and Zaniboni, 2016). Although this line of research provides insights on aspects of retail competition that affect price transmission, it has not emphasised the interaction between strategic complementarities and differences in mark-up elasticities across retail chains. This is a gap that this paper seeks to address.

Vertical control in food markets also has a potential influence on price transmission. In a vertically-related market with mark-ups at successive stages, the transmission of shocks can be further diminished by the existence of double marginalisation. Bonnet *et al*. (2015) investigate how alternative vertical restraints can impact on price transmission and show that price transmission can increase if the form of vertical restraint ameliorates double marginalisation.

In this regard, Hong and Li (2017) highlight the distinction between national brands and private labels, where the latter addresses the potential for retail chains to exercise vertical control over prices. They show that the impact of private labels on price transmission is potentially ambiguous: on the one hand, private labels are associated with higher transmission of cost shocks through to retail prices owing to greater control over suppliers; against this, and to the extent that private labels impact on horizontal competition, the increase in market shares of private labels/retail chains may reduce price transmission. Employing scanner data relating to a single retail chain in the US and multiple chains in Los Angeles, their results indicate that private labels exhibit higher price transmission compared with national brands, pointing to the dominance of the vertical effect. This issue has significance since our data covers both national brands and private labels in all the main UK food retail chains. Like many countries in northern Europe, UK retail chains command dominant positions in a market where private labels represents a distinctive feature of food retailing and is one of the key ways in which retail chains differentiate themselves.

In this context, we add to the literature on price transmission in food markets in a number of ways. Specifically, following recent developments in the international macroeconomic literature, we use a reduced form approach that recognises strategic complementarities across retail chains as a determinant of price transmission but, unlike that literature, we exploit the time series properties of the data to circumvent issues regarding endogeneity.[7] This distinguishes our empirical approach from that of Amiti *et al.* (2019) and Auer and Schoenle (2016) who also highlight the role of mark-up elasticities in determining price transmission. The underlying theoretical framework is nevertheless the same, incorporating CES demand with large firms that encompasses different characterisations of competition. With our data covering multiple retail chains in a national setting characterised by dominant retailers and private label proliferation, the context offers a useful contrast to studies employing data relating to North American retail food markets

Finally, the heterogeneity in price transmission that we estimate also provides a basis for new insights into the role of competition and price setting by retailers as determinants of price transmission. In the context of Amiti *et al*. (2019) and Auer and Schoenle (2016), the relationship between price transmission and market shares is U-shaped given the expression for the mark-up elasticities they derive; Antoniades and Zaniboni (2016) on the other hand suggest that price transmission and market shares will be positively correlated, this relationship being due to differences in mark-ups across retail chains and/or the importance of local costs. Moreover, Gopinath and Itskhogi (2015) show that the frequency of price adjustment and price transmission should be positively correlated. Our data coverage allows us to explore these issues in the context of the UK food retail sector.

Framework

Following Amiti *et al*. (2019) let the static profit maximising price be summarised by the following relation (with all variables being defined in logs):

$$\boldsymbol{p}_{it}^{r} = \boldsymbol{mc}_{it}^{r} + \boldsymbol{\mathcal{M}}_{i}^{r}(\boldsymbol{p}_{it}^{r}, \boldsymbol{p}_{it}^{-r}) \quad (1)$$

where $\boldsymbol{p}_{it}^{r}$ is the vector of profit maximising prices for the retail chain, r, $\boldsymbol{mc}_{it}^{r}$ is a vector of marginal costs which we assume to be common across products within each retail chain, $\boldsymbol{\mathcal{M}}_{i}^{r}$ is the vector of mark-ups across products within the retail chain and $\boldsymbol{p}_{it}^{-r}$ is the vector of prices across other retail chains. Since we are focussing on the role of the mark-up elasticity at the retailer level and how this varies across retailers, we assume that profit maximisation relates to a vector of prices for products within each retail chain *i.e.* the mark-up for product i in retailer

r depends only on the prices charged for i across retailers and not in relation to the prices of other products within a retailer r.[8] Totally differentiating (1), we have:

(2) $$d\boldsymbol{p}_{it}^{r} = dmc_{it}^{r} + \frac{\partial \boldsymbol{\mathcal{M}}_i^r(\boldsymbol{p}_{it}^{r})}{\partial \boldsymbol{p}_{it}^{r}} d\boldsymbol{p}_{it}^{r} + \sum_{j \neq r} \frac{\partial \boldsymbol{\mathcal{M}}_i^r(\boldsymbol{p}_{it}^{-r})}{\partial \boldsymbol{p}_{it}^{-r}} d\boldsymbol{p}_{it}^{-r}$$

Let $\Gamma_{it}^{r} = \frac{\partial \boldsymbol{\mathcal{M}}_i^r(\boldsymbol{p}_{it}^{r})}{\partial \boldsymbol{p}_{it}^{r}} < 0$ be the elasticity of retailer's mark-up with respect to own prices (the direct mark-up elasticity) and $\Gamma_{it}^{-r} = \frac{\partial \boldsymbol{\mathcal{M}}_i^r(\boldsymbol{p}_{it}^{-r})}{\partial \boldsymbol{p}_{it}^{-r}} = \sum_{j \neq r} \frac{\partial \boldsymbol{\mathcal{M}}_i^r(\boldsymbol{p}_{it}^{-r})}{\partial \boldsymbol{p}_{it}^{-r}} > 0$ be the retailer's mark-up with respect to competitors' prices (the indirect mark-up elasticity). Intuitively, retailers reduce mark-ups in face of increases in costs which ameliorates the rise in costs on consumer food prices but increase prices as competitor prices rise.

Re-arranging (2), we have:

(3) $$d\boldsymbol{p}_{it}^{r} = \frac{1}{1+\Gamma_{it}^{r}}\, d\boldsymbol{mc}_{it}^{r} + \frac{\Gamma_{it}^{-r}}{1+\Gamma_{it}^{r}}\, d\boldsymbol{p}_{it}^{-r}$$

or, in summary form:

(3') $$d\boldsymbol{p}_{it}^{r} = \varphi_1\, d\boldsymbol{mc}_{it}^{r} + \varphi_2 d\boldsymbol{p}_{it}^{-\boldsymbol{r}}$$

As Amiti *et al.* (2019) and Auer and Schoenle (2016) show, this characterisation is consistent with alternative forms of firm behaviour, so the framework does not rely on a specific strategic game structure (Bertrand or Cournot) for the determinants of price transmission and nor does it require a specific structural model to identify the role played by the mark-up in determining price transmission.[9] Note that if the direct mark-up elasticity played no role in determining price transmission (*i.e.* $\Gamma_{it}^{r} = 0$), the price transmission elasticity would equal 1.

Equation (3') forms the basis for our estimating equation. From this, the price transmission elasticity φ_1 is conditional on the strategic complementarity effect, φ_2; as Amiti *et al.* (2019)

and Auer and Schoenle (2016) show, omitting the role of strategic complementarities will bias the price transmission effect and by implication the direct mark-up elasticity Γ_{it}^{r}. Also note that the influence of the direct mark-up elasticity on price transmission contingent on the presence of strategic complementarities can be retrieved from the estimates of φ_1.While both mark-up elasticities can be derived, our main focus is on the direct mark-up elasticity with respect to costs as this is the main determinant that underpins how 'low' price transmission may arise.

To highlight the variation in price transmission our empirical approach deals with the heterogeneity issue non-parametrically. This reflects two features of note. First, price dynamics vary across retail chains and this, in turn, will likely be reflected in the dispersion of price transmission estimates. Although we start with an aggregate estimate of the price transmission elasticity across all retail chains, we subsequently estimate (3') at the chain level and highlight the extent of dispersion in price transmission that is observed. Second, the role of the direct mark-up elasticity may differ across national brands and private labels given the potential differences in price transmission arising from the interaction between vertical control and the horizontal competition effect. As noted above, the net effect on the mark-up elasticity is however uncertain given that these influences are likely to be off-setting. We remain agnostic about what effect is likely to dominate in our sample and explore this issue by separating national brands from private labels across the sample as a whole and at chain level.

Retail Prices

Our data is a panel of unique identifier code (UIC)-level prices of orange juice and coffee products sold in the UK's largest seven supermarket chains over 130 weeks from October 2009 to March 2012 sourced from Nielsen UK. A UIC represents a barcode-specific product stocked by a particular retail chain (*i.e.* a unique retailer-product combination) and the panel contains 293 of them, 89 in orange juice and 204 in coffee, including major national brands (60%) and private labels (40%) though, as we note below, there are significant differences in the distribution across commodity categories. In all there are 38,090 price observations. While all the supermarket chains are national retailers, there are noticeable differences in their market positions. The four largest chains, Tesco (which has the largest market share), Sainsbury, Asda and Morrisons, operate large-format one-stop-shop full-range superstores, Waitrose and Marks and Spencer are premium/upmarket large-format grocery retailers, whereas the Co-op operate medium-format supermarkets used more for top-up shopping. Asda is the only national chain to operate an 'Everyday Low Pricing' (EDLP) marketing strategy.[10] Together these chains account for around three-quarters of all retail food sold in the UK, a dominance that has attracted the scrutiny of competition authorities over the years, instigating two public enquiries and a number of reports (*inter alia*, Competition Commission 2000, 2008, Competition and Markets Authority 2015).

The price data provided by Nielsen UK are unit values of the products sold in all of the stores of each national chain every week.[11] As such, they are retail chain level national averages. This matches to the practice of national level pricing which is a distinctive feature of UK food retailing, in contrast to other countries such as the US where assessment of multiple retail chain pricing has often focussed on a state level or localised markets (see footnote 2). National level pricing is also reinforced by advertising campaigns that are also at the national level. Although there may be some degree of deviation from national level pricing (for example, between city centre (metro) outlets where local costs may be higher), national pricing strategies are understood to be the norm (Thomassen *et al.*, 2017). As a recent UK media outlet described it, "…if you look at Britain's biggest supermarkets, they do all basically operate national grocery pricing…The national pricing includes promotions" BBC (2018).

Table 1 summarises the distribution of prices across various classifications.[12] Coverage by retailer is comprehensive and broadly representative of market share in both categories. A key difference between the coffee and orange juice data relates to the importance of private labels. As noted above, the proliferation of private labels is an important feature of the UK food retail sector where they account for over half of all grocery spending in supermarkets. Private label products also appear in all strata of the quality spectrum, each retailer typically offering private labels in, regular and premium segments, the latter experiencing rates of growth in excess of 5 per cent, four times the rate of grocery sales as a whole in recent years (Food Navigator, 2014). With private labels accounting for 74 per cent and 26 per cent of products in our orange juice and coffee categories respectively, the contrast offers a potential basis for assessing differences in price transmission by retail chains between national brands and private labels. In the empirical section where we focus on the heterogeneity across retail chains, we also report the distribution of national brands and private labels at the retail chain level.

Price promotions are a common feature of food retailing the UK, not least since some 40 per cent of all food sold in supermarkets is 'on sale' at the time of purchase, (the highest in Europe, DHSC, 2018). Since Nielsen do not record when a product is on price promotion, we detect sale prices as temporary price reductions of at least 10, 25 or 35 per cent corresponding to shallow, typical and deep discounts following Lloyd *et al*. (2014). In Table 1, we report the incidence of sale prices over the data as a whole using the 10 per cent threshold. Sales are more common in the coffee category, accounting for around 18 per cent of price observations compared to 7 per cent in orange juice. On average, nationally branded products are more commonly promoted than private labels. Promotional behaviour also varies across retail chains. While most national retailers operate some form of Hi-Lo pricing, Marks and Spencer (a niche upmarket retailer) and Asda (an EDLP) retailer seldom use sales. We are ambivalent on whether sales matter for the long-term price transmission process and therefore undertake analysis using price data that are inclusive and exclusive of sales, although it matters little to the (long-run) results that are obtained.

TABLE ONE HERE

Table 1 also points to substantial differences in average prices by retailer reflecting a varied use of promotions and the range of products offered. In general, upmarket retailers are the most expensive and national brands are more expensive than private labels. To give a flavour of price heterogeneity at the micro level, Figure 1 shows the price of four (two orange juice and two coffee) products in each retail chain. Despite representing a small fraction of the data that is analysed, they exhibit features that are representative, in that while the influence of promotions and the long-run trend over time is broadly discernible, there is surprisingly little similarity in the prices of identical (or near-identical in the case of private labels) products.

FIGURE 1 HERE

Econometric Approach

Data

Equation (3') forms the basis for our main estimating equation which is applied to separate panels of UIC-level prices for orange juice and coffee (denoted p_{irt}) reviewed in Section 4. Importantly, these data represent prices of identically barcoded (or similarly barcoded products in the case of private label) products in the seven major food retail chains operating in the UK market. For the orange juice models, our measure of marginal cost mc_t is the natural log of the Merrill Lynch commodity index eXtra (MLCX) weekly spot returns of frozen concentrated orange juice (FCOJ) in the world commodity market acquired from Bloomberg (see the online supplementary appendix, Figure S1). For coffee we use the natural log of the spot price for coffee traded in New York as the measure of marginal cost (the online supplementary appendix, Figure S2). For both series, prices are converted into UK pounds using the Dollar-Sterling spot exchange rate obtained from the Bank of England. We do not have access to wholesale prices but given the importance of the raw commodity in the final product, world prices represent an appropriate means to capture changes in costs at the UIC level.[13]

To deal with competitor prices ($\boldsymbol{p_{it}^{-r}}$ in 3'), we construct indices of rival retailers' prices weighted by market share (denoted rp_{irt} in the empirical analysis) where:

(4) $$rp_{irt} = \frac{\sum_{k \neq r} s_k p_{ikt}}{\sum_{k \neq r} s_k}$$

for $i = 1, \ldots, I$ products, $k, r = 1, \ldots, 7$ retailers in week $t = 1, \ldots, 130$ where s_k denotes the market share of retailer k.[14] Separate indices are constructed for orange juice and coffee categories. Equation (4) defines the rival price as the identical product sold in other supermarket chains weighted by market share. For private label products, the rival price represents the price of the generic product (*e.g.* 1 litre tetra pack standard orange juice from concentrate) sold in the other retailers. In practice, the precise set of rivals at the product-retailer level is not known but is likely to be complex and differ by retail chain, even for the identical products considered here. For example, an upmarket retailer may compete with similarly positioned chains rather than the market leader. While we have no way of accurately defining the appropriate set of rival prices for each product-retailer combination, we do evaluate five variants of (4) as part of the checks for robustness although empirical results appear to differ little (see Section 6).[15]

Non-stationarity

Given the panel nature of the retail price data, we test for unit roots in the retail price series (p_{irt}) and rival price (rp_{irt}) series using the Hadri (2007) panel stationarity test. Orange juice and coffee commodity prices (mc_t) are evaluated using the Augmented Dickey-Fuller (1979) test. Results infer that the data are non-stationary in levels, as indicated by the examples plotted in Figures 1 and 2.[16]

Econometric Specification

Given the non-stationarity of the data, we estimate the long-run parameters of the pass-through relationship posited in equation (3') by initially specifying an Autoregressive Distributed Lag (ADL) (*u*,*v*,*w*) panel data model:

(5) $$p_{irt} = \sum_{j=1}^{u} \lambda_{irj}\, p_{irt-j} + \sum_{j=0}^{v} \delta_j mc_{t-j} + \sum_{j=0}^{w} \beta_{irj} rp_{irt-j} + \alpha_{ir} + \zeta_{irt}$$

where mc_t is the log commodity price at week *t* (which is common to all UICs within each category), α_{ir} is a UIC-specific fixed effect, ζ_{irt} is an error term and the other variables are as previously defined. In the empirical analysis, equation (5) is augmented with a dummy for sale prices and monthly seasonal dummies.

Following Pesaran *et al.* (1999), we re-parameterise (1) into its error correcting form:

(6) $$\Delta p_{irt} = \phi_{ir}(p_{irt-1} - \theta_{ir} mc_t - \vartheta_{ir} rp_{irt}) + \sum_{j=1}^{u-1} \lambda_{irj}^{*}\, \Delta p_{irt-j} + \sum_{j=1}^{v-1} \delta_{irj}^{*}\, \Delta mc_{t-j} + \sum_{j=1}^{w-1} \beta_{irj}^{*}\, \Delta rp_{irt-j} + \alpha_{ir} + \zeta_{irt}$$

where $\phi_{ir} = -(1 - \sum_{j=1}^{u} \lambda_{irj})$, $\theta_{ir} = \sum_{j=0}^{v} \delta_{irj} / (1 - \sum_{j=1}^{u} \lambda_{irj})$ and $\vartheta_{ir} = \sum_{j=0}^{w} \beta_{irj} / (1 - \sum_{j=1}^{u} \lambda_{ij})$are the parameters that describe the long-run part of the model and $\lambda_{irj}^{*} = -\sum_{m=j+1}^{u} \delta_{im}$ $\delta_{irj}^{*} = -\sum_{m=j+1}^{v} \delta_{irm}$ and $\beta_{irj}^{*} = -\sum_{m=j+1}^{w} \beta_{irj}$ with $j = 1,2, \ldots$ are terms that allow short and long-run adjustments to differ. Of primary interest is θ_{ir} the long-run price transmission elasticity, ϑ_{ir} the long-run strategic complementarity elasticity and ϕ_{ir} the error-correction coefficient summarising the average rate of retail price adjustment to long run equilibrium. Separation of the long-and short-run parts of the model in the error-correction representation also has some technical advantages. When the variables co-integrate, estimation of the long-run parameters in (6) is 'super-consistent' (Stock, 1987) and endogeneity issues that characterise regression with stationary variables no longer apply (Engel *et al*., 1983).[17] Furthermore, given the isomorphism between error-correction and co-integration, the statistical significance of ϕ_{ir} provides a convenient test for co-integration, the estimate of ϕ_{ir} indicates the speed at which retail prices adjust to return to the long-run equilibrium.

In order to investigate the effect of heterogeneity on price transmission, we estimate (6) for increasingly disaggregated sub-sets of the data for both product categories. Specifically, (6) is estimated for the entire sample of orange juice and coffee categories respectively, then by brand status (i.e. separate models for national brands and private labels), then by retailer and finally by brand status within each retail chain for each category. Mindful that the sample size falls at each level of disaggregation, our estimation strategy involves the application of two estimators: the Mean Group (MG) estimator proposed by Pesaran and Smith (1995) and the Pooled Mean Group (PMG) proposed by Pesaran *et al.* (1999). While the MG estimator (which involves estimating separate time-series regressions for each UIC and averaging the coefficients) is consistent, the PMG estimator delivers an improvement of efficiency by pooling the UIC data together by constraining the long-run coefficients to be equal across UICs. A Hausman test (for slope homogeneity) is conducted to determine which of the estimators is appropriate in each model. In the interest of brevity, we report results from the preferred model in the empirical analysis that follows. Interestingly, for both product categories, the pattern of Hausman test results indicates that it is the retailer dimension where the heterogeneity is most apparent.

Specifically, the Hausman test rejects slope homogeneity when estimating (6) using the full data set and thus results from the MG estimator are reported here. This also applies to the models for branded products and private labels. However, when we estimate the retailer-specific models (for all products as one and then by brand status), the Hausman test cannot reject the null of slope homogeneity, so in these cases we report results using the PMG estimator.

Results

Price Transmission

In Table 2, we present the long-run parameters and the error-correction coefficients obtained from estimating (6) using all the data followed by subsets comprising national brands and private labels in both orange juice and coffee categories, pooling over retail chains. In each case, we estimate the model with and without rp_{irt} the index of prices for the identical product in other retailers.[18]

TABLE 2 HERE

There are several outcomes to note from these results. First, omitting the prices of competing retailers (rp_{irt}) tends to over-estimate the price transmission effect, considerably so in some cases, pointing to a positive bias in the estimation of price transmission when rival prices are excluded. Accordingly, we find that the strategic complementarity effect (the coefficient on rp_{irt}) is statistically significant at the 1 per cent level. As such, these results are consistent with the theoretical prediction of equation (3’). Second, the strategic complementarity effect is strongest for private labels in the orange juice category and for national brands in the coffee category. This is likely to reflect the dominance of private labels (national brands) in the orange juice (coffee) categories which is indicated by the relative data coverage (*Obs*) in each of the columns above. Third, when account is taken of strategic complementarity, the price transmission effect for private labels is lower than for national brands in both product categories. In the theoretical model presented by Hong and Li (2017) this transpires when the horizontal competitive effect dominates the vertical effect on price transmission.[19] Fourth, and consistent with the estimates of price transmission, the speed of adjustment to the long-run equilibrium is found to be generally slower in private labels than national brands in both commodity categories. This slower adjustment for private labels may well reflect retail chains' greater control over pricing compared with national brands.

To inspect the role of retailer heterogeneity in price transmission, we repeat the exercise reported in Table 2 but cut the data by retail chain. The results (which pool over brand type) offer an initial indication of the extent to which the market level results of Table 2 are common across retailers. Results for both categories (orange juice in Table 3(a) and coffee in Table 3(b)), are consistent with those presented in Table 2 in that the strategic complementary effect is significant (in all cases at the 1 per cent level) and its omission exerts a marked upward bias on price transmission (in 12 out of 14 cases). While price transmission in orange juice is shown to be approximately double that in coffee, what Table 3 brings to the fore is the heterogeneity in price transmission by retailer, which is more striking than the differences observed between product categories or brand type. For example, based on models that include strategic complementarities, the dispersion ranges from 0.072 (Co-op) to 0.575 (Tesco) in orange juice and, from 0.038 (Waitrose) to 0.156 (Asda) in coffee; factors of nearly 8 and 4 respectively. With the exception of one case, the speed of adjustment in coffee is generally higher than that for orange juice across retail chains illustrating category-specific differences in pricing although the dispersion among the speed of adjustment coefficients across retail chains independent does not suggest any obvious ranking across retail chains.

TABLE 3 HERE

Finally, to reveal the full extent of the heterogeneity in price transmission, we estimate models at the most granular level permitted by the data. This involves the estimation of models for national brands and private label products separately within each retailer for both orange juice and coffee. Key findings from previous cuts of the data regarding the significance of strategic complementarity and bias carry over to this dis-aggregated level also. However, it is the variation in price transmission by retailer that is most apparent from the results. To illustrate these features more easily, price transmission elasticities from models including strategic complementarity are presented in Figure 2 (see the online supplementary appendix, Table S8 for the full tabulated results). To benchmark the extent of heterogeneity, we also include the averages for national brands and private labels from Table 2. As these averages show, price transmission for private labels is lower than national brands for both commodity categories, a feature that holds at the retail chain level in 9 of the 13 cases.

Even more apparent is that the dispersion of price transmission by retailer noted in Table 4 is common to both national brands and private label products. In essence, these results highlight that the dispersion of price transmission across retail chains is greater than it is by product (or brand) type. While highlighted by Nakamura (2008), this finding is an underplayed aspect of the micro-dynamics of price behaviour, which has tended to focus on product group heterogeneity. Further, it also suggests that retail chain-specific results are unlikely to be representative of price adjustment across all retail chains in markets characterised by a small number of national chains.

FIGURE 2 HERE

Implications for Mark-Up Elasticities

In broad terms, mark-up elasticities are a measure of how willing/able retail chains are to adjust their mark-ups in the face of cost shocks and, as the discussion around equation (3') makes clear, estimates of the price transmission elasticity φ_1 can be used to retrieve values of the direct mark-up elasticity, Γ_{it}^{r}. Consequently, bias in the estimates of price transmission that has been uncovered in the models that ignore strategic complementaries also has implications for the mark-up elasticity. To gauge the impact of this bias, we express the effect as a percentage of the mark-up elasticity from models that include the measure of strategical complementarity, rp_{irt}. The size of the bias derived from the estimates from models reported above are presented in Figure 3. There are three reasons for reporting the results in this way. First, since the share of raw commodity costs varies across the two commodities, the relative effect of strategic complementarities allows us to have a 'unit free' measure for comparison. Second, since other costs across retail chains may be missing from the analysis, the relative effects with and without the strategic complementarity effect will not be affected. Finally, although we can report the estimates of the mark-up elasticities for each case, it is difficult to benchmark these effects in the absence of estimates from studies that also use micro-level high frequency data.[20]

In almost all cases, we find that mark-up elasticities are biased downward when strategic complementarities are not accounted for, thereby understating the responsiveness of prices in retail chains to cost shocks.[21] In other words, accounting for competitors' prices suggest that retail chains' mark-ups are more responsive to cost shocks than would be inferred from the price transmission coefficient when competitors' prices are ignored. The effect is particularly evident in the orange juice category (where the bias is 76 per cent) and, more specifically, with respect to private labels (where the bias is 84 per cent). In the coffee category, the bias is estimated at 66 per cent with this mainly being associated with national brands. Note that the bias is most apparent for private labels in orange juice and national brands in coffee, matching the segments in which private labels and national brands proliferate. While the size of the bias is typically high in all retailers for in both product categories, we again see dispersion across retail chains, and within chains (e.g. ASDA, Tesco and M&S) suggesting that differences in factors such as the product mix within categories and rivalries between firms are complex.

FIGURE 3 HERE

Discussion

In this section, we reflect on our results in light of recent research and how they address competition issues in retail food chains. We find price transmission in private labels to be lower than in national brands, indicating that the horizontal competitive effect that dampens price transmission dominates the positive vertical control effect. Given the importance of private labels to food retailers and the highly concentrated nature of UK food retailing sector, this result seems plausible. Interestingly, Hong and Li (2017) find the reverse in the US markets they study, in which private labels are a less prevalent feature of retail competition. Such differences serve to underscore that context appears to matter in determining the relative speed of price adjustment.

Recent multi-category, multi-retail structural studies, most notably Thomassen *et al*. (2017) and Richards *et al*. (2018) have focussed on shopping baskets rather than single categories and highlight that the impact of changing prices in one category of the shopping basket will not only generate price changes within a specific retail chain's basket but also the shopping baskets in other retail chains. As a result, these studies suggest that estimates of price changes from single-category studies potentially underestimate the overall impact on consumers, although the impact of these demand complementarities depend on types of shoppers (notably ‘one’ or ‘two’ stop shoppers, Thomassen *et al*., 2017), shopping costs and, related to this, the intensity of store (chain) competition, all of which reflect the richness of the structural approach.

However, there are some similarities in the insights from these recent multi-category, multi-chain studies and the results presented above with both approaches providing insights in addressing retail competition.[22] Based on these recent structural multi-chain studies, we observe the following. First, price effects are retail chain specific: just as direct price transmission varies by retail chain, so do the own-price elasticities for specific commodity groups. Second, the cross-price effects across stores for specific categories also depends on the store-category combination. Finally, the store-category combinations are not symmetric:[23] In all, these multi-category-store combinations highlight dimensions of heterogeneity across the retail food sector.

The intuition that would extend from these multi-category, multi-chain studies is that the relative importance of the strategic complementarity effects that we have highlighted in our results above (including the magnitude of the effects for different retail chains and the impact it has on the direct price transmission effect) suggests that the significance of competitor prices constrains the extent of price transmission. More specifically, in the context of the magnitude of the mark-up elasticities, they increase suggesting that retail chains internalise the cost increases to ameliorate the impact of one-store shoppers transferring all their purchases elsewhere. However, the relationship between retail chains and the strategic complementarity variable are asymmetric reflecting different incentives for consumers to switch across retail chains.

Taken together, the main mechanisms that are associated with multi-category, multi-chain effects are consistent with the results reported above (i.e. retail chain specific price transmission, lower price transmission when accounting for strategic complementarities and the effect of strategic complementarities being retail chain-specific) and underpin the importance of acknowledging retailer heterogeneity and the combinations thereof in addressing competition issues in food retailing.

Robustness

Here we check the resilience of our key results (principally the bias, strategic complementarity and lower price transmission in private labels) to three aspects of the empirical strategy, namely the definition of sales, inclusion of other costs and alternative measures of rival prices (see the online supplementary appendix for details).

Sales

When estimating the price transmission effects in Section 5 we accounted for sales with a dummy variable to capture 10 per cent sale episodes in each UIC. Results (Tables S9 to S14) are almost identical for alternative depths of sales of 25 and 35 per cent. Estimation without a sales dummy (see S15) also made no qualitative (and very little quantitative) difference to the estimates reported above implying that temporary price reductions have little bearing on the long-run coefficients.

Other Costs

As food categories go, orange juice and coffee represent retail products that differ relatively little from the unprocessed raw materials from which they originate (see footnote 14). Nevertheless, to accommodate the influence of other costs, we augment equation (6) with the retail price of diesel as a proxy for distribution and other energy-based costs in food marketing (diesel prices being available at weekly frequency). Ideally, wholesale prices (capturing, *inter alia*, labour and energy costs in addition to commodity prices) would be used but this measure is not available at a weekly frequency in the UK. Regression models reported in S16-S18 offer a somewhat mixed picture. While in orange juice the main results generally survive the addition of diesel price (where diesel price is mostly statistically significant), this is less evident in coffee (where diesel is mostly statistically insignificant). Moreover, the strength and significance of the key results weaken in both categories as we drill down from the market level to the more disaggregate models. Statistical issues are particularly apparent in coffee where price transmission coefficients are typically insignificant and occasionally negative and are more likely to differ according to the estimator (MG or PMG) used. Overall, we find retail diesel prices (arguably a rather poor proxy for food manufacturing costs) play a confounding role in the empirical analysis, underlining the challenge in obtaining retail chain-specific costs at the appropriate frequency.

Alternative Measures of Rival Prices

The index of rival prices (rp) used in the foregoing analysis relates to the price of the identical product (or 'nearly so' in the case of private labels) weighted by retailer market share. As such, rp captures competition in a tightly defined sense, namely the price of the identical product in rival retailers. Given the complexity of competition in food retailing, it seems plausible that other classifications of rival products are more relevant. To investigate the possibilities, several alternatives indices have been constructed that incorporate the prices of a broader set of products within the same category in other retailers, both in isolation ($rp1$) and in combination with other products within the same category stocked by the base retailer ($rp4$), as well as the identical products measure in combination with products of each brand type in the base retailer ($rp3$ and $rp5$) and finally the prices of within-retailer products only ($rp2$). For full definitions see Table S1 although note that the inclusion of within-retailer effects ($rp2$, $rp3$ and $rp5$) is intended to capture the possibility that a change in the price of one product (whether this be a national brand or private label) may trigger the retailer to change prices of other products in the same category. This reflects the approach to within-retailer price changes that have been highlighted in the marketing literature noted above. Results reported in S18 show that two of the main results are robust to the definition of rival retailer prices (positive bias at the retailer level being evident in 27 of the 30 cases; strategic complementarity effects being significantly positive in 26 of the 30 cases) but less so to the third, (price transmission in private labels being lower than national brands in 5 out of 10 cases). As in the evaluation of diesel prices, the PMG estimator occasionally delivered negative price transmission coefficients so the MG estimator is preferred in these cases. The results also show that models involving the prices of products in other retailers (whether identical products [rp] or more broadly defined [$rp1$]) have higher explanatory power than the measure that uses within-retailer products only ($rp2$), which performs least well of all, indicating that the keenest source of competitive pressure emanates from rival retailers rather than within category effects in the retailer itself.

Price Transmission and Retailer Characteristics

Finally, we explore the links between the size of price transmission and some characteristics of food retailers that the recent literature has proposed play a role, specifically, the propensity to change prices in the face of cost shocks and market share. To do so, we run regressions relating the 293 price transmission coefficients (θ_{ir}) estimated in the retailer-category-brand models inclusive of strategic complementarities in Section 6 to the frequency of price adjustment ($Freq_{ir}$) and retailer market share (RMS_r) in linear and quadratic form with dummies to allow for category ($Coffee_{ir}$) and brand type ($Label_{ir}$) fixed effects. The regression is therefore given by:

(7) $\theta_{ir} = \eta_0 + \eta_1 Freq_{ir} + \eta_2 RMS_r + \eta_3 RMS^2{}_r + \eta_4 Coffee_{ir} + \eta_5 Label_{ir} + \eta_6 CoffeeXlabel_{ir} + \varsigma_{ir}$

where $Freq_{ir}$ is the price change frequency (%)-measured as the number of price changes over the sample period-by UIC and $RMS_r$is the share of each retailer in the total grocery market.[24]

As discussed in Section 2, Gopinath and Istkhoki (2010) present a theoretical framework (complemented by empirical evidence on exchange rate pass-through) that links mark-up elasticities and price transmission with the frequency of price adjustment. Interpreting the frequency of a price change as the probability of price re-setting, they show that high mark-up elasticities reduce firms' desired price adjustment and hence low rates of price transmission and price changes. In terms of (7) above, we should therefore expect a positive relation between price frequency and price transmission ($\eta_1 > 0$).

In the setting that is consistent with the model set out in Section 2 (i.e. CES demand with variable mark-ups), the relationship between market share and price transmission is U-shaped ($\eta_2 < 0, \eta_3 > 0$) across the spectrum of market share reflecting full pass through in both the perfectly competitive and monopoly settings (see Amiti *et al.*, 2019, Appendix C; Auer and Shoenle 2016).While we allow market share to enter quadratically in (7), a U-shaped relation may be difficult to determine empirically given that our sample contains only national chains and thus no small regional chains and independents.

A summary of results is presented in Table 4. Two key findings emerge. First, we find that the relationship between the frequency of price adjustment and price transmission is significantly positive across all specifications, in line with Gopinath and Itskhoki (2010). To put the estimates of 0.002 into context, those products that are most likely (top quartile) to change price have a rate of price transmission of (0.002$\times$ 35 $=$) 0.136, twice that of products that are least likely (bottom quartile) to change price (0.002$\times$ 68 $=$) 0.07.

TABLE 4 HERE

Second, while there is some evidence for a U-shaped relationship in some of the models (see, for example, equation [1]), non-linear effects are not statistically significant at conventional levels and do not survive the inclusion of fixed effects. In general, we find a positive relationship between retailer market share and price transmission in all linear models (e.g. [3] to [6]) implying that our data may well be tracing the relationship to the right of any turning point. Estimates from the linear models in Table 8 of around 0.017 suggest a 10 percentage point increase in market share increases the elasticity by 0.17, although the precise quantitative impact of changes in market shares will depend on how this variable interacts with other determinants of the mark-up elasticity. It is also noteworthy that the positive relationship aligns with recent work using scanner data across retail food chains by Antoniades and Zaniboni (2016).[25]

In summary, the results here provide some new insights into price-setting behaviour by food retailers in the UK. With reference to the links between market share and price transmission, the results suggest that the interaction between the functional form and market shares may challenge conventional views on how price transmission is influenced by competition. Further research with more disaggregate market share data is needed but our findings are suggestive of the underpinning role played by retail chains in explaining price transmission in highly concentrated retail food markets.

Summary and Conclusion

Heterogeneity in price dynamics across product groups has been highlighted in recent research but less so heterogeneity across retail food chains. Using data covering two product categories including private label and national brands across all the main retail food chains in the UK, the evidence highlights considerable variation in price dynamics across retailers even for products with the same barcode. Our findings highlight a simple yet neglected aspect of price transmission in many previous studies, that strategic complementarities matter and that it is the mark-up elasticity that is the principal determinant of price transmission in food retailing. Our results show that, in the absence of rival prices, estimates of price transmission are biased upwards, and hence overstate the importance of input costs in price setting. By extension, mark-up elasticities - which underpin price transmission in imperfectly competitive markets - are also likely to be greater when we account for strategic complementarities. Using a reduced-form approach that allows us to exploit the diverse nature of price dynamics across retail chains in the UK, we show that price transmission and the role of mark-up elasticities varies by retail chain, between national brands and private labels and by commodity category, but it is the first of these that plays the most decisive role. Finally, we show that the observed heterogeneity ties with new insights about price setting behaviour by retail chains and the role of competition more generally.

Taken together, the existence of retailer heterogeneity and the insights that arise with respect to price transmission give a more nuanced insight into the micro-price dynamics of the price transmission issue and, by extension, the functioning of retail chains and competition in the food retail sector. Future research could complement the results reported here by broadening scanner price studies involving data for single retail chains to cover a wider range of product categories and recognise that, when limited to single chain data, that the data may not accurately capture the extent of heterogeneity in price dynamics that exist across the retail sector as a whole. More generally, further research on price dynamics across food retailers at the micro-level will also improve our understanding of the macroeconomic aspects of food price inflation.

Footnotes

1. For a recent overview of the range of competition issues that can be addressed by structural models in differentiated product markets and the data required to address them, see Ghandi and Nevo (2021).
2. Hong and Li (2017) note that "…several European countries have private label shares around 50 per cent versus about 20 per cent in North America. Because the associated high retail concentration…, may have additional effects on cost pass-through, a comparison of commodity to retail pass-through across countries or markets with very different retail/manufacturer concentrations would help translate our micro findings into more direct macro implications" (p.165).
3. This issue is neatly summarised in Bakucs *et al*. (2014).
4. Weyl and Fabinger (2013) provide a recent comprehensive coverage of this issue. See also Hong and Li (2017).
5. To fix ideas on the mark-up elasticity in a standard food chain model, McCorriston *et al*. (1998) show the change in retail prices ($d\ln R$) due to a cost shock ($d\ln C$) contingent on the change in the mark-up (μ) is given by:

   $$d\ln R = -\mu d\ln R + d\ln C = d\ln C/(1+\mu)$$

   where $\mu = \omega\theta/(\eta - \theta)$, $\omega = \partial\ln\eta/\,\partial\ln R$ and θ is the intensity of competition (in a quantity setting model) and η is the absolute value of the elasticity of demand. In other words, the mark-up elasticities capture the interaction between competition, the elasticity of demand and the functional form of the demand function. Given the role of ω, it is common for theoretical and (where relevant) empirical approaches to assume specific functional forms. As such, the links between price transmission and competition are contingent on this assumption.

6. The data employed in Richards and Hamilton (2015) and Richards *et al*. (2014) relates to ready-to-eat cereals in Los Angeles; the data in Loy and Weiss (2019) relates to the retail yoghurt market in Germany. Hong and Li (2017) also provide results based on multi-chain data relating to Los Angeles.
7. The marketing literature on retail food prices is also relevant here. Though focusing mainly on promotion pass-through rather than the transmission of costs and - with limited exceptions - focusing on prices within single retail chains, this literature nevertheless highlights the importance of channel-level pricing *i.e.* that the price of a specific product within a category will also be dependent on price changes of products in a specific channel (such as national brands or private labels) within a retail chain. Examples here include Besanko *et al*. (2005), Dubé and Gupta (2008), Ailawadi and Harlam (2009) and Nijs *et al.* (2010). We deal with these issues in relation to the robustness of our main results.
8. This simplifying assumption is relaxed in the empirical analysis but makes little difference to the results.
9. The specific price transmission expressions that both Amiti *et al.* (2019) and Auer and Schoenle (2016) derive are based on CES demand with large firms based on Dornbusch (1987) and Krugman (1986). As we note below, this underpinning theoretical framework has implications for the relationship between price transmission and competition as reflected in the role of the direct mark-up elasticity.
10. The two national discount chains, Lidl and Aldi do not supply price data to Nielsen but combined accounted for around 6 per cent of the market in the sample period (Kantar *WorldPane*l, 2013).
11. The use of scanner data is now becoming a more standard approach to addressing competition and price transmission issues though the focus on differences across retail chains and the issue of retailer heterogeneity is less common in price transmission research.

12. M&S offered only private label products on orange juice during the sample frame. Further details of the data are presented in the online supplementary results file, Table S2.
13. Durevall (2018) reports that green coffee beans are estimated to equal 50-90 per cent of marginal costs. Orange juice is mandated in law to contain at least 50% concentrate or pure juice https://www.legislation.gov.uk/uksi/2013/2775/made. Other costs such as labour etc are unlikely to vary much particularly given the time period and the frequency of the data we employ here. We also explore the sensitivity to other retail (distribution) costs in the robustness section.
14. The seven largest national retailers account in our dataset account for 74% of all food sold in the UK, hence to standardise price levels retailer shares appear in both the numerator and denominator.
15. See the online supplementary appendix, Table S18 for details. Note that we weight prices by the market share of each supermarket to recognise that prices in the largest national retailers are implicitly more important than those in smaller chains. Other weightings are also possible. In principle, prices could be weighted by product share (as in, for example, Auer and Schoenle (2016) and Hong and Li (2017)); however, quantities are redacted by Nielsen UK to prevent disclosure of individual retailer's performance which rendered this infeasible for the price data we employ here.
16. See the online supplementary appendix, Tables S4 and S5 for details.
17. While the theoretical approach to address the role of strategic complementarities and mark-up elasticities follows Amiti *et al.* (2019), our empirical approach does not. Specifically, since their data are stationary and their focus is on short-run price transmission, this requires them to explore an instrumental variables approach to identify the strategic complementarity effect. However, since we have non-stationary data and our focus is on long-run price transmission, we can circumvent this issue. Note also that weak exogeneity

delivers an efficient estimator but given the large data available here, this is unlikely to be an issue. It should be noted that, in this context, the estimated coefficients do not have a causal interpretation. We provide the results for weak exogeneity using the tests of Moral-Benito and Serven (2015) in the online appendix in Table S6.

18. A sales dummy (c.f. discussion on price dynamics in Section 2) and an appropriate lag structure selected on the basis of the SBC are included in all regressions but suppressed for brevity.
19. In the US markets studied by Hong and Li (2017), price transmission was significantly higher in private labels. While this may point to differences in retail competition between the UK and North America, it may also reflect differences in private label quality (US private labels typically being perceived of lower quality than national brands) and pricing practice (EDLP being more prevalent in the US). We are grateful to a referee for pointing this out.
20. For the aggregate results, the mark-up elasticities in the absence of strategic complementarity effects for orange juice and coffee are 1.00 and 1.04 respectively; with strategic complementarities, the mark-up elasticities are 4.13 and 10.24 respectively. These results compare with mark-up elasticities greater than 5 that are commonly used in macro-economic models. Inclusive of strategic complementarities, the mark-up elasticities for orange juice and coffee private labels are 4.78 and 17.18 respectively; for national brands, the corresponding figures are 2.86 and 7.62 respectively.
21. In the orange juice category, estimates of price transmission elasticity for Tesco and Marks and Spencer rise with the inclusion of strategic complementarities. Given that the changes are small we set the bias implied by the estimates to zero in the figure. We discuss the robustness issues in Section 7.

22. The results from Thomassen *et al*. (2017) are particularly relevant for the present study as the data refers to UK food retailing and the characteristics of competition between UK food retailing chains, As we note below, Richards *et al*. (2018) report similar effects with their data referring to Eau Claire area in Wisconsin, US.
23. The magnitude of these demand complementarity effects highlight the significance of the multi-retail chain context: for example, the own-price elasticity for meat products in Asda is -0.84 but -1.46 in Aldi (a discounter); in relation to differences in cross elasticity effects, the cross-elasticity for meat between Asda and Tesco is 0.21 but for Asda and Aldi, 0.01; the asymmetry in store category combinations is also highlighted with the cross-elasticity for meat between Asda and Tesco is 0.21 but for Tesco and Aldi is 0.14. All estimates of the demand complementarity effects are taken from Thomassen *et al.* (2017) based on UK data.
24. As noted previously, product-specific market shares within and across retail chains would be most pertinent for this analysis but are unavailable since quantity data is redacted by Nielsen to preserve commercial confidentiality.
25. Depending on the specification, Hong and Li (2017) also report a positive relationship between market share and price transmission in their multi-chain analysis.

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Table 1: Summary of Price Data

	Orange Juice			Instant Coffee		
	Obs.	Percent	Mean (£)	Obs.	Percent	Mean (£)
Asda	1430	12	1.41	3900	15	3.43
Sainsbury	2340	20	1.35	5200	20	3.65
Morrisons	1560	13	1.32	3770	14	3.12
Tesco	2080	18	1.30	4810	18	3.94
Co-op	1560	13	1.39	4420	17	4.21
Waitrose	1690	15	1.48	3510	13	4.12
Marks & Spencer	910	8	1.72	910	3	3.91
National Brand	2990	26	1.50	19760	75	4.12
Private Label	8580	74	1.36	6760	25	2.33
Regular Price	10753	93	1.39	21708	82	3.76
Sale Price	817	7	1.47	4812	18	3.24
Total	11570	100	1.40	26520	100	3.76

Table 2: Estimates of Long-Run Price Transmission and Strategic Complementarities

Orange Juice

	Full Data		National Brands		Private Labels	
mc_t	0.499***	0.195***	0.290***	0.235***	0.571***	0.173***
	(0.043)	(0.036)	(0.082)	(0.091)	(0.048)	(0.033)
rp_{irt}		0.626***		0.153 ***		0.639***
		(0.083)		(0.072)		(0.075)
EC	-0.131***	-0.186***	-0.228***	-0.252***	-0.097***	-0.156***
	(0.011)	(0.013)	(0.025)	(0.027)	(0.010)	(0.012)
Obs.	11,303	11,303	2,921	2,944	8,382	8,382
R^2	0.43	0.41	0.39	0.37	0.55	0.53

Coffee

	Full Data		National Brands		Private Labels	
mc_t	0.190***	0.089***	0.217***	0.116***	0.058***	0.055***
	(0.023)	(0.006)	(0.014)	(0.018)	(0.006)	(0.005)
rp_{irt}		0.518***		0.338***		0.155***
		(0.022)		(0.052)		(0.033)
EC	-0.159***	-0.141***	-0.172***	-0.229***	-0.089***	-0.093***
	(0.009)	(0.008)	(0.011)	(0.014)	(0.014)	(0.015)
Obs.	25,420	25,296	18,848	18,696	6,604	6,656
R^2	0.31	0.32	0.47	0.45	0.37	0.36

Notes: Results are based on equation (6) using the mean group (MG) estimator following application of the Hausman test of slope homogeneity (see text for details). All specifications also include seasonal dummies and a control for sales. Standard errors are reported in brackets. ***, ** and * denotes significance at the 1, 5 and 10 per cent levels respectively.

Table 3: Price Transmission and Strategic Complementarities by Retail Chain

Table 3(a): Orange Juice UICs

	Asda		*Sainsbury*		*Morrison*		*Tesco*		*Co-op*		*Waitrose*		*M&S*	
$\boldsymbol{mc_t}$	0.695***	0.455***	0.532***	0.217***	0.309***	0.080*	0.568***	0.575***	0.284***	0.072**	0.377***	0.077	0.014	0.123***
	(0.065)	(0.092)	(0.051)	(0.054)	(0.038)	(0.041)	(0.046)	(0.064)	(0.035)	(0.026)	(0.049)	(0.055)	(0.015)	(0.042)
$\boldsymbol{rp_{it}}$		0.405***		0.704***		0.786***		-0.010		0.549***		0.769***		0.635***
		(0.118)		(0.080)		(0.069)		(0.109)		(0.072)		(0.067)		(0.081)
EC	-0.122***	-0.133***	-0.086***	-0.101***	-0.106***	-0.168***	-0.155***	-0.155***	-0.049**	-0.082***	-0.079***	-0.104***	-0.146**	-0.084**
	(0.043)	(0.043)	(0.024)	(0.024)	(0.022)	(0.026)	(0.030)	(0.031)	(0.016)	(0.022)	(0.026)	(0.023)	(0.066)	(0.033)
Obs.	1397	1397	2286	2286	1524	1524	2032	2032	1524	1524	1651	1651	889	889
$\boldsymbol{R^2}$	0.45	0.46	0.60	0.61	0.60	0.61	0.57	0.57	0.26	0.27	0.45	0.48	0.48	0.49

Table 3(b): Coffee UICs

	Asda		*Sainsbury*		*Morrison*		*Tesco*		*Co-op*		*Waitrose*		*M&S*	
$\boldsymbol{mc_t}$	0.161***	0.185***	0.263***	0.125***	0.205***	0.077***	0.174***	0.049***	0.145***	0.077***	0.148***	0.038**	0.147***	0.081**
	(0.024)	(0.053)	(0.022)	(0.016)	(0.036)	(0.012)	(0.019)	(0.015)	(0.021)	(0.020)	(0.036)	(0.016)	(0.022)	(0.041)
$\boldsymbol{rp_{it}}$		0.314**		0.585***		0.849***		0.598***		0.259***		0.558***		0.230***
		(0.153)		(0.050)		(0.048)		(0.048)		(0.084)		(0.057)		(0.089)
EC	-0.159***	-0.226***	-0.074***	-0.094***	-0.119***	-0.140***	-0.159***	-0.194***	-0.229***	-0.238***	-0.102***	-0.114***	-0.148***	-0.195***
	(0.022)	(0.027)	(0.012)	(0.017)	(0.019)	(0.017)	(0.019)	(0.025)	(0.026)	(0.020)	(0.013)	(0.013)	(0.040)	(0.038)
Obs.	3780	3720	4960	4960	3683	3683	4736	4662	4216	4352	3456	3456	896	896
$\boldsymbol{R^2}$	0.33	0.30	0.31	0.30	0.35	0.33	0.36	0.32	0.31	0.35	0.35	0.30	0.36	0.35

Notes: Results are based on equation (6) using the pooled mean group (MG) estimator following application of the Hausman test of slope homogeneity (see text for details). All specifications also include seasonal dummies and a control for sales. Standard errors are reported in brackets. ***, ** and * denotes significance at the 1, 5 and 10 per cent levels respectively

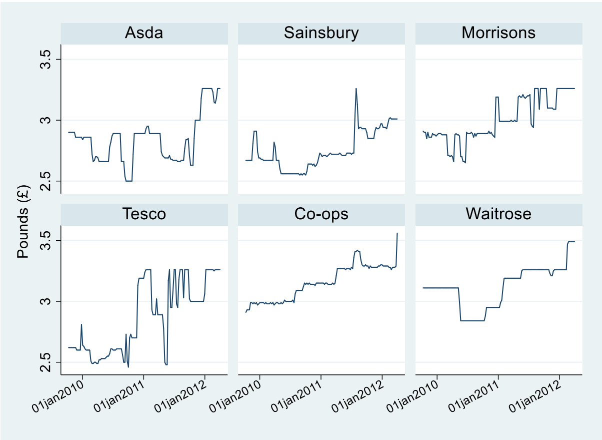
Table 4: Retailer Characteristics and Price Transmission

	(1) lrpt	(2) lrpt	(3) lrpt	(4) lrpt	(5) lrpt
	Non-linear			Linear	
Freq	0.002^{*}	0.002^{**}	0.002^{**}	0.002^{**}	0.002^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RMS	-0.006	0.005	0.016^{***}	0.016^{***}	0.017^{***}
	(0.006)	(0.013)	0.002^{**}	(0.003)	(0.003)
RMS2	0.001^{***}	0.000			
	(0.000)	(0.000)			
Label		-0.019	-0.014		
		(0.079)	(0.082)		
Coffee		0.073	0.150^{*}	0.161^{***}	0.167^{***}
		(0.089)	(0.085)	(0.051)	(0.053)
Label*Coffee		0.036	0.032	0.019	
		(0.100)	(0.101)	(0.060)	
_Cons	0.026	-0.051	-0.134	-0.147^{**}	-0.142^{**}
	(0.060)	(0.102)	(0.099)	(0.057)	(0.060)
Obs.	293	293	293	293	293
R^2	0.12	0.12	0.12	0.12	0.12

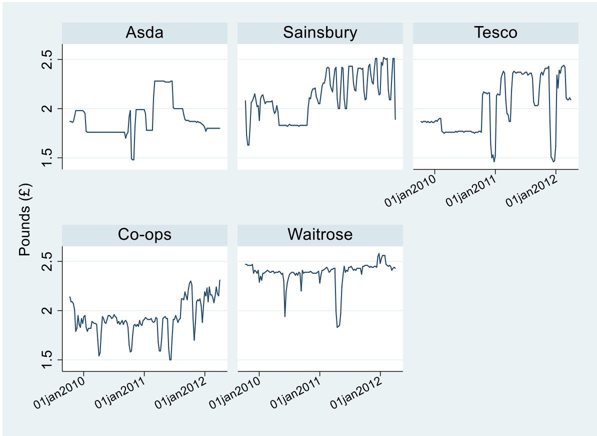
Notes: Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: Price Dynamics across Retail Chains and Product Type

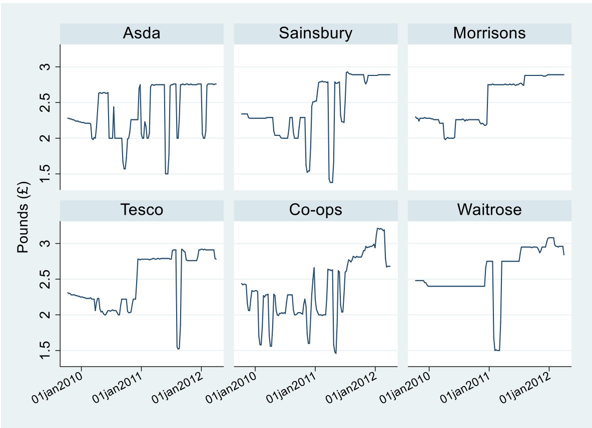
Freshly-Squeezed Orange Juice, PL 1 Litre



Long Life Orange Juice, PL Orange 1 Litre



Nescafe Decaffeinated Granules, 100gram



Kenco Rich Freeze Dried, 100gram

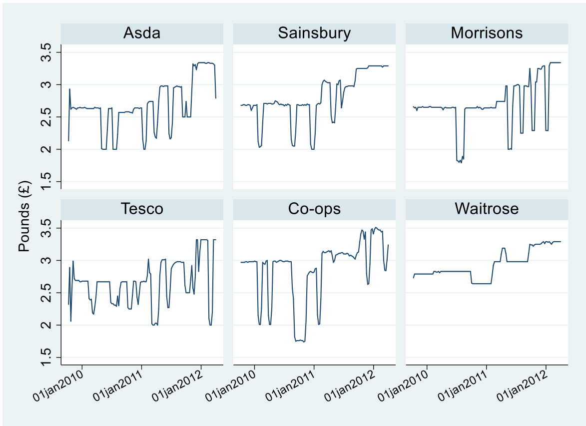
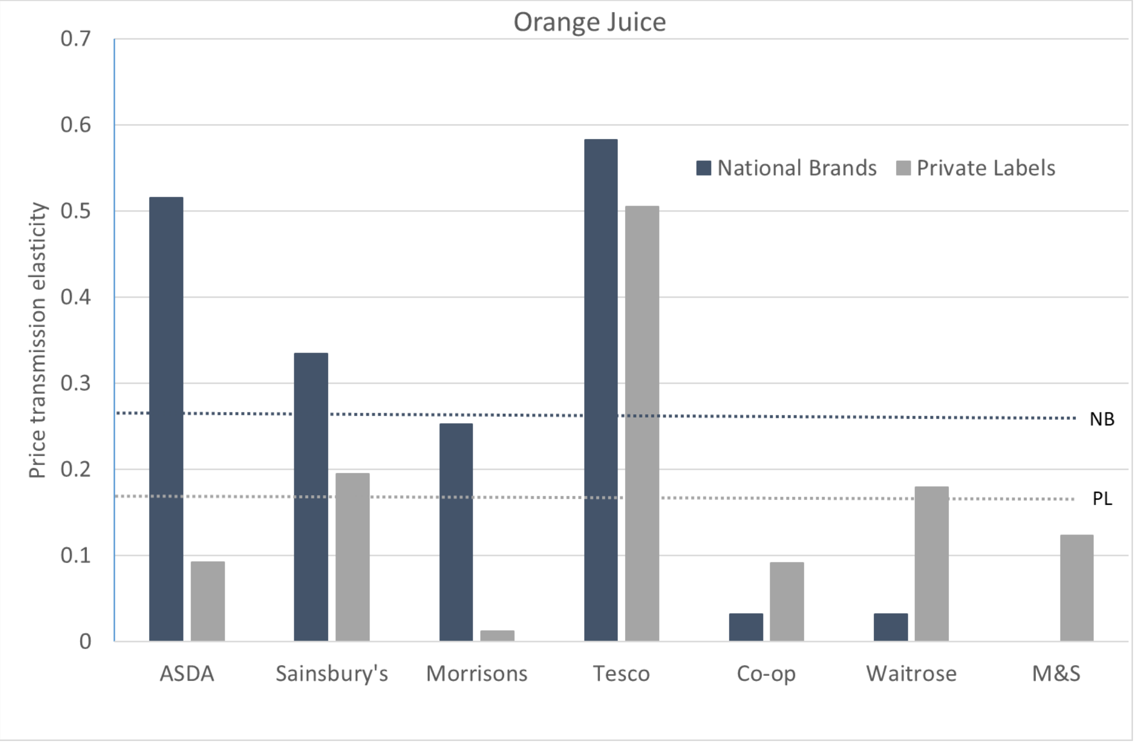
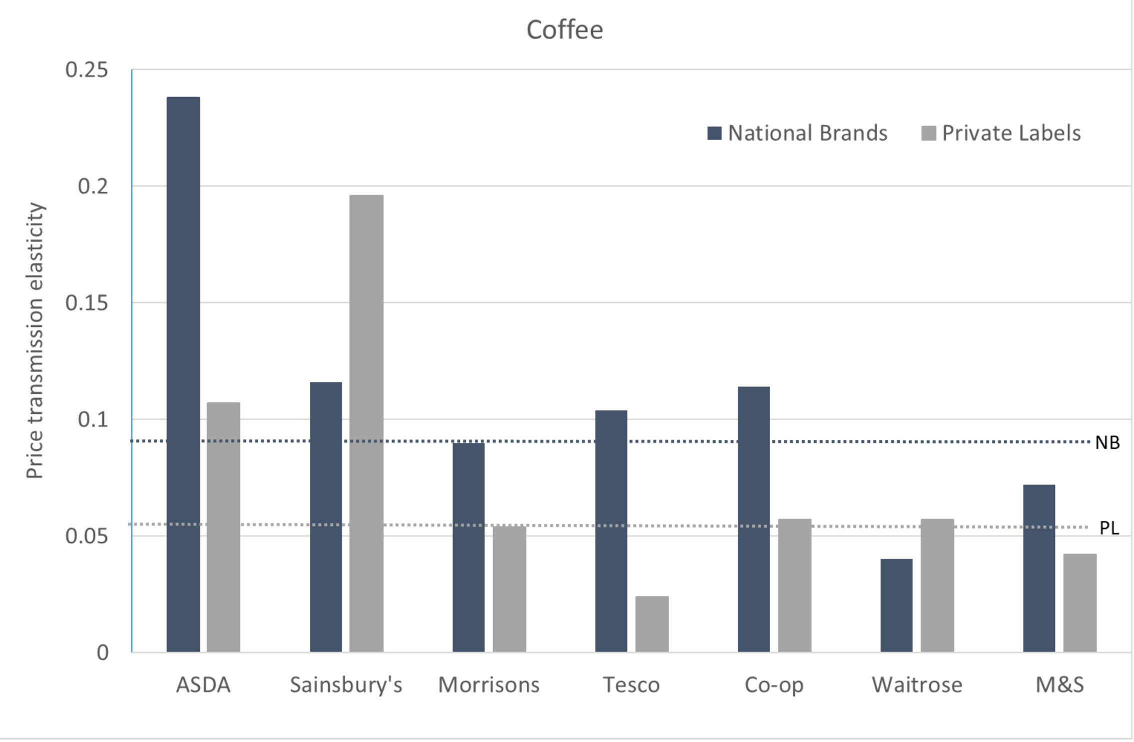


Figure 2: Price Transmission Elasticities across Retail Chains by Brand Type for Orange Juice and Coffee





Notes: Price transmission elasticities are from models that include the strategic complementarity variable. NB and PL denote national brands and private averages from Table 3. See Table S8 in the online supplementary appendix for tabulated regression results.

Figure 3: Implied Bias in the Mark-Up Elasticities by Category, Brand Status and Retail Chain