# Price transmission at the micro-level: what accounts for the heterogeneity?

Hao Lan[1], Tim Lloyd[2], Steve McCorriston[3], Wyn Morgan[4]

[1] University of East Anglia, UK. Hao.Lan@UEA.ac.uk
[2] Bournemouth University, UK. tlloyd@bournemouth.ac.uk
[3] University of Exeter, UK. S.mccorriston@exeter.ac.uk
[4] University of Sheffield, UK. w.morgan@sheffiled.ac.uk

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## Abstract

We use high-frequency scanner data to estimate product-specific price transmission elasticities across product types, between national brands and private labels and across retail chains in the UK. The results provide new insights into the determinants of price transmission including the role of vertical control in the retail chain, the elasticity of retail mark-ups and retailer market power. Using data on 106 orange juice products over 130 weeks for 7 UK retail chains, we highlight significant variation in price transmission by chain and that the characteristics of pricing behaviour and differences in vertical control across are important determinants of price transmission.



**Keywords:** [Scanner data; retailers; price transmission]


## Introduction

The empirical analysis of price dynamics using high frequency scanner data is a growing research area. Much of this research has originated in macroeconomics where large data sets, providing highly detailed product coverage often at a weekly frequency, have been employed to evaluate the predictions of menu cost models and, more generally, to explore the nature of price adjustment. Klenow and Malin (2011) summarise the main features of this research strand. One main insight from this research is that that the nature of price adjustment is heterogeneous with price dynamics varying both within and across sectors and product groups. The insights that arise from scanner data sources have however often been limited to single retail chains; the limited exceptions to the single retail chain focus have reported that price dynamics may be more heterogeneous across retail chains than across product groups (see, most notably, Nakamura *et al*., 2011).

In this paper, we focus on the issue of price transmission using high frequency scanner data and highlight the role of heterogeneity across retail chains where our coverage of the retail food sector includes all the main retail chains in the UK.  For our purposes, coverage across all retail chains in a specific national market serves two principal purposes. First, retail chains differ across a number of dimensions. These include market share and upstream bargaining power, pricing practices, the use and timing of promotions, and the use of private labels among others. As a consequence, and which is evident from the data we exploit, the pricing decisions and the corresponding nature of price dynamics varies across retail chains even for identical or closely-related specific products.

Second, the use of scanner data allows us to measure price transmission at the specific product level and in specific retail chains. We show that the measurement of price transmission results in a range of price transmission elasticities that indicate a significant dispersion of price transmission elasticities that are more revealing than a single price transmission elasticity that arises from time-series studies based on highly aggregated product group and monthly data. The results indicate that there are wide differences in price transmission across product types, between private labels and national brands and across retail chains. Notably, price transmission varies across the retail chain dimension than across any other cut of the data. Even for the same specific product, the price transmission elasticity can vary substantially across retailers.

However, the heterogeneity in price transmission across retailers and products offers another advantage insofar as we can exploit the observations on price dynamics to assess how the characteristics of vertical food chains influence price transmission. Specifically, there are features of our data that, coupled with additional observations on retailer characteristics, enable us to provide some insights into the factors that may determine price transmission. For example, as is known from theoretical approaches to price transmission, when markets are not perfectly competitive, one of the key determinants of less-than-complete price transmission is (conditional on the shape of the demand function) the *elasticity* of firms' mark-up (i.e. the responsiveness of the mark-up as input costs change). Further, the nature of vertical control throughout the food chain can also be an important determinant to the extent that it influences the role of double marginalisation (i.e. mark-ups at successive stages) as a determinant of price transmission.

In the absence of a structural model accompanied by detailed cost data and a method to assess the nature of vertical relations within a vertical chain, it is difficult to confirm whether the elasticity of the mark-up is likely to play a significant role in determining the nature of pass-through. In this context, retailer heterogeneity allows us to identify the potential determinants of price transmission since the variation in the use of private labels and differences in the frequency of price adjustment across retail chains can proxy for differences in the mark-up elasticities that are known to determine price transmission. For example, Hong and Li (forthcoming) have shown that price transmission is likely to be related to the penetration of private labels, the role of private labels compared to national brands being a proxy for vertical control. Gopinath and Itskhoki (2010) have shown that the frequency of price adjustment by firms is also likely to be associated with the mark-up elasticity and hence, by extension, the extent of price transmission. In addition, the role of market power in the retail sector may influence price transmission via bargaining power with respect to the suppliers of national brands. In sum, by exploiting the characteristics of price transmission across specific brands and retail chains and matching with the corresponding observations on the frequency of price adjustment and the proliferation of private labels that we directly observe across the retail chains in our data set, we can provide new insights into the factors that are likely to influence price transmission. Specifically, we use weekly data over a 130 week period covering 106 orange juice UICs sold across 7 retail chains in the UK food sector.[1] The product groups delineate between national brands and private label products, across fresh and processed orange juice as well as retail chain.

The paper proceeds in three parts. First, we report on the substantial variation in price dynamics across product groups and retail chains as we will employ these observations on price dynamics to proxy for the adjustment of product-specific mark-ups. Second, we measure the extent of price transmission from the world spot price of orange juice through to retail prices for each of the 106 orange juice UICs sold across the main grocery retail chains in the UK. Third, we tie the characteristics of price dynamics relating to national brands and private labels and the frequency of price adjustment to the distribution of the price transmission elasticities. The main insights from this three-part investigation are as follows: price dynamics vary across retail chains as does the extent of price transmission; the extent of vertical control in the food chain is a significant determinant of price transmission; the frequency of price adjustment is also important though the role of this factor varies between national brands and private labels; retail market power influences price transmission mainly via price transmission for national brands and is consistent with the impact of retail market power on price transmission being realised through increased retailer bargaining power.

The paper is organised as follows. In Section 1, we briefly report on the relevant literature that relates to the use of scanner data to estimate price transmission effects and the potential drivers of price transmission. In Section 2, we report on the main characteristics of price dynamics that are a feature of the data we employ and highlight the extent of retailer heterogeneity as revealed in

[1] A Unique Item Code (UIC) is defined as the combination of product and retailer codes, for example the one litre carton of Tropicana Orange Juice (with bits) sold in Tesco would represent a single UIC; the identical product sold in Sainsbury would represent another UIC.

differences in price dynamics across retail chains. We then employ a two-stage approach to using scanner data to evaluate the range of price transmission differences across products and retail chains and the features of retailer heterogeneity which may explain these differences. In Section 3, we outline our econometric approach to measuring price transmission elasticities. This is followed by Section 4, where we assess the key factors which determine the distribution of price transmission elasticities which provides insights into the features of the food chain which account for these differences. We summarise and conclude in Section 5.

## 1 Recent Perspectives on Determinants of Price Transmission

Economic theory gives important insights into the factors that will determine price transmission but it remains a considerable challenge to verify empirically these factors particularly in markets characterised by imperfect competition. These challenges arise for a number of reasons, most notably identifying the main mechanisms via which competition can affect price transmission and, related to this, the absence of detailed data to provide a basis for evaluating the change in firms' mark-ups which is key to understanding the role of competition. Empirical research on this is limited to the most notable recent advances on empirically addressing the role of competition have had access to cost data for a specific retail chain (Eichenbaum *et al*., 2011, Nakamura and Zerom, 2010, Hong and Li, forthcoming), used proxies for the mark-up elasticity (Gopinath and Iskhoki, 2010) or relied on estimating a structural model of a specific market and simulating the impact of shocks or policy changes to a specific market (e.g. Bonnet and Dubois, 2010).

These challenges are even more difficult to address in the context of addressing price transmission in food markets where the vertical nature of the food chain adds considerable complexities to the role of competition beyond single stage markets. These challenges are both theoretical and empirical. From the theoretical perspective, changes in competition within a given stage of the food chain will also have a vertical dimension; similarly, changes in vertical relations between stages will also affect competition within a given stage. This adds to the empirical challenges as the determinants of price transmission will not only depend on competition within a given stage but also by the nature of vertical relations (e.g. bargaining, vertical restraints, vertical control), the details of which are unlikely to be observed by researchers. Recent progress on this have either simulated the outcomes of unobservable vertical restraints (Bonnet and Dubois, 2010) or used proxies for vertical control (Hong and Li, forthcoming).

To highlight the key insights regarding the links between competition and price transmission, it is useful to start with the single stage setting. If a market is perfectly competitive, firm mark-ups obviously play no role in determining price transmission. With imperfect competition, the key mechanism in determining price transmission is the *elasticity* of firm mark-ups. This has also been referred to as the 'super-elasticity' (Klenow and Malin, 2011). Two factors determine this elasticity: the shape of the demand function and the intensity of competition. Weyl and Fabinger (2013) provide a review of these issues, the main insight being that as long as the demand function is not 'too' convex, the intensity of competition will determine this elasticity. In general terms, as competition weakens, the elasticity of the mark-up increases and dampens the effect of cost changes through to price changes i.e. price transmission declines.

As noted above, given the role of this mechanism, the challenge is to empirically identify the role the elasticity of firm mark-ups as a determinant of price transmission. This challenge is particularly severe when using retail scanner price data: while this has the attraction of providing new insights of price dynamics at the retail end, it imposes considerable constraints on product specific cost data to identify the role of the mark-up elasticity. Nevertheless, the mark-up appears to be an important determinant of price transmission though the available evidence is limited: Nakamura and Zerom (2010) estimate this mark-up elasticity to account for around 30 per cent of the price transmission effect in the US coffee market. Gopinath and Iskhoki (2010) take an alternative approach to identifying the role of the mark-up elasticity: they show that the extent of price transmission (in their context, the focus is on exchange rates) is related to the frequency of price changes. Specifically, the frequency of price adjustment is associated with less elastic mark-ups and, by extension, the price transmission effect. Their empirical results confirm the positive relationship between price transmission and the frequency of price adjustment.

The successively-related nature of food markets where competition issues arise at different stages (retailing and manufacturing) raises a wider range of issues. In one sense, the effect of competition in this vertically-related set-up will extend from the single stage setting. In the presence of double marginalisation with mark-ups at both stages, the issue is how both aggregate mark-ups will change in response to supply shocks. With arms-length pricing, price transmission should be even lower with successive oligopoly compared to the single stage case. However, the interaction between vertical and horizontal issues comes into play when we depart from the arms' length pricing assumption. With bargaining between firms at different stages, the effect on price transmission is ambiguous. For example, the use of vertical restraints may ameliorate the double marginalisation issue but provide a competitive advantage to firms who benefit from lower unit prices. Similarly, vertical control will also diminish the double marginalisation issue but decrease the intensity of horizontal competition.

Unfortunately, the nature of vertical ties is difficult to observe in practice and there are several ways in which the departure from arm's length pricing may arise through, for example, vertical contracts, vertical integration and various forms of vertical restraints. Some recent research has, however, shown that these vertical issues matter in determining price transmission. Bonnet and Dubois (2010) simulate the role of alternative vertical restraints on price transmission and show that price transmission can increase when used. Hong and Li (forthcoming) use observations on private labels in Canadian food markets: since the use of private labels gives the retailer control of the food chain and hence diminishes the double marginalisation issue, though the theoretical effect is ambiguous, the empirical results show that price transmission is higher for private label products than it is for national brands.

In exploring the determinants of price transmission in Section 4, we draw on these recent insights. There are inevitably some compromises in the data available to carry out these tests, but we do have weekly retail prices over a two and half year period for different types of Orange juice products, both branded and private labels for a large number of UICs. One of the main advantages of the data we employ is that, in contrast to Eichenbaum *et al*. (2011) and Hong and Li (forthcoming), we are not constrained by retail scanner price data from a single retail chain. The coverage across the 7 main retail chains in the UK helps inform our identification strategy given the observed differences in price dynamics (particularly the frequency of price adjustment) and the proliferation of private label products at the chain level. In addition, we control for market power at the chain level and how the interaction of this variable with manufactured branded products impacts on the distribution of price transmission elasticities.

## 2 Characteristics of Price Dynamics across Retail Chains

Our data is a panel of unique identifier code (UIC)-level prices for orange juice products sold in the main supermarket chains in the UK over 130 weeks from October 2009 to March 2013 sourced from Nielsen. The panel includes long-life orange juice prices (35 UICs) and fresh orange juice (71 UICs) and we can also delineate between national brands and private labels sold in each of the 7 retail supermarket chains which cover most retail food sales in the UK. The 7 retail chains are: Asda, Tesco, Sainsbury, Morrison, Waitrose, the Cooperative, and Marks and Spencer. These represent a broad spectrum of the retail landscape in the UK, covering mainstream, up-market and soft discounters.[2] The price data is provided by Nielsen UK as unit value; they do not provide quantity data nor identify when a product is on sale. Since sales are a feature of retailer behaviour, we identify sales by using an algorithm employed by Lloyd *et al.* (2014) and define sales to be an x% temporary reduction in retail prices where the depth of the temporary reduction relates to a price reduction of 10%, 25% or 25% reduction in retail prices. We are ambivalent on whether sales matter for the long-term price transmission process and therefore report results from the price data inclusive and exclusive of sales. We use these data to provide an overview of price dynamics in the retail food sector and highlight the extent of heterogeneity across product types, branded and private labels, and across the 7 retail chains.

To visualise the variation in price dynamics for orange juice products across retail chains, consider Figures 1 and 2. In Figure 1, we present price data for different orange juice products in a single retail chain (Sainsbury) over the sample period. It is clear that price behaviour differs across product type (long-life and fresh) and by brand status (national brand versus private label). Long-life product prices are less volatile than fresh and all price series are characterised by short periods of price reductions; we report below on the incidence of sales in the data set and account for sales in the econometric analysis presented below. In Figure 2, the heterogeneity across retailers is highlighted. Here, we take a given national brand for a fresh orange juice product that is sold across retailers (although not all 7 retailers stock this specific national brand). Again, the heterogeneity in the price data is clear with, most obviously, the pattern of price behaviour being different between the two main retail chains, Tesco and Sainsbury. The main point to note from Figures 1 and 2 is that the high-frequency scanner data indicates significant differences in price dynamics by product type, brand status and by retailer that would not be apparent from more aggregate data.

A few noteworthy features of the dataset are as follows. Unsurprisingly, on average, fresh orange juice products have higher prices than long-life products. The price differential between national brands and private labels varies by product type: private labels on average have higher (lower) prices than national brands in the long-life (fresh) categories though the variation in prices is considerably higher for long-life national brands than private labels. Finally, there are substantive (mean) price differences across retail chains by product type and by brand status. Over the sample period, mean prices were highest in the Morrison retail chain and lowest in Tesco but the ranking across retailers differs by product type.

Scrutiny of the dataset reveals the nature of price dynamics across retail chains by product type and brand status. Focussing on the relative 'stickiness' of prices (i.e. implied duration) across all product types and retail chains, prices change approximately every two weeks. Asda changes prices less frequently than other retailers (with an implied duration of almost 3 weeks) with Tesco and the Cooperative changing prices approximately every 2 weeks. The direction of price changes is almost equally split between price rises and price falls. Retail chains tend to change private label prices less frequently than the prices of national brands with the implied duration of private labels being around 2.5 weeks compared with national brands with an implied duration of less than 2 weeks. Across all retail chains, there is an upward drift in price changes as the magnitude of price rises is larger than price falls.

An oft-cited feature of retail chains is the use of sales (see, for example, Hosken and Rieffen, 2004) and it is therefore important to account for the role of sales in price dynamics; the existence of sales as a feature of price dynamics is apparent from Figures 1 and 2[3]. Using a 10% sales definition, analysis of the dataset reveals that sales behaviour is a key feature of price dynamics across retail chains though the use of sales varies markedly. Sales are seldom used by Marks and Spencer but are

[2] Hard discounters, notably Aldi and Lidl do not supply data to Nielsen and are not included. Combined they represent about 5% of the British food sales in 2012.

[3] Although this is a feature of pricing in retail chains, the role of sales may be inconsequential for macroeconomic policy and hence, by extension, long-run price transmission.

more common in Sainsbury; nationally branded products are more commonly on sales compared with private labels; the number of UICs that have been on sale also varies across retail chains and national brands are more likely to have been placed on sale than private labels. On average, there is not much difference on the duration of sales across retailers or by brand, with the typical duration of sales being 5 weeks.

**Figure 1: Individual Retail Price Series of Orange Juice (2009 - 2012) by Product Type and Brand Status in Single Retailer (Sainsbury)**

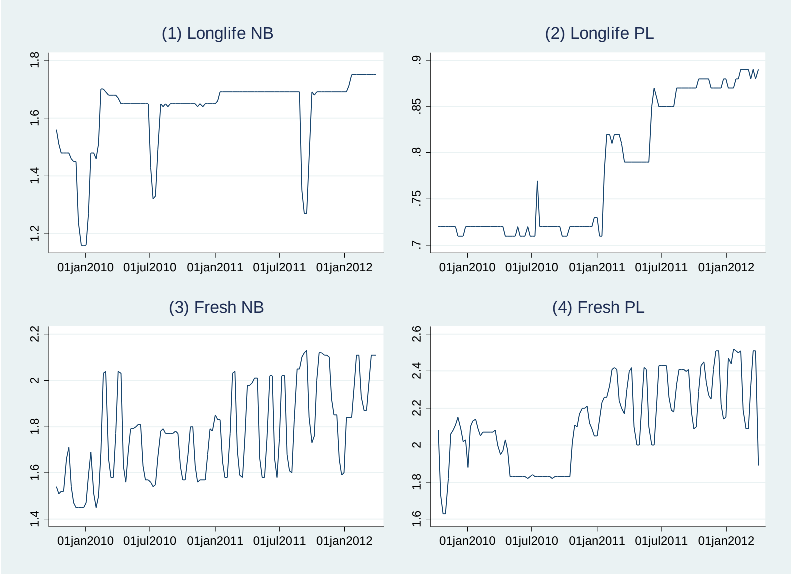
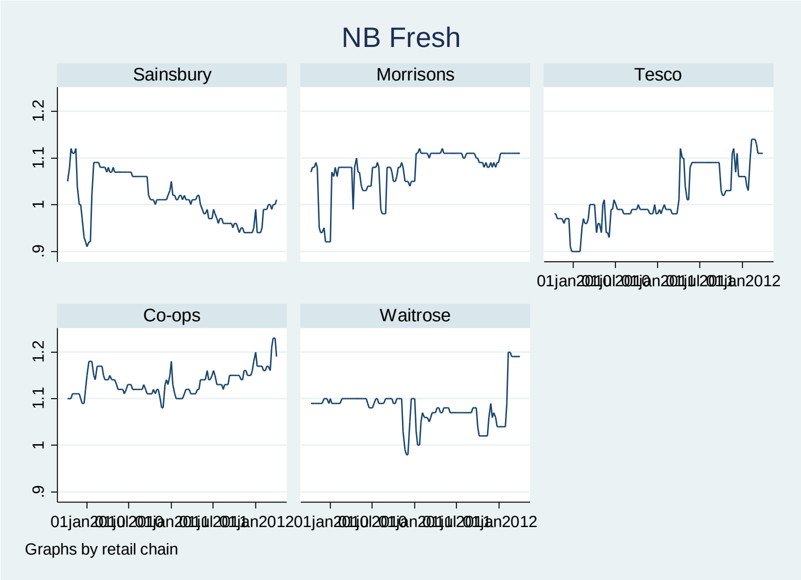



**Figure 2: Individual Retail Price Series of Specific National Brand Fresh Orange Juice (2009 - 2012) Sold Across Retail Chains**




In summary, the key features are as flows: First, and most obviously, there is substantive variation in the behaviour of prices by orange juice type (fresh versus long-life) and by brand status (national brand versus private label). Second, sales are also a feature of retailing of orange juice products. Third, while the heterogeneity in price dynamics is consistent with other micro-pricing research, the data presented above also point to substantive variation in the dynamics of prices across retail chains. The heterogeneity across retail chains is evident in average prices, the frequency of price adjustment, and the use of sales. The extent of heterogeneity in the data set is greater across retail chain than by product type; since many recent retail pricing studies (with limited exceptions) have exploited data limited to only a single retail chain, the significance of retailer heterogeneity in price dynamics has not been highlighted. We exploit this dimension of price dynamics along with the more commonly focussed features to highlight the differences in price transmission by retail chain and to provide insights into the characteristics of the food sector that may influence price transmission.

## 3 Estimating Price Transmission

*(i) Preliminary Issues*

Given the panel nature of the retail price data, we test for unit roots for individual retail price series using panel unit root tests proposed by Hadri (2007) and the CIPS test discussed by Peseran (2007); both of which allow for cross-sectional dependence in the data. The results (available upon request) show clearly that retail price series (both including and excluding sales) are I(1).

Since our focus is on price transmission, we tie retail orange juice price with the main commodity input price which we take as the world orange juice commodity price index; this series is also available at a weekly frequency. Standard unit root tests on this price series suggests commodity prices are I(1). Of course, we acknowledge that other factors may influence movements in retail prices but relevant cost data (e.g. labour costs) are not available at a weekly frequency, would be unlikely to account for the heterogeneity in price behaviour across retail chains. Furthermore, and in common with many studies of price transmission in food chains, we are unable to identify either manufacturing cost data associated by brand status, any differences in upstream costs by product type nor the costs incurred at the individual retail chain level. Despite this caveat in determining the price transmission effect, the heterogeneity in retail price dynamics across retail chains coupled with identifying brand status allows us to identify what characteristics of the supply chain can account for the range of price transmission elasticities we observe.

*(ii) Econometric Specification*

We estimate a long-run pass-through relationship between retail and commodity prices and start from the following an ADL(*p*,*q*) model in a panel data setting:

$$\log p_{it} = \sum_{j=1}^{p} \lambda_{ij} \log p_{i,t-j} + \sum_{j=0}^{q} \delta_{ij} \log c_{t-j} + \alpha_i + \varepsilon_{it} \qquad (1)$$

where $\log p_{it}$ is log retail price in the *ith* UIC at week *t*. $\log c_t$ is log commodity price at week *t*, which is common to all UICs. $\beta_{ij}$, $\lambda_{ij}$ are parameters to be estimated, which may interpret as pass-through and price persistence across UICs. $\alpha_i$ is the intercept term and $\varepsilon_{it}$ is the error term in the regression model. As noted above, the price data comprises 106 UICs across 7 retail chains over 130 weeks. We may include other control variables including monthly dummies in equation (1) to account for seasonality and brand specific dummies to account for unobservable brand effects.

Following Pesaran *et al.* (1999), we re-parameterise (1) into the error correction equation:

$$\Delta \log p_{it} = \phi_i (\log p_{it-1} - \theta_i \log c_t) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta \log p_{it-j} + \sum_{j=1}^{q-1} \delta_{ij}^{*} \Delta \log c_{t-j} + \alpha_i + \varepsilon_{it} \qquad (2)$$

where $\phi_i = -(1-\sum_{j=1}^{p}\lambda_{ij})$, $\theta_i = \sum_{j=0}^{q}\delta_{ij}/(1-\sum_k \lambda_{ik})$, $\lambda_{ij}^* = -\sum_{m=j+1}^{p}\lambda_{im}$ and $j = 1, 2, \ldots, p-1$, $\delta_{ij}^* = -\sum_{m=j+1}^{q}\delta_{im}$ and $j = 1, 2, \ldots, q-1$. Thus, $\theta_i$ and $\delta_{ij}^*$ are separate to refer to the long-run (LRPT) and short-run transmission elasticity (SRPT) respectively. $\phi_i$ is the error-correcting speed of adjustment term. If $\phi_i = 0$, then there would be no evidence for a long-run relationship. The parameter is expected to be significantly negative under the prior assumption that the variables show a return to a long-run equilibrium. By estimating the error correction equation (2), we are able to handle a number of econometric problems in the data including (i) I(1)/I(0) commodity price series on the RHS; (ii) potential serial correlation in the error term; and (iii) potential simultaneous equation bias[4].

We estimate equation (2) using the Mean Group (MG) estimator proposed by Pesaran and Smith (1995), which relies on estimating *N* time-series regressions and averaging the coefficients. We also tried Pooled Mean Group (PMG) proposed by Pesaran *et al.* (1999) as an improvement of efficiency by pooling all UIC data together but constraining the long-run coefficients to be equal across UICs. However, the Hausman test rejects slope homogeneity in PMG case and suggests that the MG estimator is preferred in our analysis. In the estimation, we tried different model specifications with different lags of $\log p_{it}$ and $\log c_t$ in ADL(*p*,*q*). SBC suggests ADL(3,3) is the best fit of our data and thus we will use it in the following analysis.

*(iii) Price Transmission Results*

As discussed above, price promotions ('sales') are an important feature of price dynamics. However, being only short-lived it is unclear whether they impact on long-term price transmission. Given this ambiguity, we work with two versions when estimating (2), whereby price data is inclusive and exclusive of sales (the sales period being accounted for by a dummy variable).

In Table 1, we report the average price transmission elasticities across the full panel and then by product type and brand status.[5] All price transmission coefficients are significant at the 1% level with the exception of the coefficient on national brands. Also, there are only marginal differences in the estimated long-run transmission elasticities that arise when sales are accounted for. To facilitate the discussion, we focus on the estimates without the sales dummies, although results are very similar.

**Table 6: Summary of Long-Run Price Transmission Estimates: Averages by All Data, Product Type and Brand Status**

| | All Price Data | Including Sales Dummy |
|---|---|---|
| All OJ Products | 0.412*** | 0.393*** |
| | Product Type | |
| Long-Life OJ | 0.535*** | 0.536*** |
| Fresh OJ | 0.351*** | 0.322*** |
| | Brand Status | |
| National Brands | 0.161 | 0.079 |
| Private Labels | 0.498*** | 0.500*** |

**Note:** Summary of Long-Run Price Transmission Elasticities from Panel Data Regressions. ***,**,* indicates 1%,5% and 10% significant levels respectively. All regressions inclusive of UIC fixed effects and monthly dummies. Details of regression results are provided in Appendix Tables 1 and 2.

[4] In the specification of (2), there was no identifiable variable at the brand/retail level to control for unobserved common influences and explicitly allow for cross-sectional dependence. In place, we used brand-specific and monthly dummy variables to account for unobserved effects.
[5] Full regression results are reported in the full version of the paper available on request.

Taking the sample as a whole, the long-run price transmission elasticity is 0.412. To benchmark this estimate, aggregating all the data to a single aggregate OJ price index at retail (albeit at weekly frequency) and applied a standard price transmission regression, the price transmission elasticity is 0.457 (also significant at the 1% level). The transmission elasticities from the ‘aggregated’ data and using the panel approach are roughly equivalent. However, Table 6 indicates substantive differences in transmission elasticities by product type and brand status. Specifically, the transmission elasticities for long-life OJ products are, on average, approximately 50 per cent higher than the estimate for fresh products (0.535 compared with 0.351). Private label products have higher long-run transmission elasticities (0.498 and significant at the 1 per cent level) while long-run transmission coefficient for national brands is not statistically different from zero.

As noted at the outset, a distinguishing feature of our data is that prices are given at the individual retail chain level; we report the average long-run price transmission elasticities at the retail chain level in Table 2. The results indicate a substantive variation in price transmission across retail chains. Excluding the results from Morrisons, the range of transmission effects is wide with the price transmission effect for Tesco being almost 80 per cent higher than the transmission effect for the Co-operative. Moreover, three of the retail chains (Asda, the Co-operative and Marks & Spencer) indicate price transmission lower than the transmission elasticity for the sample as a whole. The results confirm considerable retailer heterogeneity in price transmission effects and, excluding non-significant effects, there is more heterogeneity by retailer compared with other dimensions of the data. Even though the use of sales varies across retail chains, these differences do not have a significant impact on the level of long-run price transmission nor on the ordering of retail chains on the extent to which cost changes are transmitted to changes in retail prices.

**Table 2: Summary of Long-Run Price Transmission Estimates: Averages by All Data and Retail Chain**

| | **All Price Data** | **Including Sales Dummy** |
|---|---|---|
| All OJ Products | 0.412*** | 0.393*** |
| | By Retailer | |
| Asda | 0.339*** | 0.336*** |
| Sainsbury | 0.463*** | 0.450*** |
| Morrisons | 0.152 | 0.034 |
| Tesco | 0.607*** | 0.619*** |
| Cooperative | 0.363*** | 0.366*** |
| Waitrose | 0.508*** | 0.505*** |
| Marks and Spencer | 0.378*** | 0.375*** |

**Note:** Summary of Long-Run Price Transmission Elasticities from Panel Data Regressions. ***,**,* indicates significance at the 1%, 5% and 10% levels respectively. All regressions inclusive of UIC fixed effects and monthly dummies. Details of regression results are provided in Appendix Tables 3 and 4.

## 4 Explaining Price Transmission

In the absence of a structural model with direct observations on (retailer-specific) costs, one of the main barriers to understanding the factors that may determine price transmission is identifying the role of the elasticity of the retailer’s mark-up. As noted in section 2, when markets are imperfectly competitive, it is the elasticity of the mark-up (conditional on assumptions about the convexity of the demand function) that is the determining factor in the size of the price transmission effect. This issue is particularly challenging to address in the context of vertically-related food chains where the existence of double marginalisation, bargaining power and alternative forms of vertical restraints can also influence how retail prices respond to changes in upstream costs. A further complexity is that any aspect of single stage market power which may affect competition between retailers (a horizontal effect) also has a vertical effect (as horizontal market power may also give increased bargaining power vis-à-vis upstream suppliers). This means that any effect via the elasticity of the mark-up on price transmission may be ambiguous (e.g. as the horizontal effect of market power may increase the elasticity of the mark-up, by countering double marginalisation, the elasticity of the mark-up decreases).

We use our observations on price dynamics across retail chains, together with other differences across retailers, to identify the factors that potentially influence price transmission. Given the considerable heterogeneity in price transmission elasticities across product groups, brand status and retailers, we draw on the information we have on private labels, the frequency of price adjustment, differences in sales behaviour across retail chains as well as additional information on retail market share to explain the heterogeneity in price transmission we observe. These observations on retailer heterogeneity across these metrics and which accord with factors associated with the elasticity of mark-ups in the food chain allows us to explore what factors may influence the range of price transmission elasticities we have estimated at the UIC level. Specifically, we take as the dependent variable the UIC-level long-run price transmission elasticities as measured above and aim to explain the range of these price transmission elasticities with variables that accord with the elasticity of mark-ups, exploiting the heterogeneity in these variables across retail chains in our sample.

Consider the determining factors in more detail. Take, first of all, the role of private labels. The proliferation of private labels is a key feature of the UK food sector which is also reflected in the orange juice category though the proliferation of private labels varies across retailers. As Hong and Li (forthcoming) have shown, higher levels of price transmission as the level of vertical control that arises via the use of retailer private labels limits the problem of double marginalisation. We would therefore expect that controlling for private labels-as a proxy for retailer control of the value chain-to be associated with higher price transmission.

Second, retail chains differ in market shares. Using data (albeit at an aggregate level and not specific to orange juice products) for the period covered by the price data used here, Tesco was market leader (accounting for 25 per cent of retail food sales in the UK), followed by Asda (14 per cent), Sainsbury (13 per cent), Morrisons (approximately 10 per cent) with the concentration ratio being 62 per cent for these 4 retailers. The other three retail chains covered by our price data accounted for another 12 per cent of retail food sales. It is not clear what the expected sign of retail market share should be as a determinant of price transmission. At one level, the increase in market power would be associated with lower price transmission (for example, with a standard single stage characterisation of the market). But retail market shares also result in increased bargaining power against upstream suppliers. Since the role of private labels accounts for vertical control in one strand of the food chain, we also interact observations on retail market shares with a dummy variable for national brands to account for retailer bargaining power vis-à-vis branded manufacturers. To the extent that horizontal market power dominates, we would expect the sign on retail market shares to be negative; to the extent that retail bargaining power dominates, we would expect the role of retail market shares with respect to national brands to be positive.

As discussed in Section 2, Gopinath and Itskhoki (2010) have noted that the frequency of price adjustment is associated with a higher elasticity of the mark-up and they use observations on this as a determinant of exchange rate pass-through. We follow the same route here but since we have observations on the frequency of price adjustment at the retail level, we can use these observations to proxy for the elasticity of mark-ups by retail chain. There is considerable heterogeneity in the frequency of price adjustment across the retail chains we cover, being relatively low for Waitrose and relatively high for the market leader, Tesco. Given the insights from Gopinath and Itskhoki

(2010), we would anticipate that the frequency of price adjustment to be associated with higher price transmission.

However, a more nuanced view of the role of this variable is suggested by inspection of the data since the frequency of price adjustment across retail chains also differs by brand status. Specifically, the frequency of price adjustment is lower for private labels than it is for national brands, This may reflect that with more vertical control in the food chain that is associated with private labels, *ceteris paribus*, the elasticity of the mark-up is lower. To account for these differences across retail chains in the frequency of price adjustment and accounting for the brand status dimension, we also interact the frequency of price adjustment with national brands. We would therefore expect the role of the frequency of price adjustment as it accords with the elasticity of the mark-up to be differentiated by brand status and that the net effect-accounting for the differences across brands-to be positively associated with price transmission.

Finally, as noted above, one of the features of price dynamics across retail chains relates to the use of sales. Our strategy in accounting for sales has been ambivalent by either accounting for it directly by replacing sales in the price data directly or leaving the price data unfiltered by the sales algorithm and measuring price transmission with sales. To the extent that sales are temporary and therefore not have an impact on long-run price transmission, we would not anticipate this variable to be statistically significant.

The results relating to the factors determining the range of long-run price transmission elasticities are presented in Table 3. There are two sets of results: one where price transmission coefficient was estimated when including a dummy variable for sales, and another where there was no sales dummy.

**Table 3 Explaining Long-Run Price Transmission**

| | Including sales dummy | | Excluding sales dummy | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (3’) | (4’) |
| PL dummy | 6.406$^{**}$ | 6.700$^{**}$ | 3.572$^{**}$ | 3.835$^{**}$ | 4.068$^{**}$ | 4.376$^{**}$ |
| | (2.908) | (2.894) | (1.634) | (1.624) | (1.751) | (1.745) |
| LnFreq of prices | -0.328$^{**}$ | -0.307$^{**}$ | -0.410$^{***}$ | -0.392$^{**}$ | -0.368$^{**}$ | -0.346$^{**}$ |
| | (0.147) | (0.145) | (0.154) | (0.154) | (0.141) | (0.140) |
| NB* LnFreq of prices | 1.278$^{*}$ | 1.257$^{*}$ | 0.725$^{*}$ | 0.692$^{*}$ | 0.868$^{**}$ | 0.846$^{**}$ |
| | (0.665) | (0.661) | (0.405) | (0.404) | (0.422) | (0.419) |
| RMS | 0.031$^{**}$ | | 0.032$^{**}$ | | 0.032$^{**}$ | |
| | (0.013) | | (0.013) | | (0.013) | |
| NB*RMS | 0.041 | 0.072$^{***}$ | 0.016 | 0.048$^{***}$ | 0.014 | 0.046$^{**}$ |
| | (0.029) | (0.026) | (0.022) | (0.018) | (0.022) | (0.018) |
| LnFreq of sales | | | 0.067 | 0.072 | | |
| | | | (0.070) | (0.074) | | |
| _cons | -6.365$^{**}$ | -6.365$^{**}$ | -3.275$^{**}$ | -3.227$^{**}$ | -3.874$^{**}$ | -3.874$^{**}$ |
| | (2.856) | (2.839) | (1.592) | (1.587) | (1.675) | (1.664) |
| *N* | 86 | 86 | 84 | 84 | 84 | 84 |
| $R^2$ | 0.210 | 0.179 | 0.163 | 0.115 | 0.155 | 0.105 |

Standard errors in parentheses: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

The results show that the private label effect is associated with higher price transmission thus highlighting the role that diminishing the impact of double marginalisation in the vertical chain has on price transmission. There is, though, some ambiguity about the role of retailer market share. On its own, this variable is positive and statistically significant which does not accord with our theoretical priors. However, when interacted with the role of national brands, the positive effect accords with the results suggested by the role of bargaining between retailers and brand manufacturers; as retailer bargaining power increases, the impact of double marginalisation is reduced, and is associated with higher price transmission.

The frequency of price adjustment is also associated with higher price transmission in the long-run. Accounting for the differences in price change frequency by brand status, the net effect of this variable is to be associated with higher price transmission. This is consistent with Gopinath and Itskhoki (2010) that the elasticity of the mark-up is associated with higher price transmission. Finally, as expected, sales have no effect on long-run price transmission. Even though sales behaviour differs across retail chains, it has no impact on price transmission effects over the long-run[6].

## 5 Summary and Conclusion

Retail food chains differ in a number of important respects, most obviously by market shares but also across other metrics including pricing strategies, how frequently they adjust prices, the use of sales, bargaining power and the proliferation of private label products. This heterogeneity has not been commonly accounted for when estimating price transmission largely due to the constraints on availability of data when researchers employ scanner data. Since retailers differ, there is no reason to assume that the extent of price transmission will be identical across retailers even though the large body of price transmission studies implicitly assume this to be the case. In this paper, we have shown that price transmission does vary across retail chains and that the extent of heterogeneity associated with price transmission is greater than other cuts of the data that have been observed in other recent studies, for example by product group. However, we exploit retailer heterogeneity not only to measure the range of price transmission elasticities but also to identify the determinants of price transmission. Specifically, we show that the elasticity of the retail mark-ups (as proxied by price frequency) and vertical control (as proxied by the proliferation of private labels), as well as other factors that account for retail power are significant determinants of price transmission.

[6] A series of robustness tests will be reported in the revised version of the paper.

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