The Welfare Effects of Supply and Demand Frictions in a Dynamic Pricing Game*†

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Abstract

We propose a dynamic pricing model in a multiproduct oligopoly setting, in which consumers exhibit inertia in their choices and firms face costly price adjustments. The primitives of the model, including firms' discount factor, are estimated from scanner data. Our context is the UK butter and margarine industry. We use the model to evaluate the effects of frictions on price dynamics, profits and consumer welfare. First, we show that manufacturers' discount rates vary between 0.92 and 0.99, suggesting that pricing decisions – even for simple consumer goods – have an important intertemporal component. Second, in line with evidence from the macro literature, we find that price adjustment costs are substantial and represent between 24-34% of manufacturers' net margins. Third, our model predicts that the removal of these costs reduces persistence in prices, increases firms' profits but has little effect on consumer surplus. Fourth, we show that when price adjustments are costly the effects of consumer inertia on prices are much more pronounced than in the standard model where firms can adjust prices freely. This implies that if price adjustment costs are not factored in researchers may underestimate the effects of consumer inertia on prices.

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1 Introduction

Prices are important strategic variables for firms operating in imperfectly competitive industries. With dynamic considerations and in frictional settings, pricing problems, however, quickly become complicated to analyse. While the theoretical literature manages to provide equilibrium predictions for highly stylized settings, there is still a strong need to understand the mechanisms generating price patterns observed in actual market situations. To bridge the gap between economic theory and practical pricing problems, this paper proposes a tractable dynamic game-theoretic model with supply and demand frictions that, according to different strands of literature, are important to explain prices dynamics. We structurally estimate the dynamic game using scanner data on consumers' choices and observed prices. We solve the model and use it to study the role of supply and demand frictions on price dynamics, firms' profits and consumer welfare.

In the model we develop, forward looking multiproduct firms simultaneously choose prices for a range of differentiated products they offer. We assume that firms incur in costs to adjust their prices[1] and consumers exhibit some degree of inertia[2] in their choices. Following a regularity documented in most scanner datasets and in a range of papers, we assume that price competition occurs through temporary price cuts (sales), and more specifically switching between regular and sale price.[3] We therefore model prices as discrete choices from a predetermined set.[4] Compared to the IO literature on dynamic pricing with consumer inertia we treat prices as discrete and allow for adjustment costs, while relative to the macro literature we offer a formal treatment of the strategic interactions between multiproduct firms whose pricing decisions are interrelated and can exhibit (dis)economies of scope. Our model is therefore based on a class of popular dynamic discrete games (e.g. Aguirregabiria and Mira (2007) or Pesendorfer and Schmidt-Dengler (2008)) and can be seen as a particular instance of the dynamic oligopoly framework of Ericson and Pakes (1995) that is known to be computationally feasible and possess an equilibrium in pure strategies. Once we have the estimates of all model parameters, including price adjustment costs and firms' discount factors, we can solve the model and perform counterfactual analyses.

We use the model to study the UK butter and margarine industry using scanner data. This industry is an example of an oligopoly with three dominant firms (Arla, Dairy Crest, and Unilever), who sell multiple products under different brand names. Their main sales chan-

[1] See Slade (1998), Aguirregabiria (1999), Ellison et al. (2015), Levy et al. (1997), Dutta et al. (1999), Zbaracki et al. (2004), Alvarez and Lippi (2014), Goldberg and Hellerstein (2013), Anderson et al. (2017) and Stella (2019).

[2] See Dubé et al. (2009), Dubé et al. (2008), Pavlidis and Ellickson (2017) and Beggs and Klemperer (1992).

[3] See Hosken and Reiffen (2004).

[4] See the discussion in Goldberg and Hellerstein (2013), and also Conlon and Rao (2019) for another recent departure from continuous models of pricing.

nels are national retail chains. We treat each of the four largest UK supermarket chains (known as *the big four*[5]) as a single market. Based on this setting, we are interested in understanding how supply and demand frictions affect prices, consumer welfare and firms' profits. More specifically we ask: (i) what is the role of dynamics in pricing decisions? (ii) what is the magnitude and the effects of price adjustment costs on prices, consumer welfare and firms' profits? (iii) what are the effects of consumer inertia on prices when price adjustments are costly?

Our results indicate that, first, firms' weekly discount factors range between 0.92 and 0.99. These estimates lie within the range of values commonly assumed by other papers and suggest that pricing decisions have an important intertemporal component. Second, our estimates of price adjustment costs are substantial in magnitude and constitute between 24% and 34% of firms' variable profits. These estimates are in line with existing evidence in the macro literature.[6] In absolute terms, these estimates are very similar across players and given that the firms we considered are the market leaders, this result may indicate that this type of price adjustment cost constitutes a much bigger fraction of the profits of smaller companies and local dairies, effectively restricting the scope of their promotional activities. This is consistent with what we observe in the data for smaller producers, who put their products on promotion much less frequently. Our results also complement findings from the marketing literature that market shares are positively correlated with the frequency of temporary price cuts.[7]

Our counterfactual study considers the implications of price adjustment costs for firm profits and consumer surplus. We find that when the costs to reduce prices are excluded from the model profits increase substantially, between 50-70%, but consumer surplus goes up by only 0.4-3.3%. This happens because manufacturers pass only a small fraction of the cost reduction to the consumers. In line with previous evidence[8], our results indicate that investments in technologies that seek to reduce the costs of adjusting prices may generate considerable returns for firms.

[5]They consist of Asda, Morrisons, Sainsbury's and Tesco.

[6]For instance, Levy et al. (1997) use store-level data to study the process of changing prices. They find that these costs represent 35.2% of net margins of retailers. Using the same approach Dutta et al. (1999) study price adjustment costs of a large US drugstore chain. Findings are similar to the findings of Levy et al. (1997). Price adjustment costs – physical and labor costs of changing prices – amounts to 27.08% of net profit margins. In addition to physical costs involved in price adjustment processes Zbaracki et al. (2004) quantify managerial and costumer costs of price adjustment using data from a large industrial manufacturer. Managerial costs are defined as the managerial time and effort spent with pricing decisions; costumer costs are defined as the costs of communicating new prices to consumers. Price adjustment costs adds up to 20.03% of company's net margins. It is worthwhile mentioning that all these evidence are direct, in the sense that they were obtained directly from accounting data.

[7]For example, Agrawal (1996) noted that smaller brands should rather focus on advertising than price promotions. In the context of slotting fees, Bloom et al. (2000) established that the existence of payments from manufacturers to retailers might be hindering competition because these costs are higher for smaller brands in relative terms.

[8]See Basker (2015) and Ellison et al. (2015).

Price adjustment costs cannot be identified without restrictions.[9] We assume that producers pay an adjustment cost only when the regular price is reduced but not when it returns to the original level. This restriction, in the context of this paper, seems to be natural. There are many promotional activities that occur when grocery products go on sales in a supermarket. Examples include relocation of products to shelves with more visibility, leaflets printing and production of TV commercials. Sales items not only reduce retailers markups but they also compete with the retailer's own brands. In general, manufacturers pay supermarkets a fee that is used to cover the costs of these promotional campaigns. The existence of these fees has been documented in the marketing literature (e.g. see Kadiyali et al. (2000), Chintagunta (2002)) as well as in the media.[10] In Appendix A we provide a series of anecdotal evidence on the importance of promotional fees. From this perspective, price adjustment costs in this paper may be interpreted, at least partially, as promotional fees and the counterfactual results mentioned in the previous paragraph may be interpreted as the partial equilibrium effect of a ban of promotional fees on firms and consumers. This result is interesting because promotional fees have been under scrutiny of competition authorities in different parts of the world. The allegation is that this practice harms smaller producers and bolsters market concentration.[11]

Finally, our demand estimates also indicate that inertia plays a key role in consumer choices in this industry. We present evidence suggesting that consumer inertia is associated with brand loyalty and therefore has non-trivial implications for price dynamics (Dubé et al., 2010). We then perform a comparative statics exercise to analyse the effects of consumer inertia on prices when firms are subject to price adjustment costs. We do this by comparing equilibrium prices across different levels of consumer inertia. Our model predicts that increases in inertia result in higher equilibrium prices. This effect is much more pronounced in the model with price adjustment costs than without. In particular, our estimates show that a three fold increase in consumer switching costs may lead to a price increase that is up to 2.5 times higher in the model with price adjustment costs vis-à-vis the price increase observed in the model without price adjustment costs. This result suggests that price adjustment costs may exacerbate potential negative effects of consumer inertia on prices and consumer welfare.

This paper contributes to different strands literature. The first is a broad literature on price rigidities. In macroeconomics and trade, high degree of observed rigidities and persistence in

[9]See, for instance, Aguirregabiria and Suzuki (2014) and Komarova, Sanches, Silva Jr., and Srisuma (2018).

[10]As an example, an excerpt from an article in The Guardian (a well known British newspaper) said that *"70% of supermarket suppliers make either regular or occasional payments toward marketing costs or price promotions"*.

[11] *"Poland banned them in 1993 as part of free-market reforms that followed the end of communism. And in 1995 America banned them on alcoholic drinks, though its main worry was that prominent displays of booze promoted irresponsible drinking. However, progress towards eliminating them on all products in America stalled after the Federal Trade Commission (FTC) concluded in 2001 that more research on them was needed before it could take any further action"*. Extracted from http://www.economist.com/news/business/21654601-supplier-rebates-are-heart-some-supermarket-chains-woes-buying-up-shelves. See Appendix A for more information.

prices is normally linked to the existence of adjustment costs.[12] Our paper presents a tractable oligopoly model that can be used to quantify the magnitude of price adjustment costs and their effects on average prices, frequency of price changes, firm profits and consumer welfare, at the same time directly accounting for strategic behaviour and multiproduct firms. We also contribute to the IO and marketing literature on dynamic pricing in the presence of consumer inertia.[13] This literature provides a justification on why firms engage in temporary price promotions but assumes away frictions in the price setting process. Our paper incorporates both features, consumer inertia and price adjustment costs. Our results indicate that when price adjustment costs are not considered, the effects of consumer inertia on prices can be substantially underestimated. Additionally, unlike other papers in these literature, we estimate firms' discount rates and show that pricing decisions – even for simple retailing products – embed a dynamic component that seems to be relevant.

Our estimation strategy combines different methodologies. We use household level scanner data to estimate a state-dependent logit demand model, and obtain a law of motion for aggregate market shares. The other components of the firm payoff functions are separated into the adjustment costs and everything else. We allow adjustment costs to be fully heterogeneous across brands and supermarkets for each market. We estimate the adjustment costs using the recent result in Komarova, Sanches, Silva Jr., and Srisuma (2018), who show that switching costs in dynamic games – for example, entry costs in entry games, capacity adjustment costs in investment games, and promotional fees in the context of our application – can be identified in closed form. Furthermore, the estimates of adjustment costs are robust to different specification of profits and the discount factor. We also estimate the discount factor, which Komarova et al. (2018) show can be identifiable when period payoffs are linear in the parameters as is the case in most applications.

The rest of the paper is structured as follows. In the next section we provide industry background and description of the data. Section 3 introduces the theoretical model. Section 4 explains our identification strategy and the estimation procedure. Section 5 gives the structural estimates and the fit of our model. Section 6 has the results of the counterfactual studies. Section 7 concludes the paper. In the Appendices we show details on the identification of price adjustment costs, computational particulars we used to estimate and solve the dynamic game, additional tables and results to support our empirical studies and several robustness checks of our empirical results.

[12] See Slade (1998), Aguirregabiria (1999), Ellison et al. (2015), Levy et al. (1997), Dutta et al. (1999), Zbaracki et al. (2004), Alvarez and Lippi (2014), Goldberg and Hellerstein (2013), Anderson et al. (2017) and Stella (2019).

[13] For recent examples of empirical work see Dubé et al. (2008), Dubé et al. (2009), Pavlidis and Ellickson (2017), Fleitas (2017), Cosguner et al. (2018).

2 Data and industry background

Data

The data used is this paper come from Kantar Worldpanel, which is a representative, rolling survey of UK households documenting their daily grocery purchases between November 2001 and November 2012. The average sample size for the wave starting in 2006 is around 25,000 households and for each of their shopping trips, SKUs (barcodes), prices, quantities and store of purchase are recorded at a daily frequency, together with product characteristics and indicators of promotional status.[14] To find a balance between analysing a stationary environment with no new product introduction and negligibly little repositioning, and having enough variation in the data, we restrict our attention to a 200-week subsample from 2009 to 2012.

We chose to focus on the butter and margarine industry for a variety of reasons. The products involved are regularly purchased, branded and expenditures within this category make up a small part of households' budgets,[15] so depending on individual preferences, there is both room for brand loyalty and switching. Moreover, dairy products are perishable and have a relatively short shelf life compared to products that are typically treated as storable in the IO literature, such as laundry detergent, ketchup or alcohol. We therefore abstract away from dynamic considerations on the demand side in this paper.

Sales channels

The most important sales channels for the manufacturers are the four largest supermarket chains. More than 83% of purchases recorded in our sample were made in one of the four: Asda, Morrisons, Sainsbury's or Tesco. As shown in Table 1, their market shares are stable year-to-year and Tesco is a clear market leader. Among the big 4 chains, Morrisons has consistently the lowest market share. The fifth largest supermarket chain, Co-op, caters on average only for 3% of the market. Given the relative importance of the 4 big supermarkets in the UK market, in what follows we will focus our attention only in purchases of butter and margarine observed in Asda, Morrisons, Sainsbury's and Tesco.

Producers

The market is dominated by three big players: Arla, Dairy Crest and Unilever. Within each of the four retail chains, their products comprise from 75% (Tesco) to approximately 80% (Asda) of total sales. Each supermarket has also its own brand. Adding the store brand, the four-

[14] Various subsamples of this large data set have been used in previous research on consumer behaviour, such as Griffith, Leibtag, Leicester, and Nevo (2009), Seiler (2013), Dubois, Griffith, and Nevo (2014), and therefore we refer the reader to these papers for details regarding the data collection procedure.

[15] The annual value of UK butter and margarine industry in 2014 is estimated to be £1.35bn.[16] Yet, at the household level, purchases of goods belonging to this category make up slightly more than 1% of total grocery expenditures (Griffith et al., 2017).

Table 1: Expenditure shares of main supermarket chains in the butter and margarine category.

STORE OF PURCHASE	Year				
	2009	2010	2011	2012	2009-2012
Aldi	1.61%	1.61%	2.19%	3.10%	2.32%
Asda	19.52%	18.94%	19.59%	20.22%	19.58%
Co-op	2.54%	3.27%	3.19%	2.91%	3.01%
Iceland	1.85%	2.03%	2.04%	2.01%	1.99%
Lidl	2.44%	2.53%	2.58%	2.69%	2.56%
Morrisons	14.43%	14.40%	14.70%	14.35%	14.47%
Netto	1.31%	1.11%	0.49%	-	1.08%
Sainsbury's	15.18%	16.27%	15.91%	15.14%	15.64%
Tesco	34.00%	33.69%	33.66%	33.70%	33.77%
Waitrose	1.83%	1.99%	1.92%	1.88%	1.91%

Note: Shares defined as sum of expenditures on butter and margarine in a given chain during the period of interest (year) divided by total expenditures in all stores. Four biggest chains and their average market shares were highlighted. Netto sold their stores to Asda in 2011. Source: own calculations using the Kantar data.

firm concentration ratio, CR_4 exceeds 90%.[17] The remaining manufacturers are either small dairies that cater local markets (such as Dale Farm Dairies in Northern Ireland), or firms that are big players in other industries.[18] Two of the three market leaders, Arla and Dairy Crest, are also major manufacturers of other dairy products (milk, cheese and yogurt), while Unilever is world's third-biggest consumer goods producer, who at the same time is the biggest margarine manufacturer in the world. The sales of margarine make up around 5% of Unilever's total revenue.[19]

Products

Butter and margarine come in different pack sizes (250g, 500g, 1kg and 2kg) and formats (block and spreadable). In our detailed data set, we observe more than 100 distinct brand-pack-format combinations produced by 12 manufacturers. Four of them are the supermarkets themselves, who sell own brand products exclusively in their outlets. Since the number of distinct brand-pack size-format combinations observed in the data is substantial we will restrict our attention to the 500g spreadable segment. We decided to focus on this subsample of all products for a number of reasons: first, this is the largest segment, comprising more than 50% of industry sales, in which butters, margarines and own brand alternatives coexist in all stores. Secondly, spreadables are much less frequently used for cooking and baking than block butters and mar-

[17]In Tesco, for instance, over the 4-year period of our sample, Unilever had a share of 30.3%, Arla 23.9%, Tesco store brand 21.2% and Dairy Crest 18.3%. $CR_4 = 93.7\%$ Similar calculations for Asda, Morrisons and Sainsbury's are available upon request.

[18]Lactalis is the manufacturer of *Président* butter, whose long-run market share is around 0.5%, but it is a much more important player in the cheese industry.

[19]See `http://www.bloomberg.com/news/articles/2014-12-04/unilever-plans-to-split-spreads-business-into-standalone-unit` (access on March 7, 2018).

garines. Therefore the consumption and, consequently, interpurchase times are quite stable. This is important for both, the discrete choice assumption in the demand model, as well as for the assumption that there are no unexpected or seasonal aggregate demand shocks in our framework. Within the 500g segment we select six branded (the largest two of Arla, Dairy Crest and Unilever in the segment) and a composite own branded product for all four largest supermarket chains. The drawback of our choice is that the outside good might also include purchases of smaller packs of the same brand, e.g. 250g packs of Lurpak or Flora, so any loyalty effect may be underestimated.[20] To stress the importance of allowing for inertia in the demand model, we calculate the probabilities of purchasing the same brand two periods in a row (see table 9), and, alternatively on two subsequent purchase occasions (if they do not coincide with two consecutive weeks, see table 10). Regardless of the definition, repeated purchases constitute the majority of all choices (between 54 and 80% of all choices). Even though brand commitment seems to play a key role in this industry, there is still a fair number of consumers who switch products every period and firms might be willing to price aggressively to fight for them.

In the 2009-2012 period, all the brands were long-term incumbents, some of them being present in the UK for more than 40 years. Long-run market shares of the brands are stable, yet one observes considerable variation at a weekly level. See Table 12 in Appendix C for more details on long-run market shares of all products.

Prices

We do not have supermarket-level price data. We only observe prices actually paid by the consumers. Therefore we construct daily time series of prices for the six spreadable products in the four big supermarket chains by taking the median price paid in a given day. This approach can be justified by the fact that after the 2000 enquiry, the Competition Commission imposed national pricing rules on the UK chain stores.[21] This also means we do not have to impute missing prices for particular stores, because we can simply take the price observed in a different outlet of the same chain.

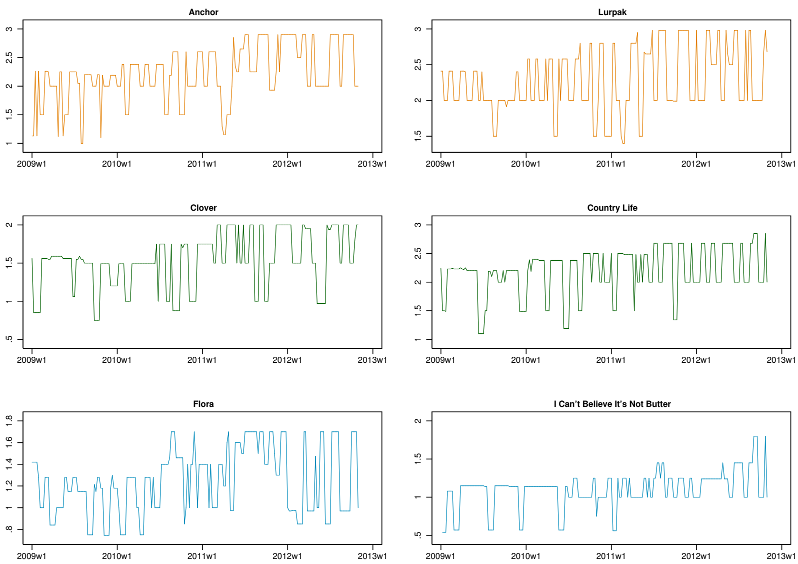
As with many other grocery products, most price variation at the SKU level comes from periodical movements between regular and sale prices. We observe that the regular price for butter and margarine typically remains at the same level for an extended period of time, up to 18 months.

[20]To check that by selecting a subset of products we do not distort the market structure, we computed expenditure- and volume-based market shares using the selected sample. Compared to the entire market, firm- and brand-level market shares in the 500g spreadable segment are quantitatively proportionate, with the only exception being Arla's higher share at the cost of lower share of the store brand. This is due to the fact that, in all 4 supermarkets, the most popular own brand products are 250g block butters. Yet, the shares of store brands remain non-negligible, and hence we believe that even after narrowing down the set of products we are still able to provide a faithful depiction of the entire industry.

[21]In a recent study of US retail prices, DellaVigna and Gentzkow (2019) show that even in the absence of regulation, there is very little variation in prices across geographically dispersed outlets belonging to the same chain.

For most branded products in our 200-week sample we observe a maximum of three changes of the regular price. At the same time, switching between regular and sale prices is relatively common, though it typically does not happen every period (week). Table 11 in Appendix C shows the number of weekly price changes by firm and market. For all firms, adjustments occur most often in Tesco, with both three firms having approximately 1 price change every second week. In the remaining three retailing chains, Unilever is the least likely to change its prices – 75% of the time it makes no adjustments. Changing both prices at the same time is rather uncommon. Figure 1 shows the evolution of prices of six 500g spreadable products in Tesco manufactured by the three biggest firms.

Figure 1: Prices of 500g spreadable butters and margarines in Tesco stores.



Note: Prices in Tesco stores between 01/01/2009 and 28/10/2012.

Promotions can be as deep as 50% and the depth might vary across supermarket chains, but over 3-6 month periods one can actually observe only two price regimes for each product. As opposed to the *high-low* pricing of national brands, supermarkets employ *everyday low price* strategies for their private labels. This implies that average prices of store brands are consistently much lower than the prices of branded products – see Table 13 in Appendix C. Within segments of the market defined by size-format combination, promotional prices of branded butters and margarines sometimes tend to match the prices of own brand products and very rarely fall below that level.

In summary, the butter and margarine industry is a typical example of multiproduct oligopoly. The market is dominated by a small number of firms selling products under different brand names. Prices of these products behave more like discrete rather than continuous variables. For branded products we observe a finite and relative small number of prices during our 200 weeks sample. Most of the price changes are between regular and sales prices. Store brands are also important in the industry. Prices of spreadable products sold under store brands are more stable and usually lower than promotional prices of branded products. These elements will play a prominent role in the construction of our dynamic pricing model. We next propose a structural model of competition that will allow us to quantify the effects of supply and demand frictions on welfare, prices and profits.

3 Model

We consider a general class of dynamic game with features that accommodate aspects that appear to be important in the UK butter and margarine industry and in other industries of differentiated products. We start by describing the elements of the game, then the decision problems for firms and consumers, and the equilibrium concept. We end the section with a brief discussion on modelling choice and possible alternatives.

3.1 Preliminaries

We assume firms compete in a dynamic pricing game with price adjustment costs, which falls into the class of Markovian games developed in the empirical IO literature.[22] In each period, firms choose whether to charge low or high price for each of the goods they produce, where the low/high prices can vary across products.

On the demand side, each household faces a discrete choice problem as it visits the stores each period, with the option of choosing the outside good. The consumers are myopic in the sense that their expectations about future prices do not play any role in their contemporaneous choices. Dynamic pricing incentives from firms arise out of consumer inertia, which can be alternatively interpreted as brand loyalty.

The sequence of events in the game is as follows. At the beginning of each period, firms observe: last period's prices, demand realisations, and a random draw from the distribution of private cost shocks. Based on this information, they simultaneously choose between high or low prices for all products they manufacture. If the prices differ from last period's ones, they pay an adjustment cost.[23] After the prices are set, consumers make purchases, firms learn the realisation of demand and receive period profits. The game moves on to the next period and state variables update according to their transition laws.

[22]For more details on this class of models, for examples, we refer the reader to surveys by Arcidiacono and Ellickson (2011) or Aguirregabiria and Nevo (2013).

[23]We will provide further details on this cost to Section 4.

3.2 Firms

We denote time periods by $t = 1, \ldots, \infty$. Firms are indexed by $i = 1, \ldots, N$. We let all products be differentiated, so that the entire set of products available to the consumer is $\boldsymbol{\mathcal{J}} = \bigcup_{i=1}^{N} \mathcal{J}_i$. Let $\mathcal{A}_i$ denote the set of actions available to player i. Since, by assumption, there are two regimes for the price of each good and the prices are set simultaneously for the entire portfolio of products of each firm, this is a finite set with cardinality equal to $|\mathcal{A}_i| = 2^{|\mathcal{J}_i|}$. In our application, $|\mathcal{J}_i| = 2$, so player i can choose among 4 actions and $\mathcal{A}_i = \{(p_{i_1}^H, p_{i_2}^H), (p_{i_1}^H, p_{i_2}^L), (p_{i_1}^L, p_{i_2}^H), (p_{i_1}^L, p_{i_2}^L)\}$, where p^H and p^L denote high and low price, respectively.

Firm i's decision problem in period t is to choose an action $a_{it} \in \mathcal{A}_i$ to maximise the expected discounted stream of payoffs: $\mathbb{E}_t \sum_{\tau=t}^{\infty} [\beta^{\tau-t}\Pi_i(\mathbf{a}_\tau, \mathbf{z}_\tau, \varepsilon_{i\tau}(a_{i\tau}))]$, where $\beta \in (0,1)$ is the discount factor and $\Pi_i(\cdot)$ denotes firm i's profit in period t. $\mathbf{a}_t = (a_{1t}, a_{2t}, \ldots, a_{Nt})$ collects the actions of all players. Occasionally we will abuse the notation and write $\mathbf{a}_t = (a_{it}, \mathbf{a}_{-it})$. $\mathbf{z}_t \in \boldsymbol{\mathcal{Z}}$ is the vector of publicly observed, payoff-relevant state variables, which in our model contains last period's market shares and actions, so $\mathbf{z}_t = (\mathbf{s}_{t-1}, \mathbf{a}_{t-1})$, and $\boldsymbol{\varepsilon}_{it} = (\varepsilon_{it}(a_i))_{a_i \in \mathcal{A}_i}$ is a vector of iid private cost shocks associated with firm i's actions. The expectation is taken over the distribution of beliefs regarding other players' actions, next period's draws of ε, and the future evolution of state variables.

The private shock enters the profit function additively, so the period profit is:

$$\Pi_i(\mathbf{a}_t, \mathbf{z}_t, \boldsymbol{\varepsilon}_{it}) = \pi_i(a_{it}, \mathbf{a}_{-it}, \mathbf{s}_{t-1}) + \sum_{\ell \in \mathcal{A}_i} \zeta \cdot \varepsilon_{it}(\ell) \cdot \mathbf{1}(a_{it} = \ell) - \sum_{\ell \in \mathcal{A}_i} \sum_{\ell' \neq \ell} SC_i^{\ell' \to \ell} \cdot \mathbf{1}(a_{it} = \ell, a_{i,t-1} = \ell'). \tag{1}$$

where $SC_i^{\ell' \to \ell}$ is the adjustment cost of switching from action ℓ' to ℓ and $\mathbf{1}(\cdot)$ is the indicator function. The first part of (1) is the static profit accrued over the time period and can be written as:

$$\pi_i(a_{it}, \mathbf{a}_{-it}, \mathbf{s}_{t-1}) = H \cdot \sum_{j \in \mathcal{J}_i} (p_{jt}(a_{it}) - mc_j) \cdot s_{jt}(a_{it}, \mathbf{a}_{-it}, \mathbf{s}_{t-1}) \tag{2}$$

We use the notation $p_{jt}(a_{it})$ to emphasise the 1-to-1 relationship between firm's action and the price of product j. mc_j is a constant marginal cost and s_{jt} is the market share derived from the consumer's problem. Note that we do not include fixed operating cost in firm's payoffs that normally appears in entry games because there is no entry or exit in our model. On the other hand, one can still interpret ε as shocks shifting fixed costs from period to period. ζ is the scaling parameter of the unobserved shocks. It facilitates the interpretation of firm's payoffs on a monetary scale.

Rewriting the expectation in terms of beliefs and perceived transition laws, firm i's best response is a solution to the following Bellman equation:

$$V_i(\mathbf{z}_t, \boldsymbol{\varepsilon}_{it}) = \max_{a_{it} \in \mathcal{A}_i} \Bigg\{ \sum_{\mathbf{a}_{-it} \in \times_{j \neq i} \mathcal{A}_j} \sigma_i(\mathbf{a}_{-it}|\mathbf{z}_t) \cdot \Big[\Pi_i(a_{it}, \mathbf{a}_{-it}, \mathbf{z}_t, \boldsymbol{\varepsilon}_{it}) \\ + \beta \sum_{\mathbf{z}_{t+1} \in \boldsymbol{\mathcal{Z}}} G(\mathbf{z}_{t+1}|\mathbf{z}_t, \mathbf{a}_t) \int V_i(\mathbf{z}_{t+1}, \boldsymbol{\varepsilon}_{it+1}) dQ(\boldsymbol{\varepsilon}_{it+1})\Big]\Bigg\} \tag{3}$$

In the expression above, we used the notation $\sigma_i(\mathbf{a}_{-it}|\mathbf{z}_t)$ to denote firm i's beliefs that given the state variable realisation $\mathbf{z}_t$, its rivals will play an action profile $\mathbf{a}_{-it}$. If $\mathbf{a}_{-it} = (\ell_1, \dots, \ell_{i-1}, \ell_{i+1}, \dots, \ell_N)$, by independence of private information in equilibrium we have:

$$\sigma_i(\mathbf{a}_{-it}|\mathbf{z}_t) = \prod_{k \neq i} \Pr(a_{kt} = \ell_k|\mathbf{z}_t)^{\mathbf{1}(a_{kt}=\ell_k)} \tag{4}$$

where the beliefs are products of the conditional choice probabilities. In the second part of expression (3), we implicitly assumed that the joint transition probabilities of public and private state variables are conditionally independent and can be factorised as $G(\mathbf{z}_{t+1}|\mathbf{z}_t, \mathbf{a}_t)Q(\boldsymbol{\varepsilon}_{it+1})$. This is a standard practice in the dynamic games literature (e.g. see assumption 2 in Aguirregabiria and Mira (2007)).

3.3 Consumers

There is a mass of households of size H that does not change over time. Consumers are assumed to arrive at the supermarket every week and choose one product from $\boldsymbol{\mathcal{J}}$ and has the outside option to not buy any of them. Following the usual convention, we denote the outside option by 0. At the instant of purchase, consumers remember what their previous choice was, as it directly affects their current utility – namely, it is higher if they purchase the same product they did on the previous occasion. Therefore firms have an incentive to charge temporarily lower prices in order to build up a base of loyal customers who will be willing to pay a higher price in the future. The presence of an outside good allows us to account for the fact that not all consumers make purchases every week, while we remain agnostic about their consumption habits.

An individual household, indexed by h, chooses an alternative from the set $\boldsymbol{\mathcal{J}} \cup \{0\}$ to maximise its contemporaneous utility given by:

$$u^h_{jt} = \delta_j - \eta \cdot p_{jt} + \gamma \cdot \mathbf{1}(y^h_{t-1} = j) + \xi^h_{jt} \qquad j = 1, \dots, |\boldsymbol{\mathcal{J}}| \tag{5}$$

$$u^h_{0t} = \xi^h_{0t} \tag{6}$$

δ_j are alternative-specific intercepts, fixed over time. $\mathbf{1}(y_{t-1}^h = j)$ equals one if household h's purchase at $t-1$ was the same as the one in the current period. γ is a parameter measuring the degree of consumer loyalty (if $\gamma > 0$).[24] Under the assumption that ξ's are independent type-I extreme value, the probability that household h will purchase good j at time t is:

$$\Pr_t^h(j|\mathbf{p}_t, y_{t-1}^h) = \frac{\exp(\delta_j - \eta \cdot p_{jt} + \gamma \cdot \mathbf{1}(y_{t-1}^h = j))}{1 + \sum_{g=1}^{|\mathcal{J}|} \exp(\delta_g - \eta \cdot p_{gt} + \gamma \cdot \mathbf{1}(y_{t-1}^h = g))} \tag{7}$$

Since we are ultimately interested in aggregate market shares, we can use the law of total probability to integrate it out from the following expression,

$$\Pr_t(j) = \sum_{g=0}^{|\mathcal{J}|} \Pr_{t-1}(g) \cdot \Pr_t(j|\mathbf{p}_t, y_{t-1} = g), \tag{8}$$

where (we have omitted conditioning sets and superscripts to ease notation) $\Pr_t(j)$ in (8) is the same as s_{jt} in (2), just like in the standard multinomial logit model. Since characteristics of the goods do not change over time, we can remove them from the set of payoff-relevant state variables, and therefore aggregate market shares are characterised by the following Markov process (Horsky et al., 2012):

$$\begin{aligned} s_{jt}(a_{it}, \mathbf{a}_{-it}, \mathbf{s}_{t-1}) &= \sum_{g=0}^{|\mathcal{J}|} s_{g,t-1} \cdot \Pr_t(j|\mathbf{p}_t(\mathbf{a}_t), y_{t-1} = g) \\ &= s_{0,t-1} \frac{\exp(\delta_j - \eta \cdot p_{jt})}{1 + \sum_{g=1}^{|\mathcal{J}|} \exp(\delta_g - \eta \cdot p_{gt})} \\ &+ s_{j,t-1} \frac{\exp(\delta_j - \eta \cdot p_{jt} + \gamma)}{1 + \sum_{g=1}^{|\mathcal{J}|} \exp(\delta_g - \eta \cdot p_{gt} + \gamma \cdot \mathbf{1}(g = j))} \\ &+ \sum_{\substack{g=1 \\ g \neq j}}^{|\mathcal{J}|} s_{g,t-1} \frac{\exp(\delta_j - \eta \cdot p_{jt})}{1 + \sum_{g'=1}^{|\mathcal{J}|} \exp(\delta_{g'} - \eta \cdot p_{g't} + \gamma \cdot \mathbf{1}(g' = g))} \end{aligned} \tag{9}$$

Since $\sum_{g=0}^{|\mathcal{J}|} s_{g,t} = 1$ for all t, (9) can be further rearranged so that firms do not have to keep track of an additional state variable (share of "no purchases" every period).

3.4 Equilibrium

We focus on stationary pure strategy Markov perfect equilbria. Stationarity means that we can abstract from calendar time and omit the time subscript and assume firms will always play

[24] In principle it is possible to have one loyalty parameter for each good in the choice set. To keep the model parsimonious we assume that the loyalty parameter is the same across brands.

the same strategies upon observing the same realisation of $(\mathbf{z}, \varepsilon)$. Formally the equilibrium to this game is a vector of firms' optimal price decisions – i.e. firms solve problem (3) taking as given their (rational) beliefs on the actions of other players – for every possible realisation of the state vector, $(\mathbf{z}, \varepsilon)$. Since the game can be seen as a particular instance of the Ericson and Pakes (1995) dynamic oligopoly framework, the proof of equilibrium existence follows from Aguirregabiria and Mira (2007), Pesendorfer and Schmidt-Dengler (2008) and Doraszelski and Satterthwaite (2010). We refer the readers to these papers for a more detailed discussion of this equilibrium and proofs of its existence.

3.5 Discussion

We end this section with a discussion on our modelling choices. In this paper we assume the manufacturers set the price and therefore are the players in the game. This seems to be reasonable because the manufacturers in our application are market leaders with substantial bargaining power.[25] On the other hand it would be difficult to justify supermarkets treating their profits in the butter/margarine category separately from their other products and activities; not to mention, it would not be practical to model supermarkets pricing decisions over all of their products and activities. Other empirical studies that use scanner data and model suppliers to be the price setters instead of supermarkets include Nevo (2001) and Dubé et al. (2009). Additionally, in our application, we will be treating the four retailing chains as separate markets, in which the pricing games are played independently. We allow cost components for the suppliers to differ for each product across markets. Store brand can also be chosen by the consumers and is considered in the demand model. As done in Slade (1998), this approach assumes that supermarkets take the residual demand and do not act as active players.[26]

On the demand side we assume consumers are myopic. While this seems innocuous in the context of our application, in principle it is possible to allow consumers to be more sophisticated. This will require careful modelling assumptions and will substantially alter how to estimate and simulate the model. For examples, see Goettler and Gordon (2011) for a Markov perfect equilibrium where consumers and firms share the same information, or see Fershtman and Pakes (2012) for a different notion of equilibrium that explicitly allows for asymmetric

[25]A further argument is that in the presence of private labels that are known to yield higher margins for the retailers, supermarkets should have no incentives to price national brands aggressively (Meza and Sudhir, 2010). Lal (1990) argues that manufacturers use price promotions to limit store brand's encroachment into the market. Moreover, in the data we also observe smaller manufacturers, whose products are never on promotion. If we endowed supermarkets with all the bargaining power, it would be hard to justify why they decide to use different pricing strategies for products coming from different manufacturers. Finally, in two independent studies, Srinivasan et al. (2004) and Ailawadi et al. (2006) find that retailers hardly ever benefit from price promotions, and it is almost exclusively the manufacturers who can enjoy increased profits from temporary sales.

[26]This means that the market share of the store brand is a payoff-relevant state variable for the remaining firms. For simplicity we assume that the price of own brand product does not change with time, otherwise it would be an additional dimension of the state space.

information between firms and consumers.

We later explore different models of consumer behaviour as parts of our robustness checks. In one model we incorporate persistent unobserved heterogeneity in households preferences by way of using a random coefficient model. We report results based on this demand model in Subsection 5.4. Results of our structural estimates and counterfactuals are close to those we obtained using our baseline formulation.

Finally, the approach we have described in Section 4.3, which assumes that consumers' memory reaches one period back, follows from Horsky, Pavlidis, and Song (2012) (also see Eizenberg and Salvo (2015) for another application). This is attractive because it enables firms to keep track of past market shares (after aggregation) and use it to predict current demand. It does not, however, keep track of consumer loyalty state for those who do not shop in consecutive periods. Alternatively, some researchers have assumed the evolution of fractions of consumers loyal to each goods to follow a finite transition state (e.g. see Dubé, Hitsch, Rossi, and Vitorino (2008), Dubé, Hitsch, and Rossi (2009), and Pavlidis and Ellickson (2017)). This approach faces a somewhat opposing problem as consumers who purchase very infrequently are treated in the same way as those who buy every period. Additionally, with such approach, the firms will need to predict demand off generic fractions of market shares rather than the actual market shares. Furthermore, our preferred method enables researchers who are interested in estimating price adjustment costs but do not have access to micro (scanner) data to use our methodology by estimating the transition law for market shares off aggregate data.

4 Identification and estimation

This section discusses our identification strategy and estimation procedure. We will focus on the dynamic pricing model, particularly on the dynamic parameters.

4.1 Identification strategy

The primitives of the dynamic game model are $\{H, mc_i, \mathbf{SC}_i, \zeta, \beta, Q, G\}_{i=1}^N$. We assume type-I extreme value distributional assumption for Q and identify G directly from the data and treat them to be known for identification. Our game is not identified without further restrictions. For example, even if β is known, we can see from the expressions in (1) and (3) that ζ cannot be separately identified from H and $\mathbf{SC}_i$. We therefore consider the reduced set of primitives: $\{H', mc_i', \mathbf{SC}_i, \beta\}_{i=1}^N$, where $H' := H/\zeta$ and $\mathbf{SC}_i' := \mathbf{SC}_i/\zeta$.

Our identification strategy is different to the traditional approach (e.g. see Pesendorfer and Schmidt-Dengler (2008)) that aims to identify all parameters at the same time as well as assuming the knowledge of the discount factor. We follow Komarova, Sanches, Silva Jr., and

Srisuma (2018) who show that $\mathbf{SC}_i'$ can be identified in closed form independently of π_i and β up to a normalisation. To apply their result, we assume the producers pay an adjustment cost only when the regular price is reduced but not when it returns to the original level. This restriction, in the context of this paper, seems to be natural. It is well documented by the literature (e.g. see Kadiyali et al. (2000), Chintagunta (2002)) and by the media (see Appendix A) that manufacturers pay fees to supermarkets to cover the expenses of promotional activities. These promotional fees are pervasive and correspond to a sizeable fraction of supermarkets profits (see Appendix A for a series of anecdotal evidence on promotional fees).

Our normalisation choice is analogous to a common practice in entry games that set scrap values to be zero.[27] Details about this identification strategy are in Appendix B. Subsequently, we can then estimate $\mathbf{SC}_i'$ that is robust against possible misspecification of π_i. For any given (H', mc_i) we can then proceed to estimate β using nonlinear least squares as suggested in Komarova, Sanches, Silva Jr., and Srisuma (2018). In our application we do not estimate parameters in π_i. We calibrate H' and take mc_i estimates from Griffith et al. (2017) that are based on a subsample of our data set.

We also considered different forms of price adjustment costs. In particular, we estimated a model assuming that firms pay a fixed fee at every period they choose low prices – in addition to the switching costs that they pay at the moment they change prices. We may interpret this component as a variable cost of promotions. In practice, this component takes into account the fact that promotional fees may be a function of the duration of promotional spells or, indirectly, of quantities sold during promotions. Estimates based on this model are discussed in Subsection 5.4.

4.2 Estimation

The estimation procedure is based on the following steps:

1. Estimate the demand system parameters $(\boldsymbol{\delta}, \gamma, \eta)$ in (5).
2. Plug $(\hat{\boldsymbol{\delta}}, \hat{\gamma}, \hat{\eta})$ into (9) to estimate $s_{jt}(a_{it}, \mathbf{a}_{-it}, \mathbf{s}_{t-1})$.
3. Estimate firms' CCPs, i.e. obtain $\widehat{\Pr}_i(a_i = \ell|\mathbf{z})$ for all i and $\mathbf{z}$.
4. Use CCPs to get $\{\widehat{\mathbf{SC}}_i'\}_{i=1}^N$ in closed form.
5. Plug the demand and $\{\mathbf{SC}_i'\}_{i=1}^N$ estimates into the conditional value functions and estimate the discount factor by minimising a nonlinear least squares objection for each H' and choose H' by a best fit criterion.

[27] Some normalisation is in general necessary as dynamic games are not identified (Pesendorfer and Schmidt-Dengler (2008)). See Aguirregabiria and Suzuki (2014) and Komarova, Sanches, Silva Jr., and Srisuma (2018) for general discussions on identifying components of the profit function that are analogous to our adjustment costs.

We estimate the demand parameters in Step 1 using maximum likelihood on the household-level data. The estimated market shares from Step 2 enter the firm's profit function (see (2)) and their lagged values are used as state variables by firms. We estimate CCPs in Step 3 using market-level data. The $\{\widehat{\mathbf{SC}}'_i\}_{i=1}^N$ can be computed directly from $\{\widehat{\mathbf{SC}}'_i\}_{i=1}^N$ following the expression in Appendix B2. A candidate for the estimate of β in Step 5 can be computed for each H', we calibrate H' to select the estimate of β. Carrying out parts of Steps 3 to 5 are conceptually and/or numerically challenging because the state space in our application is large. We next highlight two particular aspects and provide further computational details used in Appendix B3.

Conditional choice probabilities

We identify the structural parameters of firms based on the CCPs. This two-step approach, pioneered by Hotz and Miller (1993), is popular in the dynamic games literature. The underlying assumption of the two-step procedure is that we can nonparametrically estimate the CCPs from the data in the first step. Many IO applications use datasets that have a short time dimension but large cross sections (say, markets), and rely on the assumption of the same equilibrium being played across markets to pool the data for identification. We have time series data so, in principle, we can avoid making an assumption on the equilibrium across markets by estimating CCPs separately for each player in each of the 4 markets. However, 200 time periods are not sufficient given the size of the state space. For example, even with a parametric specification using each component of $\mathbf{z}_t$ as covariates there will be 51 coefficients per player to estimate. To increase the sample size, we pool data from four supermarkets and include fixed effects to account for the fact that equilibrium strategies might differ across markets. We then estimate the CCPs using multinomial logit. CCPs estimates are in Table 14 in Appendix C.

Value functions

Carrying out Steps 4 and 5 requires estimation of the expected value functions – the term $\int V_i(\mathbf{z}_{t+1}, \varepsilon_{t+1}) dQ(\varepsilon_{i,t+1})$ in equation (3). When the variables in the state space are continuous and/or the state space is large, as is the case in this paper, traditional methods to compute value functions – see Hotz et al. (1994), Aguirregabiria and Mira (2007), or Pesendorfer and Schmidt-Dengler (2008) – are known to not work well. In this paper we follow Sweeting (2013) and compute value functions using a flexible parametric approximation; also see Fowlie et al. (2016) and Barwick and Pathak (2015) for other applications using the same techniques. Once the estimate of the value function is available Step 4 is trivial. Step 5 generally requires nonlinear optimisation search that is susceptible to local maxima/minima. We use a grid search method that gives the global solution for each H'.

5 Estimation results

We begin by providing the estimates from the demand system and then the adjustment costs and discount factors. Some structural estimates of firms depend on the calibration choice discussed previously. This section also explains how to use model fit criteria to guide calibration and ends with a sensitivity analysis of these choices.

5.1 Demand estimation

Table 2 contains our demand estimates for the model described in Section 4.3. We find consumer loyalty (measured by γ) plays a crucial role in determining consumers' choices in all markets. In fact, given the magnitude of the negative alternative-specific intercepts, within an acceptable range of prices, we can see that it is almost the loyalty effect alone making a purchase more attractive than the outside option. The price coefficients, η, are negative in all cases and reflect possible differences in the composition of each supermarket's clientele, e.g. due to differences in store format or geographic locations.

Table 2: Demand estimates

	ASDA	MORRISONS	SAINSBURY'S	TESCO
δ_{Anchor}	−2.775 [−2.899; −2.651]	−2.883 [−3.043; −2.723]	−3.175 [−3.314; −3.036]	−3.836 [−3.910; −3.763]
δ_{Lurpak}	−2.064 [−2.193; −1.945]	−2.083 [−2.236; −1.930]	−2.862 [−3.004; −2.719]	−3.375 [−3.445; −3.306]
δ_{Clover}	−3.077 [−3.175; −2.980]	−2.757 [−2.860; −2.654]	−3.507 [−3.605; −3.409]	−3.814 [−3.866; −3.761]
$\delta_{Country\ Life}$	−2.930 [−3.051; −2.810]	−3.213 [−3.363; −3.063]	−3.792 [−3.934; −3.649]	−4.519 [−4.596; −4.442]
δ_{Flora}	−2.450 [−2.524; −2.375]	−2.334 [−2.415; −2.253]	−2.756 [−2.836; −2.676]	−3.075 [−3.117; −3.033]
δ_{ICBINB}	−2.516 [−2.580; −2.453]	−2.819 [−2.892; −2.745]	−3.369 [−3.447; −3.291]	−3.624 [−3.665; −3.583]
δ_{SB}	−2.903 [−2.970; −2.835]	−2.919 [−2.994; −2.845]	−2.772 [−2.844; −2.699]	−3.149 [−3.184; −3.115]
η	−0.745 [−0.799; −0.691]	−0.655 [−0.717; −0.594]	−0.356 [−0.414; −0.299]	−0.159 [−0.190; −0.128]
γ	3.037 [3.002; 3.071]	3.008 [2.967; 3.049]	2.931 [2.896; 2.967]	3.277 [3.256; 3.297]
N	104,946	71,294	102,939	280,828
pseudo-R^2	0.285	0.363	0.137	0.180

Note: Estimates obtained using the baseline definition of loyalty (only purchases in $t-1$ matter). All parameters are significantly different from 0 at the 1% level. 95% confidence intervals reported below estimated coefficients, constructed using robust standard errors. SB denotes store brand.

A potential concern with the estimates in Table 2 is the magnitude of γ (compared to η). It is well know that (persistent) unobserved consumer heterogeneity may inflate γ and have consequences for the interpretation of our model.[28] In the limit, if the coefficient γ is capturing only persistent unobserved heterogeneity (implying that brand loyalty does not play any role in this market), it would be hard to justify temporary price reductions within our framework. To check the implications of persistent unobserved consumer heterogeneity to our results we re-estimate the demand (and, subsequently, supply side parameters and counterfactuals) using a formulation that controls for more flexible forms of consumer heterogeneity. We discuss the results of this model in Subsection 5.4.

Since our estimation samples consist of households that were recording butter/margarine purchases in only one of the supermarkets in the sample period, we also check whether restricting the sample to *non-shoppers* does not induce non-random selection. We compare the distribution of market shares in the full and restricted samples. We find no substantial differences apart from a moderately higher share of store-brand products at the expense of Arla's brands.

We remark that we are not particularly concerned about the issue of prices being endogenous, which is a typical problem in classic demand estimation (Berry et al., 1995), for our application. The reason is, it is hard to imagine that there can be any product characteristics unobserved by the consumers and potentially correlated with prices that are not captured by product-specific intercepts for an everyday product like butter and margarine. Moreover, due to the timing assumption in our model, we know that prices are set prior to the realisation of individual demand shocks. Thus, similarly to Griffith et al. (2017) and Pavlidis and Ellickson (2017), we treat prices as exogenous regressors in estimating the demand system.

5.2 Dynamic game estimation

We first report the costs of switching from high to low prices scaled by ζ, i.e. $\{\widehat{\mathbf{SC}}_i'\}_{i=1}^N$. These are reported in Table 3. All the estimates are negative and all costs are highly significant for Diary Crest and Unilever. Although we do not see statistical significance for Arla, due to relatively larger standard errors, their cost estimates are similar in size to the other firms'. The large standard errors appear to be an artifact of the sampling variation in the Arla data, rather than a feature of the industry making Arla different from their competitors.[29]

While it is easy to estimate $\{\mathbf{SC}_i'\}_{i=1}^N$, its economic interpretation is limited by the unknown scaling of ζ. We need to estimate other components of the dynamic model in order to provide a clearer picture of the magnitude of these costs. Due to the similarities of the estimates across markets, and bearing the computational costs in mind, we henceforth only focus on Tesco and Morrisons, who are respectively the biggest and smallest supermarkets in terms of annual sales.

[28] See, for example, discussions in Dubé et al. (2010).

[29] We do not see a lot of variation across supermarkets. These results are consistent with the estimates in Slade (1998) and reflects the fact that the magnitude of supermarket fixed effects is relatively small in the CCPs.

Table 3: Price adjustment costs.

	ASDA	MORRISONS	SAINSBURY'S	TESCO
Arla				
SC_{Anchor}	2.177	2.508	2.511	2.497
	(2.15)	(2.56)	(2.72)	(2.33)
SC_{Lurpak}	2.388	2.438	2.451	2.441
	(2.05)	(2.50)	(2.6)	(2.25)
SC_{Both}	4.430	4.746	4.765	4.745
	(3.00)	(3.52)	(3.60)	(3.25)
DC				
SC_{Clover}	2.589***	2.584***	2.583***	2.582***
	(0.68)	(0.78)	(0.88)	(0.83)
$SC_{Country\,Life}$	2.149***	2.154***	2.131***	2.155***
	(0.64)	(0.79)	(0.9)	(0.85)
SC_{Both}	4.536***	4.544***	4.547***	4.557***
	(0.84)	(0.95)	(1.06)	(1.01)
Unilever				
SC_{Flora}	1.526**	1.612**	1.633**	1.627**
	(0.50)	(0.52)	(0.51)	(0.51)
SC_{ICBINB}	2.251***	2.445***	2.446***	2.451***
	(0.63)	(0.61)	(0.6)	(0.6)
SC_{Both}	4.111***	4.291***	4.311***	4.319***
	(1.67)	(1.64)	(1.58)	(1.52)

Note: Price adjustment costs are scaled by scaling parameter of the distribution of ε, which is assumed type-I extreme value with location parameter 0 and scaling parameter ζ^2. Standard errors obtained using 100 bootstrap replications given in parentheses below the point estimates. Significance levels: *** 1%, ** 5%, * 10%.

The upper panel of Table 4 reports the ratio of the present value of adjustment costs for firms by their variable profits. The discount factor estimates are in the bottom panel of the Table. The latter confirms that firms are forward-looking, with the discount factors close to the typical values assumed in models calibrated using weekly data. Focusing on the former, over the horizon of 200 weeks, firms have to sacrifice approximately 24-32% of their variable profits in order to be able to charge promotional prices in some periods. Such large magnitudes align with the argument in the last paragraph of the concluding section of Aguirregabiria (1999), who argues that costs associated with downward price movements are borne by manufacturers and not retailers.

We can then summarise the game estimates as follows:

1. Our adjustment cost estimates represent a large fraction of manufacturers' payoffs. The magnitudes of our adjustment costs are in line with anecdotal evidence we collect from various newspapers articles[30] and, judging by their relative importance on manufacturers' payoffs, it is likely that price adjustment costs have implications for the structure of this market.

[30] See Appendix A.

Table 4: Magnitude of adjustment costs.

	MORRISONS			TESCO		
	Arla	DC	Uni	Arla	DC	Uni
	31.80%	28.61%	24.94%	31.12%	32.27%	27.29%
β		0.929*** (0.02)			0.991*** (0.01)	

Note: The numbers in the table are ratios of adjustment costs to variable profits for each firm in two different supermarkets. Both components of the payoff are calculated as average present values for 200 periods, averaged across 1000 simulated paths.

2. The estimates of the discount factor point to a high degree of forward-looking behaviour and their size is similar to the β's typically assumed in the literature.

5.3 Model fit

Results in Table 4 depend on the scaled market size, H/ζ. We select this ratio separately for each market by examining two measures of model fit (see Table 5). To calculate these measures, we take the vector of market shares observed in the first period of our data as initial conditions, and simulate the model 199 periods ahead using the equilibrium CCPs. We repeat the simulation 1,000 times and compare simulated and real data to calculate: (i) the sum of absolute differences between the fractions of periods in which each action was played by the three firms; (ii) sum of absolute differences between market shares of all brands.

While the numbers in the table may not have an obvious interpretation, it is clear that we want to minimise both of them. For both markets, values of H higher than 9 yielded much worse fit. Moreover, the expected payoffs quickly reach (computer) infinity as H increases making the computation of counterfactual equilibrium infeasible. For the values of $H \in \{0.1, \ldots, 10\}$, we observe that in general, lower values give rise to a better fit of the market shares, though the differences are very small. We observe more noticeable differences for the fit of actions, and hence rely on this metric for our choice of the best model ($H = 8$ for Morrisons and $H = 3$ or $H = 4$ for Tesco).

For the models providing best fit, we decompose the above measures of fit by firm and brand, respectively (see figures 3 and 4 in Appendix C). The model does a good job fitting market shares and predicting firms' pricing behaviour. Only for Arla, we underestimate the number of periods in which one of the brands is on sale. For the other firms we manage to replicate the distribution of actions quite accurately.

5.4 Robustness

In order to show that our main conclusions remain internally valid, we now explore the sensitivity of our baseline results to changes in a range of assumptions. Appendix D shows the main results of these robustness exercises.

Table 5: Measures of model fit.

H/ζ	MORRISONS		TESCO	
	Actions	Shares	Actions	Shares
0.1	0.802	0.021	0.987	0.011
0.5	0.803	0.021	0.982	0.011
1.0	0.802	0.022	0.984	0.011
2.0	0.790	0.022	0.984	0.012
3.0	0.775	0.022	**0.980**	**0.012**
4.0	0.750	0.022	**0.981**	**0.012**
5.0	0.716	0.023	0.990	0.012
6.0	0.673	0.023	1.007	0.012
7.0	0.617	0.024	1.038	0.013
8.0	**0.591**	**0.024**	1.079	0.013
9.0	0.686	0.025	1.131	0.013
10.0	0.860	0.026	1.180	0.013

Note: For both supermarkets, two measures of model fit are reported for different calibrations of H. The first one (second and fourth column) is the sum of absolute differences between the fractions of periods with a given action being played observed in the data and simulated from the equilibrium of the model. The second statistic, reported in columns 3 and 5, measures the absolute difference between observed and simulated market shares. Data from the equilibrium of the model were simulated 1,000 times, 199 periods ahead, using the state observed in week 1 of the data as initial conditions.

■ **Market size calibration.** In Appendix D, tables 15 and 16 respectively show the estimates of the discount factors and adjustment cost magnitudes for different values of H/ζ. Over the entire range under consideration, the discount factors are significant and close to the usually assumed values and the average adjustment costs, while decreasing in market size, remain close to 30% of average profits.

■ **Consumer heterogeneity.** To allow for persistent taste heterogeneity, we treat the brand fixed effects as random coefficients (see Table 18 in Appendix D for results).[31] Unsurprisingly, heterogeneous brand fixed effects absorb away persistent differences in tastes, which in the baseline specification are captured by γ together with any loyalty effect. The results indicate that even controlling for more flexible forms of consumer heterogeneity the parameter γ is still large. This suggests that inertia in consumer choices may be due to some form of brand loyalty, and not only by unobserved consumer heterogeneity. Instead of assuming firms anticipate infinitely many consumer types, which would make the analysis computationally infeasible[32], we assume that firms only look at the median consumer when making pricing decisions and estimate the game taking the medians of the random coefficients. Table 19 in Appendix D analyses the same measures of fit as the ones in Table 5 for the alternative specification showing that the fit is slightly worse in terms of the distribution of actions and almost identical for market shares. Table 20 shows that in absolute terms the price adjustment costs are also almost

[31] Similar results with additional random coefficients on price and the state-dependence parameter are available upon request.

[32] It is not obvious if one should prefer the random coefficient model even if estimating it is computationally feasible. Adopting it would require a rather strong assumption that firms can observe each consumer's purchases instead of relying on aggregate market shares from last periods when setting prices.

unchanged relative to the baseline model.

■ **Other type of promotional costs.** The only type of promotional cost considered in the baseline model was a price adjustment cost incurred when changing from high to low price. This assumes that the promotional cost is independent of the duration of the sale – or, indirectly, on the quantities sold during promotions. To model the situation where the firm needs to compensate the retailer for her lower markups every period the product is on promotion, we subtract an additional term $\sum_{s\in\mathcal{J}_i} PC_i^s \cdot \mathbf{1}(a_{it} \in \{(p_r^H, p_s^L); (p_r^L, p_s^L)\})$ from the payoff function (1), which a variable component of promotional costs. Since this is not a cost associated with changing actions, it is not identified separately of the rest of the payoff function and needs to be estimated jointly with the discount factor. We present the estimation results in Table 23, concluding that they are not significantly different from zero for neither supermarkets and none of the products. This result is consistent with the estimates in Slade (1998), which finds that the variable component of price adjustment costs is very small compared to the fixed component. Additionally, the bottom row of that table shows that the estimated β's are quite robust to the different assumption about costs.

6 Counterfactual studies

We now turn to our two counterfactual studies. Our reduced form and structural estimates suggest that costs firms pay to reduce prices are fundamental to the understanding of the price process in this market. We wish to understand (i) how price adjustment costs affect firms' profits, equilibrium prices and consumer welfare and, given the importance of consumer inertia in this market, (ii) how consumer loyalty affects price dynamics in the presence of price adjustment costs.

■ **Price adjustment costs, profits and consumer surplus.** We start with an analysis of the effects of costs firms pay to reduce prices on profits and consumer surplus. The results of this study are shown in Table 6.

To construct this table we compute the percentage differences between baseline (model with price adjustment costs) and counterfactual (model without price adjustment costs) profits and market shares of each manufacturer and consumer surplus.[33] To compute equilibrium profits, shares and consumer welfare we solve the model using the value function approximation method described in Appendix B4. Starting from the state vector observed at the first week in our sample we simulate the model 199 periods ahead 1000 times and compute average shares,

[33]While we focus on the results for the calibration based on the best fit of the model, Appendix D Table 17 includes also welfare measures for alternative values of the parameter to show that our main qualitative conclusion is robust. We also ran the same counterfactual taking medians of the estimated random coefficients in the demand system finding no substantial differences, see tables 21 and 22 in Appendix D.

profits and consumer welfare across periods and simulations. To detect possible multiplicity of equilibria, we solve the model using different initial guesses for the vector of equilibrium probabilities, finding our algorithm to converge to the same equilibrium every time.

Not surprisingly, eliminating this type of friction has a large positive effect for firms' profits, ranging from 50 to almost 75%. This is considerably more than the magnitude of the adjustment costs alone, which represent 20-30% of firms' variable profits. This difference is mainly explained by an increase in the expected value of the profitability shock for the firms. Also, as previously alluded, these findings suggest that price adjustment costs may have, in the long-run, considerable influence on market structure. Without price adjustment costs potential entrants will expect considerably higher profits in the long-run. This effect might, in the end, induce the entry of new competitors in the industry.

Table 6: Counterfactual results with $\mathbf{SC} = 0$.

	MORRISONS			TESCO		
	Arla	**DC**	**Uni**	**Arla**	**DC**	**Uni**
Δs	3.97%	3.80%	2.77%	0.63%	0.26%	0.27%
$\Delta\Pi$	74.51%	64.16%	50.52%	71.49%	72.89%	55.08%
ΔCS		3.27%			0.37%	

Note: Numbers in the table are percentage differences between the counterfactual scenario and the baseline model in: average market share ($\Delta\mathbf{s}$), firm profits ($\Delta\Pi$) and consumer surplus (ΔCS). The figures were obtained by simulating the two models according to MPE choice probabilities 200 periods ahead, and averaging across 1,000 simulation paths.

Consumer surplus, on the other hand, increases only by a modest percentage when price adjustment costs are removed from the model. Competition in this market appears to be limited, which means that incumbents do not have incentives to pass the cost reduction to consumers. To understand this result better, we further decompose our findings and look at other margins in Table 7.

In both supermarkets, under costless price adjustment, we observe an increase in the number of weeks where each firm has at least one of its brands on promotion. However, the drop in the average long-run price paid by the consumers ranges only between 1 and 6p, which explains the aforementioned modest increase in consumer surplus. The most important difference between the baseline scenario and the counterfactual is in the duration of promotional periods – the lack of adjustment costs makes firms choose shorter, albeit more frequent, periods of temporarily reduced prices. We would therefore no longer be observing the persistence of prices which we spotted in the original data, though this difference turns out to have very little effect on consumer surplus.

The results of this counterfactual may be interpreted as partial equilibrium response to a ban on promotional fees. While such regulation has not been proposed in the UK yet, similar policies have been implemented in some countries to increase the degree of transparency in the retailer-manufacturer relationships.[34] Our results indicate that such a regulation would have a modest impact on consumer welfare and would simply shift the profits from retailers to manufacturers in the vertical channel. This part of the result should be interpreted with caution because we are not analysing the general equilibrium response of the downstream firms (supermarkets). Another caveat is that our estimates of price adjustment costs captures other costs firms incur when changing prices as, for example, menu costs and managerial costs associated to price changes.

■ **Consumer loyalty under price adjustment costs.** To examine the effects of consumer loyalty in the presence of price adjustment costs we simulate the pricing game using the estimated parameters and different values for the inertia parameter, γ. We redo the same exercise setting $\mathbf{SC}_i = 0$ for all firms and compare equilibrium prices (averaged across the 6 brands) produced by the models with and without price adjustment costs. Table 8 shows the results for Morrisons and Tesco. The first column has the factor that we use to scale the parameter capturing consumer loyalty (γ in Table 2). Columns 2 and 3 show average prices and the percentage difference of prices between the model in the corresponding row and the model without consumer loyalty (i.e. the model in the first row) for the MPE simulations where price adjustment costs are set to zero. The two subsequent columns have the same statistics for the models with price adjustment costs. The last column has the price variation between the models with and without price adjustment costs. Therefore, these results must be interpreted as the upper limit of the effects of a ban of promotional fees on firms and consumers.

The results in the table are to be interpreted as follows: first, increases in consumer inertia are associated with increases in equilibrium prices in the models with and without price adjustment costs. This observation holds for both supermarkets. For lower levels of inertia the effects of increases in γ on prices are relatively small (but still positive). When the levels of inertia are already high, increases in the loyalty factor lead to a increase in prices. These patterns are similar to those found in Dubé et al. (2009) with one important exception – in Dubé et al. (2009) prices initially fall for lower consumer loyalty levels, whereas in our case firms seem to have an insufficient incentive to invest in building up their consumer base.

Second, the consequences of consumer loyalty for prices are more pronounced in the model with price adjustment costs. For example, in Tesco, a change in the loyalty factor from 0 to 3 causes a price variation of 1.62% in the model where price adjustment costs are zero and of 5.63% in the model with price adjustment costs. The same conclusion holds for Morrisons and for each brand separately. The differences in the magnitudes of these effects between Tesco and Morrisons may be explained by differences in H. In particular this parameter is much smaller for Tesco than Morrisons', which suggests that changes in consumer switching costs will have more relevant implications in Morrisons than in Tesco. Our conclusion is that price adjustment

[34] See Appendix A for details.

Table 7: Decomposition of main counterfactual results.

		Morrisons		Tesco	
		Baseline	Counterfactual	Baseline	Counterfactual
Arla	No promotions				
	◇ *Frequency*	37.82%	26.50%	31.39%	26.56%
	◇ *Avg. duration*	3.08	1.36	2.79	1.36
	One promotion				
	◇ *Frequency*	46.88%	49.91%	49.09%	49.97%
	◇ *Avg. duration*	2.43	1.33	2.49	1.33
	Two promotions				
	◇ *Frequency*	15.29%	23.59%	19.51%	23.47%
	◇ *Avg. duration*	2.07	1.31	2.24	1.31
	$\overline{p}_{\text{Anchor}}$	£2.25	£2.20	£2.23	£2.21
	$\overline{p}_{\text{Lurpak}}$	£2.45	£2.39	£2.38	£2.34
Dairy Crest	No promotions				
	◇ *Frequency*	35.96%	26.19%	28.81%	25.70%
	◇ *Avg. duration*	2.88	1.36	2.40	1.33
	One promotion				
	◇ *Frequency*	47.80%	49.97%	49.14%	49.90%
	◇ *Avg. duration*	2.37	1.33	2.40	1.33
	Two promotions				
	◇ *Frequency*	16.23%	23.83%	22.05%	24.40%
	◇ *Avg. duration*	2.05	1.32	2.30	1.33
	$\overline{p}_{\text{Clover}}$	£1.49	£1.43	£1.48	£1.46
	$\overline{p}_{\text{Country Life}}$	£2.14	£2.10	£2.09	£2.08
Unilever	No promotions				
	◇ *Frequency*	38.46%	27.99%	30.14%	26.62%
	◇ *Avg. duration*	2.71	1.39	2.37	1.37
	One promotion				
	◇ *Frequency*	47.72%	50.26%	49.95%	50.04%
	◇ *Avg. duration*	2.13	1.34	2.17	1.33
	Two promotions				
	◇ *Frequency*	13.83%	21.75%	19.92%	23.33%
	◇ *Avg. duration*	1.77	1.29	2.00	1.31
	$\overline{p}_{\text{Flora}}$	£1.25	£1.21	£1.28	£1.26
	$\overline{p}_{\text{ICBINB}}$	£1.05	£1.01	£1.07	£1.06

Note: The table compares various summary statistics in the baseline scenario where price adjustment is costly and in the counterfactual with no promotional costs. For each firm, we present simulated frequency and duration of different actions (first six rows), and average long-run prices of each brand, weighted by market shares, denoted as $\overline{p}_*$.

costs may act as an additional barrier for firms that want to invest in consumer loyalty through temporary price reductions.

Finally, price adjustment costs appear to be more important to explain price dynamics than consumer loyalty itself. From our baseline estimates (rows in bold) the inclusion of price adjustment costs in the model leads to a increase of 3% in average prices for Morrisons and of 1% for Tesco. This contrasts with the effects of consumer loyalty on prices. In the model with price adjustment costs, an increase in the loyalty factor from zero (no consumer loyalty) to

Table 8: Implications of consumer loyalty with and without price adjustment costs.

Scaling factor	SC= 0		Estimated SC		$\frac{\text{Price SC}}{\text{Price SC=0}}$
	Price	Difference	Price	Difference	
			Morrisons		
0.00	1.750	-	1.797	-	2.69%
0.25	1.750	0.01%	1.798	0.02%	2.70%
0.50	1.751	0.03%	1.799	0.07%	2.73%
0.75	1.751	0.07%	1.800	0.18%	2.80%
1.00	**1.753**	**0.16%**	**1.805**	**0.41%**	**2.94%**
2.00	1.811	3.49%	1.896	5.47%	4.66%
3.00	1.858	6.16%	1.944	8.17%	4.63%
			Tesco		
0.00	1.740	-	1.754	-	0.80%
0.25	1.741	0.00%	1.755	0.01%	0.80%
0.50	1.741	0.01%	1.755	0.04%	0.82%
0.75	1.741	0.03%	1.756	0.10%	0.87%
1.00	**1.742**	**0.07%**	**1.758**	**0.22%**	**0.95%**
2.00	1.760	1.14%	1.816	3.50%	3.15%
3.00	1.769	1.62%	1.853	5.63%	4.77%

Note: Columns labeled 'Price' contain average prices (across the 6 branded products); columns labeled 'Difference' contain the percentage difference between prices in the corresponding row with respect to the price obtained from the model where the loyalty factor is zero (i.e. prices in the first row); the last column has the price difference between the models with and without price adjustment costs in the corresponding row. The figures were obtained by simulating the two models according to MPE choice probabilities 200 periods ahead, and averaging across 1,000 simulation paths.

one (baseline estimates of consumer loyalty) causes a price increase of approximately 0.4% in Morrisons and of 0.2% in Tesco.

7 Summary and conclusions

The paper proposed a new dynamic multiproduct pricing game with supply and demand frictions. Following an empirical regularity documented in data on retail prices and in a range of papers, we assumed that price competition occurs through temporary price cuts (sales), and more specifically switching between regular and sale prices. We therefore model firms' decisions as discrete choices. To learn about the degree of forward-looking behaviour and the magnitude of price adjustment costs, we estimated the structural parameters of the model using scanner data from the butter and margarine market in the UK. We solved the model and analysed the effects of price adjustment costs and consumer inertia on prices, consumer welfare and firms' profits.

First, using the methodology proposed in Komarova et al. (2018) , we estimated producers' discount factor. Our estimates show that firms' discount factor is between 0.92 and 0.99, suggesting that dynamics must be taken into account even when researchers are modelling pricing decisions of simple consumer goods, such as butter and margarine.

Second, our estimates show that price adjustment costs are substantial and correspond to 24-34% of producers variable profits. Our counterfactual analysis shows that removing these costs from the market causes a significant increase in profits but has little effect on prices and consumer welfare. Third, we also studied how consumer inertia affects prices when price adjustment is costly. We show that adjustment costs dampen firms incentives to invest in consumer loyalty, which exacerbates potentially negative effects of consumer inertia on prices.

Finally, given their magnitudes, it is very likely that price adjustment costs may have consequences for market structure. Smaller firms may not have the capacity to pay these costs to lower their prices frequently which, in turn, lowers their ability to enter and compete in this market. A systematic investigation of price adjustment costs on entry and exit dynamics would be an interesting topic for future research.

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Appendix A: Anecdotal evidence on promotional fees

This appendix presents anecdotal evidence describing practical aspects of promotional fees.

- Supermarkets often demand payments to cover the cost of promotional activities:

    1. "*The Gfk report revealed that 70% of supermarket suppliers make either regular or occasional payments towards marketing costs or price promotions. About 43% said they paid some other rebates".*[35]
    2. "*Terms are commercially sensitive but in general the payments, (...), are made for various activities (...)".*[36]

- It is hard to infer how much retailers receive from promotional fees:

    1. *"British retailers don't publish how much money they receive from commercial income(...)".* [37]
    2. *'"In the last competition inquiry one supplier told the watchdog that, it would be commercial suicide for any supplier to give a true and honest account of their dealings with the big retailers".*[38]

- Promotional fees are a very important source of revenues to supermarkets[39]:

    1. *"According to Fitch, the credit rating agency, the payments are the equivalent to 8% of the cost of goods sold for the retailers, equal to virtually all their profit. [An analyst] conservatively estimates supplier contributions to be worth around £5bn a year to the top four supermarkets. But that sum is still more than they made in combined pre-tax profits last year ".*
    2. *"(...) it's far more attractive for a supermarket to get ever larger supplier rebates than it is to encourage the likes of you and I to spend more money at the till (...)", the same analyst says".*
    3. *"Analysts reckon that American retailers may now rake in $18 billion or more in rebates each year, up from $1 billion in the 1990s. In Britain, by some estimates the big four supermarkets receive more in payments from their suppliers than they make in operating profits".*
    4. *"In Australia, growing supplier rebates have boosted food retailers profit margins by an average of 2.5 percentage points, to 5.7%, over the past five years, according to a report last month by UBS, a bank".*[40]

[35] https://www.theguardian.com/business/2007/aug/25/supermarkets

[36] http://www.independent.co.uk/news/business/comment/supermarkets-dealings-with-suppliers-are-a-world-away-from-the-shop-floor-9749826.html

[37] http://www.bbc.com/news/business-29629742

[38] https://www.theguardian.com/business/2007/aug/25/supermarkets

[39] http://www.bbc.com/news/business-29629742

[40] http://www.economist.com/news/business/21654601-supplier-rebates-are-heart-some-supermarket-chains-woes-buying-up-shelves

- Competition authorities around the world are worried about the effects of promotional fees on suppliers. They admit however that the issue is controversial:

  1. *"The Competition Commission, which is nearing the end of its third full-scale inquiry into the grocery business in seven years, last week ordered Asda and Tesco to hand over millions of emails sent and received over a five-week period in June and July. They leapt into action after unearthing email evidence that the big two supermarkets had been threatening suppliers and demanding cash payments to finance this summer's round of supermarket price wars. The emails, it is understood, employed threatening language".*[41]
  2. *"Some countries have tried to protect consumers by making rebates illegal. Poland banned them in 1993 as part of free-market reforms that followed the end of communism. And in 1995 America banned them on alcoholic drinks, though its main worry was that prominent displays of booze promoted irresponsible drinking.* ***However, progress towards eliminating them on all products in America stalled after the Federal Trade Commission (FTC) concluded in 2001 that more research on them was needed before it could take any further action****".*[42]

[41] https://www.theguardian.com/business/2007/aug/25/supermarkets

[42] http://www.economist.com/news/business/21654601-supplier-rebates-are-heart-some-supermarket-chains-woes-buying-up-shelves

Appendix B1: Main identification result

In this Appendix we present our main identification result. To make it self-contained, we will repeat some of the notational assumptions we have been making throughout the main body of the paper. Also, to make the exposition clearer, we will be referring to a specific number of players, actions and cardinality of the set of possible market shares which will be the same as in our empirical application.

Preliminaries

There are three players, producing two products each (four actions per player). There is also a generic good that can be chosen by consumers, but its price is exogenously given (hence there are 7 lagged market shares to keep track of). The vector of publicly observed state variables is $\mathbf{z}_t = (\mathbf{s}_{t-1}, \mathbf{a}_{t-1})$. We discretise last period's market shares into 3 bins, therefore the dimension of the state space $\boldsymbol{\mathcal{Z}}$ is: $|\boldsymbol{\mathcal{Z}}| = 4^3 \cdot 3^7 = 64 \cdot 2187 = 139,968$. For simplicity we will refer to the action $(p^H_{i_1}, p^H_{i_2})$ as HH. The payoff function of player i is:

$$\Pi(\mathbf{a}_t, \mathbf{z}_t, \varepsilon_{it})) = \pi_i(a_{it}, \mathbf{a}_{-it}, \mathbf{s}_{t-1}) + \sum_{\ell \in \mathcal{A}_i} \varepsilon_{it}(\ell) \cdot \mathbf{1}(a_{it} = \ell) \\ + \sum_{\ell \in \mathcal{A}_i} \sum_{\ell' \neq \ell} SC_i^{\ell' \to \ell} \cdot \mathbf{1}(a_{it} = \ell, a_{i,t-1} = \ell'), \tag{10}$$

Derivation

The non-stochastic dynamic payoff from choosing $a_{it} = \ell$ is:

$$\bar{v}_i(\ell, \mathbf{z}_t) = \sum_{\mathbf{a}_{-it} \in \times_{j \neq i} \mathcal{A}_j} \sigma_i(\mathbf{a}_{-it} | \mathbf{z}_t) \Big[\pi_i(\ell, \mathbf{a}_{-it}, \mathbf{s}_{t-1}) + \beta \sum_{\mathbf{z}_{t+1}} G(\mathbf{z}_{t+1} | \mathbf{s}_{t-1}, \ell, \mathbf{a}_{-it}) \\ \underbrace{\cdot \int V_i(\mathbf{z}_{t+1}, \varepsilon_{t+1}) dQ(\varepsilon_{i,t+1})}_{\tilde{V}(\mathbf{z}_{t+1})} \Big] + \sum_{\ell' \neq \ell} SC_i^{\ell' \to \ell} \cdot \mathbf{1}(a_{i,t-1} = \ell') \tag{11}$$

Defining the differences with respect to the reference action HH we have:

$$\begin{aligned} \Delta \bar{v}_i(\ell, \mathbf{z}_t) &= \bar{v}_i(\ell, \mathbf{z}_t) - \bar{v}_i(HH, \mathbf{z}_t) \\ &= \sum_{\mathbf{a}_{-it} \in \times_{j \neq i} \mathcal{A}_j} \sigma_i(\mathbf{a}_{-it} | \mathbf{z}_t) \Big\{ \underbrace{\pi_i(\ell, \mathbf{a}_{-it}, \mathbf{s}_{t-1}) - \pi_i(HH, \mathbf{a}_{-it}, \mathbf{s}_{t-1})}_{\Delta \pi_i^\ell(\mathbf{a}_{-it}, \mathbf{s}_{t-1})} \Big\} \\ &+ \sum_{\mathbf{a}_{-it} \in \times_{j \neq i} \mathcal{A}_j} \sigma_i(\mathbf{a}_{-it} | \mathbf{z}_t) \Big\{ \beta \sum_{\mathbf{z}_{t+1}} \big[\underbrace{G(\mathbf{z}_{t+1} | \mathbf{s}_{t-1}, \ell, \mathbf{a}_{-it}) - G(\mathbf{z}_{t+1} | \mathbf{s}_{t-1}, HH, \mathbf{a}_{-it})}_{\Delta G^\ell(\mathbf{z}_{t+1} | \mathbf{a}_{-it}, \mathbf{s}_{t-1})} \big] \tilde{V}(\mathbf{z}_{t+1}) \Big\} \\ &+ \underbrace{\sum_{\ell' \neq \ell} \big[SC_i^{\ell' \to \ell} \cdot \mathbf{1}(a_{i,t-1} = \ell') - SC_i^{\ell' \to HH} \cdot \mathbf{1}(a_{i,t-1} = \ell') \big]}_{\Delta SC_i^\ell(a_{i,t-1})} \end{aligned}$$

Using the newly introduced notation, we have:

$$\Delta\bar{v}_i(\ell,\mathbf{z}_t) = \sum_{\mathbf{a}_{-it}\in \times_{j\neq i}\mathcal{A}_j} \sigma_i(\mathbf{a}_{-it}|\mathbf{z}_t)\Big\{ \underbrace{\Delta\pi_i^\ell(\mathbf{a}_{-it},\mathbf{s}_{t-1}) + \beta\sum_{\mathbf{z}_{t+1}}\Delta G^\ell(\mathbf{z}_{t+1}|\mathbf{a}_{-it},\mathbf{s}_{t-1})\tilde{V}(\mathbf{z}_{t+1})}_{\lambda_i(\ell,\mathbf{a}_{-it},\mathbf{s}_{t-1})} \Big\}$$
$$+ \Delta SC_i^\ell(a_{i,t-1}) \tag{12}$$

Thinking back about the dimension of the problem, for each of the three remaining (that is, excluding HH) actions of player i, there are $4^2\cdot 3^7 = 16\cdot 2187 = 34992$ $\lambda_i(\ell,*)$ terms. Rewriting (12) in vector form:

$$\Delta\bar{v}_i(\ell,\mathbf{z}_t) = \boldsymbol{\sigma}_i(\mathbf{z}_t)'\boldsymbol{\lambda}_i(\ell,\mathbf{s}_{t-1}) + \Delta SC_i^\ell(a_{i,t-1}), \tag{13}$$

where $\boldsymbol{\sigma}_i(\mathbf{z}_t) = [\sigma_i(\mathbf{a}_{-it}|\mathbf{z}_t)]_{\mathbf{a}_{-it}}$ and $\boldsymbol{\lambda}_i(\ell,\mathbf{s}_{t-1}) = [\lambda_i(\ell,\mathbf{a}_{-it},\mathbf{s}_{t-1})]_{\mathbf{a}_{-it}}$ are 16×1 column vectors. (13) holds for all of the 139,968 points in the state space. To make things more explicit, use the fact that $\mathbf{z}_t$ can be partitioned into $(\mathbf{a}_{t-1},\mathbf{s}_{t-1})$. Furthermore:

$$\begin{aligned}\mathbf{a}_{t-1} &= \{\mathbf{a}_{t-1}^1,\mathbf{a}_{t-1}^2,\dots,\mathbf{a}_{t-1}^{64}\}\\ \mathbf{s}_{t-1} &= \{\mathbf{s}_{t-1}^1,\mathbf{s}_{t-1}^2,\dots,\mathbf{s}_{t-1}^{2187}\}\end{aligned}$$

For $\mathbf{s}_{t-1}^1$ the system can be written as:

$$\begin{cases}\Delta\bar{v}_i(\ell,\mathbf{a}_{t-1}^1,\mathbf{s}_{t-1}^1) = \boldsymbol{\sigma}_i(\mathbf{a}_{t-1}^1,\mathbf{s}_{t-1}^1)'\boldsymbol{\lambda}_i(\ell,\mathbf{s}_{t-1}^1) + \Delta SC_i^\ell(\mathbf{a}_{t-1}^1)\\ \Delta\bar{v}_i(\ell,\mathbf{a}_{t-1}^2,\mathbf{s}_{t-1}^1) = \boldsymbol{\sigma}_i(\mathbf{a}_{t-1}^2,\mathbf{s}_{t-1}^1)'\boldsymbol{\lambda}_i(\ell,\mathbf{s}_{t-1}^1) + \Delta SC_i^\ell(\mathbf{a}_{t-1}^2)\\ \qquad\vdots\\ \Delta\bar{v}_i(\ell,\mathbf{a}_{t-1}^{64},\mathbf{s}_{t-1}^1) = \boldsymbol{\sigma}_i(\mathbf{a}_{t-1}^{64},\mathbf{s}_{t-1}^1)'\boldsymbol{\lambda}_i(\ell,\mathbf{s}_{t-1}^1) + \Delta SC_i^\ell(\mathbf{a}_{t-1}^{64})\end{cases}$$

Vectorizing again:

$$\Delta\bar{\mathbf{v}}_i(\ell,\mathbf{s}_{t-1}^1) = \boldsymbol{\sigma}_i(\mathbf{s}_{t-1}^1)\boldsymbol{\lambda}_i(\ell,\mathbf{s}_{t-1}^1) + \Delta\mathbf{SC}_i^\ell, \tag{14}$$

where $\bar{\mathbf{v}}_i(\ell,\mathbf{s}_{t-1}^1) = [\Delta\bar{v}_i(\ell,\mathbf{a}_{t-1},\mathbf{s}_{t-1}^1)]_{\mathbf{a}_{t-1}}$ is a 64×1 vector, $\boldsymbol{\sigma}_i(\mathbf{s}_{t-1}^1) = [\boldsymbol{\sigma}_i(\mathbf{a}_{t-1},\mathbf{s}_{t-1}^1)']_{\mathbf{a}_{t-1}}$ is a 64×16 matrix and $\Delta\mathbf{SC}_i^\ell = [\Delta SC_i^\ell(\mathbf{a}_{t-1})]_{\mathbf{a}_{t-1}}$ is a 64×1 vector. In matrix notation, for all $\mathbf{s}_{t-1}$, this becomes:

$$\Delta\bar{\mathbf{v}}_i(\ell) = \underbrace{\begin{bmatrix}\boldsymbol{\sigma}_i(\mathbf{s}_{t-1}^1) & & \mathbf{0}\\ & \ddots & \\ \mathbf{0} & & \boldsymbol{\sigma}_i(\mathbf{s}_{t-1}^{2187})\end{bmatrix}}_{(2187\cdot 64)\times(2187\cdot 16)}\underbrace{\begin{bmatrix}\boldsymbol{\lambda}_i(\ell,\mathbf{s}_{t-1}^1)\\ \vdots\\ \boldsymbol{\lambda}_i(\ell,\mathbf{s}_{t-1}^{2187})\end{bmatrix}}_{(2187\cdot 16)\times 1} + \Delta\widetilde{\mathbf{SC}}_i^\ell \tag{15}$$

We will be referring to the block-diagonal matrix containing player i's beliefs as $\boldsymbol{\sigma}$. It can be written more compactly as a Kronecker product of an identity matrix I and matrix containing beliefs:

$$\Delta\bar{\mathbf{v}}_i(\ell) = \left[I_{2187} \otimes \begin{bmatrix} \boldsymbol{\sigma}_i(\mathbf{s}^1_{t-1}) \\ \vdots \\ \boldsymbol{\sigma}_i(\mathbf{s}^{2187}_{t-1}) \end{bmatrix} \right] \begin{bmatrix} \boldsymbol{\lambda}_i(\ell, \mathbf{s}^1_{t-1}) \\ \vdots \\ \boldsymbol{\lambda}_i(\ell, \mathbf{s}^{2187}_{t-1}) \end{bmatrix} + \Delta\widetilde{\mathbf{SC}}^{\ell}_i$$
$$= \boldsymbol{\sigma}_i \boldsymbol{\lambda}_i(\ell) + \Delta\widetilde{\mathbf{SC}}^{\ell}_i$$

Everything we showed so far was for a selected action $\ell \in \mathcal{A}_i \backslash \{HH\}$. We can now define $\Delta\bar{\mathbf{v}}_i = [\bar{\mathbf{v}}_i(HL); \bar{\mathbf{v}}_i(LH); \bar{\mathbf{v}}_i(LL)]'$, so that:

$$\Delta\bar{\mathbf{v}}_i = [I_3 \otimes \boldsymbol{\sigma}_i] \begin{bmatrix} \boldsymbol{\lambda}_i(HL) \\ \boldsymbol{\lambda}_i(LH) \\ \boldsymbol{\lambda}_i(LL) \end{bmatrix} + \begin{bmatrix} \Delta\widetilde{\mathbf{SC}}^{HL}_i \\ \Delta\widetilde{\mathbf{SC}}^{LH}_i \\ \Delta\widetilde{\mathbf{SC}}^{LL}_i \end{bmatrix} \tag{16}$$
$$= \mathbf{Z}_i \boldsymbol{\lambda}_i + \Delta\widetilde{\mathbf{SC}}_i$$

The dimension of the object on the LHS of (16) is $(139968 \cdot 3 \times 1) = 419904 \times 1$. Define the following 419904×419904 projection matrix:

$$\mathrm{M}^{\mathbf{Z}}_i = I_{419904} - \mathbf{Z}_i(\mathbf{Z}'_i \mathbf{Z}_i)^{-1} \mathbf{Z}'_i \tag{17}$$

So far we have not discussed $\Delta\widetilde{\mathbf{SC}}_i$ in detail, but it can be written as: $\Delta\widetilde{\mathbf{SC}}_i = \widetilde{\mathbf{D}}_i \Delta\mathbf{SC}_i$ where $\widetilde{\mathbf{D}}_i$ is a $419904 \times \kappa_i$ matrix of zeros and ones which are a natural consequence of the indicator functions used while defining the profit function. κ_i is the number of dynamic parameters to estimate for player i and $\Delta\mathbf{SC}_i$ is a $\kappa_i \times 1$ vector of parameters to identify. Multiplying both sides of (16) by the projection matrix defined in (17), we have:

$$\mathrm{M}^{\mathbf{Z}}_i \Delta\bar{\mathbf{v}}_i = \mathrm{M}^{\mathbf{Z}}_i \widetilde{\mathbf{D}}_i \Delta\mathbf{SC}_i$$
$$\widetilde{\mathbf{D}}'_i \mathrm{M}^{\mathbf{Z}}_i \Delta\bar{\mathbf{v}}_i = \widetilde{\mathbf{D}}'_i \mathrm{M}^{\boldsymbol{\lambda}}_i \widetilde{\mathbf{D}}_i \Delta\mathbf{SC}_i$$
$$\Delta\mathbf{SC}_i = (\widetilde{\mathbf{D}}'_i \mathrm{M}^{\mathbf{Z}}_i \widetilde{\mathbf{D}}_i)^{-1} (\widetilde{\mathbf{D}}'_i \mathrm{M}^{\mathbf{Z}}_i \Delta\bar{\mathbf{v}}_i) \tag{18}$$

(18) defines the identifying correspondence for player i. We can proceed in an identical fashion to recover the parameters for the remaining players. There is also a straightforward way to incorporate equality restrictions across players an estimate $\{\Delta\mathbf{SC}_i\}_{i=1}^N$ for all players in one step.

Computation

The main computational challenge here lies in the construction of the projection matrix $\mathrm{M}^{\mathbf{Z}}_i$ which involves inverting the matrix $\mathbf{Z}'_i \mathbf{Z}_i$ of size $3 \cdot 34992 \times 3 \cdot 34992$. However, a closer inspection reveals that this matrix is block-diagonal. To see this, rewrite $\mathbf{Z}_i$:

$$\mathbf{Z}_i = \begin{bmatrix} \begin{bmatrix} \boldsymbol{\sigma}_i(\mathbf{s}^1_{t-1}) & & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & & \boldsymbol{\sigma}_i(\mathbf{s}^{2187}_{t-1}) \end{bmatrix} & & \mathbf{0} \\ & \begin{bmatrix} \boldsymbol{\sigma}_i(\mathbf{s}^1_{t-1}) & & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & & \boldsymbol{\sigma}_i(\mathbf{s}^{2187}_{t-1}) \end{bmatrix} & \\ \mathbf{0} & & \begin{bmatrix} \boldsymbol{\sigma}_i(\mathbf{s}^1_{t-1}) & & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & & \boldsymbol{\sigma}_i(\mathbf{s}^{2187}_{t-1}) \end{bmatrix} \end{bmatrix}$$

Recall that each of the $\boldsymbol{\sigma}_i(\cdot)$'s is a 64×16 matrix. Multiplying $\mathbf{Z}_i$ by its transpose we have:

$$\mathbf{Z}_i'\mathbf{Z}_i = \begin{bmatrix} \begin{bmatrix} \boldsymbol{\sigma}_i(\mathbf{s}^1_{t-1})'\boldsymbol{\sigma}_i(\mathbf{s}^1_{t-1}) & & 0 \\ & \ddots & \\ 0 & & \boldsymbol{\sigma}_i(\mathbf{s}^{2187}_{t-1})'\boldsymbol{\sigma}_i(\mathbf{s}^{2187}_{t-1}) \end{bmatrix} & & \mathbf{0} \\ & [\ ] & \\ \mathbf{0} & & [\ ] \end{bmatrix}$$

Now each of the $\boldsymbol{\sigma}_i(\cdot)'\boldsymbol{\sigma}_i(\cdot)$ entries is a 16×16 matrix, so in the end to obtain the inverse of $\mathbf{Z}_i'\mathbf{Z}_i$ we have to invert 2187 16×16 matrices, which in principle should be much faster and accurate than inverting one big matrix. In practice we can proceed as follows:

1. Construct 2187 projection matrices:

$$\mathrm{M}^{\mathbf{Z}}_i(\cdot) = I_{64} - \boldsymbol{\sigma}_i(\cdot)[\boldsymbol{\sigma}_i(\cdot)'\boldsymbol{\sigma}_i(\cdot)]^{-1}\boldsymbol{\sigma}_i(\cdot)'$$

2. Build the matrix $\mathrm{M}^{\boldsymbol{\lambda}}_i$
3. Recover $\Delta\mathrm{SC}_i$

Appendix B2: Identification of promotional costs

This Appendix shows how assuming that adjustment costs are only paid by firms if they change prices from high to low allows to point-identify the vector of costs consisting of a separate parameters for each product. We start with assumptions R1-3:

Assumption (R1). *Adjustment costs are incurred only when switching from high to low price.*

Assumption (R2). *Adjustment cost associated with one product is independent of the current and lagged promotional status of other products.*

R2 is a natural assumption, and allows us to impose equality restriction across $\mathbf{a}_{-i,t-1}$ in the switching cost part of (1). Finally, consider the situation in which prices of more than one product of a firm move in the same direction. R3 says that we can express the cost of taking this action as a sum of individual price adjustments of the products involved:

Assumption (R3). *There are no economies of scope associated with price promotions on multiple products of the same firm.*

R1-2 will be sufficient to identify one cost of adjusting prices per product, and R3 can be just used to reduce the dimension of the parameter vector. The identifying power of our assumptions is summarised by the following proposition:

Proposition 1. *Under assumptions R1-2, the matrix $\widetilde{\mathbf{D}}_i$ satisfies the requirements of theorem 2 in Komarova et al. (2018) and for each player one can identify $|\mathcal{A}_i|-1$ parameters in $\mathbf{SC}_i$. Adding assumption R3 reduces the number of parameters to $|\mathcal{J}_i|$.*

For clarity of exposition we prove proposition 1 for a two-product duopoly case. Generalising it to more players and products is straightforward.

Setup

Consider a simplified version of the model described in Section 3: suppose there are **two** players which we denote as $i = \{a, b\}$ producing **two** differentiated goods each, whose sets we denote as $\mathcal{J}_i = \{i_1, i_2\}$.

Conditional on $(\mathbf{s}_{t-1}, \mathbf{a}_{t-1}, \varepsilon_{it})$, player i chooses an action a_{it} from the set $\mathcal{A}_i$ to maximise the discounted sum of profits given her beliefs about the actions of the competitor. The decision variable in this game is the vector of prices of all goods manufactured by a player. Since prices are constrained to take only two values, regular (H) and sale (L), the cardinalities of both $\mathcal{A}_a$ and $\mathcal{A}_b$ are $2^{|\mathcal{J}_a|} = 2^{|\mathcal{J}_b|} = 4$.

Specifically $\mathcal{A}_a = \{\underbrace{(p^H_{a_1}, p^H_{a_2})}_{HH}; \underbrace{(p^H_{a_1}, p^L_{a_2})}_{HL}; \underbrace{(p^L_{a_1}, p^H_{a_2})}_{LH}; \underbrace{(p^L_{a_1}, p^L_{a_2})}_{LL}\}$, where H/L denotes regular/sale price, $\mathcal{A}_b$ is defined analogously.

This implies that without further restrictions there are 12 parameters per player:

$\mathbf{SC}_i$=[$SC_i^{HL\to HH}$, $SC_i^{LH\to HH}$, $SC_i^{LL\to HH}$, $SC_i^{HH\to HL}$, $SC_i^{LH\to HL}$, $SC_i^{LL\to HL}$, $SC_i^{HH\to LH}$, $SC_i^{HL\to LH}$,$SC_i^{LL\to LH}$, $SC_i^{HH\to LL}$, $SC_i^{HL\to LL}$,$SC_i^{LH\to LL}$]'.

Under R1-2 there are three dynamic parameters to identify for each player, that is $SC_i^{HH\to LL}$, $SC_i^{HH\to HL}$ whereas R3 reduces this number to just two. With an arbitrary number of actions, $|\mathcal{A}_i|$ initially there are $|\mathcal{A}_i| \cdot (|\mathcal{A}_i| - 1)$ possible adjustment costs, $(|\mathcal{A}_i| - 1)$ under R1-2 and $|\mathcal{J}_i|$ under R1-3.

Identification

As previously, we take HH to be the reference action, so that: $\Delta\bar{v}_i(\ell, \mathbf{a}_{-it}, \mathbf{s}_{t-1}) \equiv \bar{v}_i(\ell, \mathbf{a}_{-it}, \mathbf{s}_{t-1}) - \bar{v}_i(HH, \mathbf{a}_{-it}, \mathbf{s}_{t-1})$. The reason why we use HH is that thanks to R1, no cost is ever incurred in period t if $a_{it} = HH$. Therefore, for player a we have:

$$\Delta\bar{v}_a(\ell, \mathbf{a}_{-it}, \mathbf{s}_{t-1}) = \sum_{\mathbf{a}_{bt}\in\mathcal{A}_b} \Pr_b(\mathbf{a}_{bt}|\mathbf{a}_{t-1}, \mathbf{s}_{t-1})\lambda_a(\ell, \mathbf{a}_{bt}, \mathbf{s}_{t-1}) + SC_a^{\ell'\to\ell} \cdot \mathbf{1}(a_{i,t-1} = \ell') \tag{19}$$

where $\lambda_a(\cdot)$ is defined as in (12). What remains to be verified is that the matrix of zeros and ones resulting from stacking the expressions (19) for all actions of player a and all possible values of the state variables is indeed of full rank and does not contain a column of ones.

To show this, we invoke lemma 5 in Komarova et al. (2018) and write the expression for one possible realisation of lagged market shares, $\mathbf{s}_{t-1}$:

$$\boldsymbol{\Delta}\bar{\mathbf{v}}_a(\mathbf{s}_{t-1}) = (I_{|\mathcal{A}_a|-1} \otimes \mathbf{Z}_a(\mathbf{s}_{t-1}))\boldsymbol{\lambda}_a(\mathbf{s}_{t-1}) + \widetilde{\mathbf{D}}_a(\mathbf{s}_{t-1})\mathbf{SC}_a \tag{20}$$

where:

- $\boldsymbol{\Delta}\bar{\mathbf{v}}_a(\mathbf{s}_{t-1}) = \left\{\Delta\bar{v}_a(a_{at}, \mathbf{a}_{t-1}, \mathbf{s}_{t-1})\right\}_{a_{at}\in\mathcal{A}_a\setminus\{HH\}}^{\mathbf{a}_{t-1}\in\mathcal{A}_a\times\mathcal{A}_b}$ is a $(|\mathcal{A}_a|-1)\cdot|\mathcal{A}_a|\cdot|\mathcal{A}_b|\times 1$ vector,
- $\mathbf{Z}_a(\mathbf{s}_{t-1}) = \{\Pr_b(a_{bt}|\mathbf{a}_{t-1}, \mathbf{s}_{t-1})\}_{(a_{bt},\mathbf{a}_{t-1})\in\mathcal{A}_b\times(\mathcal{A}_a\times\mathcal{A}_b)}$ is a $|\mathcal{A}_a|\cdot|\mathcal{A}_b|\times|\mathcal{A}_b|$ matrix,
- $\boldsymbol{\lambda}_a(\mathbf{s}_{t-1}) = \{\lambda_a(a_{at}, a_{bt}, \mathbf{s}_{t-1})\}_{(a_{at},a_{bt})\in(\mathcal{A}_a\setminus\{HH\},\mathcal{A}_b)}$ is a $(|\mathcal{A}_a|-1)\cdot|\mathcal{A}_b|\times 1$ vector,
- $\widetilde{\mathbf{D}}_a(\mathbf{s}_{t-1})$ is a $(|\mathcal{A}_a|-1)\cdot|\mathcal{A}_a|\cdot|\mathcal{A}_{-b}|\times\kappa$ matrix,
- $\mathbf{SC}_a$ is a $\kappa\times 1$ vector of parameters to identify.

To show the content of the objects in (20) we rewrite it as (21). For the sake of brevity, $\mathbf{s}_{t-1}$ was dropped from the notation. We can immediately see from there that $\widetilde{\mathbf{D}}_a(\mathbf{s}_{t-1})$ satisfies the rank condition. Imposing R3 only changes the last component of the sum on the RHS of (21), so that it becomes:

$$\widetilde{\mathbf{D}}_a(\mathbf{s}_{t-1})\mathbf{SC}_a = \left[\begin{array}{cc} 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ \hdashline 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ \hdashline 1 & 1 \\ 1 & 1 \\ 1 & 1 \\ 1 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{array}\right] \left[\begin{array}{c} SC_a^{HH\to HL} \\ SC_a^{HH\to LH} \end{array}\right]$$

To arrive at (16) we vertically stack the vectors and matrices in (20) for all possible combinations of $\mathbf{s}_{t-1}$. But since $\widetilde{\mathbf{D}}_a(\mathbf{s}_{t-1})$ does not vary across $\mathbf{s}_{t-1}$, then $\widetilde{\mathbf{D}}_a = \mathbf{j} \otimes \widetilde{\mathbf{D}}_a(\mathbf{s}_{t-1})$, where $\mathbf{j}$ is a column vector of ones whose dimension is equal to the cardinality of $\mathbf{s}_{t-1}$.

We can now directly use the identifying correspondence (18) to recover the costs.

$$
\begin{bmatrix}
\Delta\bar{v}_a(HL,(HH,HH))\\
\Delta\bar{v}_a(HL,(HH,HL))\\
\Delta\bar{v}_a(HL,(HH,LH))\\
\Delta\bar{v}_a(HL,(HH,LL))\\
\Delta\bar{v}_a(HL,(HL,HH))\\
\Delta\bar{v}_a(HL,(HL,HL))\\
\Delta\bar{v}_a(HL,(HL,LH))\\
\Delta\bar{v}_a(HL,(HL,LL))\\
\Delta\bar{v}_a(HL,(LH,HH))\\
\Delta\bar{v}_a(HL,(LH,HL))\\
\Delta\bar{v}_a(HL,(LH,LH))\\
\Delta\bar{v}_a(HL,(LH,LL))\\
\Delta\bar{v}_a(HL,(LL,HH))\\
\Delta\bar{v}_a(HL,(LL,HL))\\
\Delta\bar{v}_a(HL,(LL,LH))\\
\Delta\bar{v}_a(HL,(LL,LL))\\
\hdashline
\Delta\bar{v}_a(LH,(HH,HH))\\
\Delta\bar{v}_a(LH,(HH,HL))\\
\Delta\bar{v}_a(LH,(HH,LH))\\
\Delta\bar{v}_a(LH,(HH,LL))\\
\Delta\bar{v}_a(LH,(HL,HH))\\
\Delta\bar{v}_a(LH,(HL,HL))\\
\Delta\bar{v}_a(LH,(HL,LH))\\
\Delta\bar{v}_a(LH,(HL,LL))\\
\Delta\bar{v}_a(LH,(LH,HH))\\
\Delta\bar{v}_a(LH,(LH,HL))\\
\Delta\bar{v}_a(LH,(LH,LH))\\
\Delta\bar{v}_a(LH,(LH,LL))\\
\Delta\bar{v}_a(LH,(LL,HH))\\
\Delta\bar{v}_a(LH,(LL,HL))\\
\Delta\bar{v}_a(LH,(LL,LH))\\
\Delta\bar{v}_a(LH,(LL,LL))\\
\hdashline
\Delta\bar{v}_a(LL,(HH,HH))\\
\Delta\bar{v}_a(LL,(HH,HL))\\
\Delta\bar{v}_a(LL,(HH,LH))\\
\Delta\bar{v}_a(LL,(HH,LL))\\
\Delta\bar{v}_a(LL,(HL,HH))\\
\Delta\bar{v}_a(LL,(HL,HL))\\
\Delta\bar{v}_a(LL,(HL,LH))\\
\Delta\bar{v}_a(LL,(HL,LL))\\
\Delta\bar{v}_a(LL,(LH,HH))\\
\Delta\bar{v}_a(LL,(LH,HL))\\
\Delta\bar{v}_a(LL,(LH,LH))\\
\Delta\bar{v}_a(LL,(LH,LL))\\
\Delta\bar{v}_a(LL,(LL,HH))\\
\Delta\bar{v}_a(LL,(LL,HL))\\
\Delta\bar{v}_a(LL,(LL,LH))\\
\Delta\bar{v}_a({\color{red}LL},({\color{blue}LL},{\color{green}LL}))
\end{bmatrix}
=
\left(
\begin{bmatrix}1&0&0\\0&1&0\\0&0&1\end{bmatrix}
\otimes
\begin{bmatrix}
\Pr_b(HH|(HH,HH)) & \Pr_b(HL|(HH,HH)) & \Pr_b(LH|(HH,HH)) & \Pr_b(LL|(HH,HH))\\
\Pr_b(HH|(HH,HL)) & \Pr_b(HL|(HH,HL)) & \Pr_b(LH|(HH,HL)) & \Pr_b(LL|(HH,HL))\\
\Pr_b(HH|(HH,LH)) & \Pr_b(HL|(HH,LH)) & \Pr_b(LH|(HH,LH)) & \Pr_b(LL|(HH,LH))\\
\Pr_b(HH|(HH,LL)) & \Pr_b(HL|(HH,LL)) & \Pr_b(LH|(HH,LL)) & \Pr_b(LL|(HH,LL))\\
\Pr_b(HH|(HL,HH)) & \Pr_b(HL|(HL,HH)) & \Pr_b(LH|(HL,HH)) & \Pr_b(LL|(HL,HH))\\
\Pr_b(HH|(HL,HL)) & \Pr_b(HL|(HL,HL)) & \Pr_b(LH|(HL,HL)) & \Pr_b(LL|(HL,HL))\\
\Pr_b(HH|(HL,LH)) & \Pr_b(HL|(HL,LH)) & \Pr_b(LH|(HL,LH)) & \Pr_b(LL|(HL,LH))\\
\Pr_b(HH|(HL,LL)) & \Pr_b(HL|(HL,LL)) & \Pr_b(LH|(HL,LL)) & \Pr_b(LL|(HL,LL))\\
\Pr_b(HH|(LH,HH)) & \Pr_b(HL|(LH,HH)) & \Pr_b(LH|(LH,HH)) & \Pr_b(LL|(LH,HH))\\
\Pr_b(HH|(LH,HL)) & \Pr_b(HL|(LH,HL)) & \Pr_b(LH|(LH,HL)) & \Pr_b(LL|(LH,HL))\\
\Pr_b(HH|(LH,LH)) & \Pr_b(HL|(LH,LH)) & \Pr_b(LH|(LH,LH)) & \Pr_b(LL|(LH,LH))\\
\Pr_b(HH|(LH,LL)) & \Pr_b(HL|(LH,LL)) & \Pr_b(LH|(LH,LL)) & \Pr_b(LL|(LH,LL))\\
\Pr_b(HH|(LL,HH)) & \Pr_b(HL|(LL,HH)) & \Pr_b(LH|(LL,HH)) & \Pr_b(LL|(LL,HH))\\
\Pr_b(HH|(LL,HL)) & \Pr_b(HL|(LL,HL)) & \Pr_b(LH|(LL,HL)) & \Pr_b(LL|(LL,HL))\\
\Pr_b(HH|(LL,LH)) & \Pr_b(HL|(LL,LH)) & \Pr_b(LH|(LL,LH)) & \Pr_b(LL|(LL,LH))\\
\Pr_b(HH|(LL,LL)) & \Pr_b(HL|(LL,LL)) & \Pr_b(LH|(LL,LL)) & \Pr_b(LL|(LL,LL))
\end{bmatrix}
\right)
\begin{bmatrix}
\lambda_a(HL,HH)\\
\lambda_a(HL,HL)\\
\lambda_a(HL,LH)\\
\lambda_a(HL,LL)\\
\lambda_a(LH,HH)\\
\lambda_a(LH,HL)\\
\lambda_a(LH,LH)\\
\lambda_a(LH,LL)\\
\lambda_a(LL,HH)\\
\lambda_a(LL,HL)\\
\lambda_a(LL,LH)\\
\lambda_a(LL,LL)
\end{bmatrix}
+
\begin{bmatrix}
1&0&0\\
1&0&0\\
1&0&0\\
1&0&0\\
0&0&0\\
0&0&0\\
0&0&0\\
0&0&0\\
1&0&0\\
1&0&0\\
1&0&0\\
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0&0&0\\
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1&0&0\\
1&0&0\\
1&0&0\\
1&0&0\\
0&0&0\\
0&0&0\\
0&0&0\\
0&0&0
\end{bmatrix}
\begin{bmatrix}
SC_a^{HH\to HL}\\
SC_a^{HH\to LH}\\
SC_a^{HH\to LL}
\end{bmatrix}
\tag{21}
$$

Explanation: a's action this period, a's action last period, b's action last period.

Appendix B3: Discount factor and value function

To estimate the discount factor and subsequently to solve the model we have to compute the value functions associated with each element of the state space. Because our state space is large and some state variables are continuous it is impossible to compute the value function for each state. Likewise we compute the value function for each of the $T = 200$ observed states (for each firm in each supermarket) assuming that value functions can be approximated by a linear function of functions of state variables. The same approach has been used in Sweeting (2013), Barwick and Pathak (2015) and Fowlie et al. (2016). Next we discuss the procedures used to estimate the discount factor.
Using the fact the state transitions in our model are deterministic – see equation (9) – we can write the *ex ante* value function in problem (3) as:

$$V_i\left(\mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right) = \sum_{\mathbf{a_t} \in \mathcal{A}_i} \sigma_i\left(\mathbf{a_t}|\mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right) \left\{\tilde{\Pi}_i\left(\mathbf{a_t}, \mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right) + \beta V_i\left(\mathbf{a_t}, \mathbf{s}\left(\mathbf{a_t}, \mathbf{s_{t-1}}\right)\right)\right\}, \tag{22}$$

where $V_i(\mathbf{z}_{t+1}) = \int V_i(\mathbf{z}_{t+1}, \varepsilon_{t+1}) dQ(\varepsilon_{i,t+1})$ and $\tilde{\Pi}_i\left(\mathbf{a_t}, \mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right)$ is the (conditional) expectation of the payoff function $\Pi_i\left(\mathbf{a_t}, \mathbf{a_{t-1}}, \mathbf{s_{t-1}}, \varepsilon_{it}\left(a_{it}\right)\right)$ with respect to ε_{it} when states are $\left(\mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right)$ and current actions are $\mathbf{a_t}$, and $\mathbf{s}\left(\mathbf{a_t}, \mathbf{s_{t-1}}\right)$ is the vector of current shares – implied by equation (9) – when past shares are $\mathbf{s_{t-1}}$ and current actions are $\mathbf{a_t}$. As in Sweeting (2013) we approximate $V_i(\mathbf{z}_t)$ using the following parametric function:

$$V_i(\mathbf{z_t}) \simeq \sum_{k=1}^{K} \lambda_{ki} \phi_{ki}\left(\mathbf{z_t}\right) \equiv \Phi_i\left(\mathbf{z_t}\right) \lambda_\mathbf{i}, \tag{23}$$

where λ_{ki} is a coefficient and $\phi_{ki}\left(\cdot\right)$ is a well-defined function mapping the state vector into the set of real numbers. In our case, $\phi_{ki}\left(\cdot\right)$ are flexible functions of shares and prices of the firms. In practice, the variables we use to approximate the value functions include (i) (past) actions of all firms, (ii) second order polynomials of (past) shares of all products, (iii) interactions between (past) actions and shares of the different products and (iv) second order polynomials of the interactions between (past) actions and shares. We experimented with third and fourth order polynomials of shares and interactions between shares and actions but the results did not change significantly.
Notice that under this formulation solving for the value function requires that one computes only K parameters (λ_{ki}'s) for each manufacturer. By substituting this equation into the *ex ante* value function we can solve for $\lambda_\mathbf{i} = [\lambda_{1i}\, \lambda_{2i} \ldots \lambda_{Ki}]'$ in closed-form as a function of the primitives of the model, states and beliefs. Substituting (23) into (22) we get:

$$\Phi_i\left(\mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right) \lambda_\mathbf{i} = \sum_{\mathbf{a_t} \in \mathcal{A}} \sigma_i\left(\mathbf{a_t}|\mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right) \left\{\tilde{\Pi}_i\left(\mathbf{a_t}, \mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right) + \beta \Phi_i\left(\mathbf{a_t}, \mathbf{s}\left(\mathbf{a_t}, \mathbf{s_{t-1}}\right)\right) \lambda_\mathbf{i}\right\}.$$

To simplify the notation let $\tilde{\Pi}_i^*\left(\mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right)$ and $\Phi_i^*\left(\mathbf{s_{t-1}}\right)$ be the conditional expectations of $\tilde{\Pi}_i\left(\mathbf{a_t}, \mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right)$ and of $\Phi_i\left(\mathbf{a_t}, \mathbf{s}\left(\mathbf{a_t}, \mathbf{s_{t-1}}\right)\right)$ with respect to current actions, respectively. Therefore, we can rewrite equation above as:

$$\left(\Phi_i\left(\mathbf{a_{t-1}},\mathbf{s_{t-1}}\right) - \beta\Phi_i^*\left(\mathbf{s_{t-1}}\right)\right)\lambda_\mathbf{i} = \tilde{\Pi}_i^*\left(\mathbf{a_{t-1}},\mathbf{s_{t-1}}\right).$$

Stacking this equation for every possible state in S we have that:

$$\left(\Phi_i - \beta\Phi_i^*\right)\lambda_\mathbf{i} = \tilde{\Pi}_i^*,$$

where Φ_i and Φ_i^* are $N_s \times K$ matrices that depend on states and beliefs and $\tilde{\Pi}_i^*$ is a $N_s \times 1$ vector of expected profits that depends on state, beliefs and parameters, N_s being the number of states observed in the data. Assuming $K < N_s$, this expression can be rewritten as:

$$\lambda_\mathbf{i} = \left[\left(\Phi_i - \beta\Phi_i^*\right)'\left(\Phi_i - \beta\Phi_i^*\right)\right]^{-1}\left[\left(\Phi_i - \beta\Phi_i^*\right)'\tilde{\Pi}_i^*\right]. \tag{24}$$

Inserting (24) into (23) we obtain the unconditional value functions associated to problem (3); given the logit assumption on ε_{it} we can calculate the probability of each action solving problem (3). Having estimated adjustment costs outside of the dynamic model and having calibrated H and marginal costs, the only parameter to be estimated inside the dynamic model is the discount factor. We do this by choosing the discount factor that minimises the difference between estimated action probabilities and the probabilities implied by the structural model, which are defined based on the approximation explained above (see Komarova et al. (2018)).

Appendix B4: Model solution

To solve the model we use an algorithm similar to that described in Sweeting (2013). The algorithm works as follows:

1. In step s we calculate $\lambda\left(\sigma^s\right)$ as a function of the vector of beliefs, σ^s, substituting equation (23) into the *ex-ante* value function and solving for $\lambda = [\lambda_1\,\lambda_2\ldots\lambda_k]$ in closed-form as a function of the primitives of the model, states and beliefs;
2. We use $\lambda\left(\sigma^s\right)$ to calculate choice specific value functions for each of the selected states and the multinomial logit formula implied by the model to update the vector of beliefs, $\tilde{\sigma}$;
3. If the value of the euclidian norm $\|\sigma^s - \tilde{\sigma}\|$ is sufficiently small we stop the procedure and save $\tilde{\sigma}$ as the equilibrium vector of probabilities implied by the model, $\tilde{\sigma} = \sigma^*$; if $\|\sigma^s - \tilde{\sigma}\|$ is larger than the tolerance we update $\sigma^{s+1} = \psi\tilde{\sigma} + (1-\psi)\,\sigma^s$, where ψ is a number between 0 and 1, and restart the procedure.

The tolerance used on $\|\sigma^s - \tilde{\sigma}\|$ was 10^{-3} and the value of ψ used to update σ^s to σ^{s+1} was 0.5. We have made several attempts using lower values for the tolerance on $\|\sigma^s - \tilde{\sigma}\|$ and for ψ. All these attempts generated very similar equilibrium probabilities, but the time to achieve convergence was larger. The initial guess used to start the algorithm, σ^0, is equal to the estimated CCPs evaluated at the corresponding state. To check the robustness of our results to changes in the initial guess we changed arbitrarily the original initial guess multiplying it by several factors between 0 and 1. For all our attempts the resulting equilibrium vector of probabilities was the same.

For the counterfactuals we have to simulate the model for states that are not observed in the data – i.e. we need estimates of σ^* for states that are not in the data. To do this we assumed that the solution of the model, σ^*, for the relevant counterfactual scenario is a logistic function of a linear index of states – i.e. the same function that we used to compute the CCPs. Mathematically, let $\sigma_i^*\left(a_i = k|\mathbf{z}\right)$ be the probability that firm i plays $a_i = k$ when the state vector is $\mathbf{z}$. We assume that:

$$\sigma_i^*\left(a_i = k|\mathbf{z}\right) = \frac{\exp\left(\mathbf{z}'\gamma_k\right)}{\sum_{k'}\exp\left(\mathbf{z}'\gamma_{k'}\right)}. \tag{25}$$

Dividing it by the probability of an anchor choice, say $a_i = HH$, normalising $\gamma_1 = 0$ and taking logs we have $\ln\left\{\sigma_i^*\left(a_i = k|\mathbf{z}\right)\right\} - \ln\left\{\sigma_i^*\left(a_i = 1|\mathbf{z}\right)\right\} = \mathbf{z}'\gamma_k$. Then the vector of parameters γ_k can be estimated by OLS – one OLS equation is estimated for each $a_i = k$, $k \neq HH$.

The probability function (25) and the Markovian transitions for actions and shares are used to simulate moments implied by the model. Starting from the initial state vector for each firm in each supermarket we forward simulate 1000 paths of 200 periods of actions and shares and computed profits for each period by averaging period profits for each path.

Appendix C: Additional tables and figures

Table 9: Consumer switching patterns for purchases made in two subsequent weeks.

Purchase at t	**Purchase at $t+1$**						
	ANC	LUR	CLO	COU	FLO	ICB	SB
ANCHOR	73.59%	6.62%	2.71%	5.21%	6.34%	2.56%	2.97%
LURPAK	3.64%	80.27%	1.52%	3.52%	5.43%	2.21%	3.41%
CLOVER	2.05%	2.93%	73.83%	1.97%	8.92%	5.48%	4.82%
COUNTRY LIFE	6.74%	9.18%	3.27%	68.40%	5.61%	3.19%	3.61%
FLORA	2.55%	4.24%	4.39%	1.79%	75.08%	6.58%	5.37%
ICBINB	1.71%	2.70%	3.85%	1.44%	10.37%	72.14%	7.79%
STORE BRAND	2.13%	4.79%	4.15%	1.80%	8.93%	8.99%	69.20%

Note: Frequencies based on a sample of 126,508 individual purchases between 01/2009 and 10/2012. Store brand here is a composite generic good including Asda, Morrisons, Sainsbury's and Tesco own brand products. The highlighted entries on the diagonal denote the percentage of loyalty-driven purchases.

Table 10: Consumer switching patterns

Purchase at t	**Subsequent purchase**						
	ANC	LUR	CLO	COU	FLO	ICB	SB
ANCHOR	62.82%	9.22%	4.02%	7.22%	8.23%	3.92%	4.57%
LURPAK	4.49%	74.26%	2.21%	4.31%	6.98%	3.09%	4.66%
CLOVER	2.83%	3.63%	58.98%	2.42%	14.59%	10.05%	7.50%
COUNTRY LIFE	9.71%	12.51%	4.88%	54.25%	8.02%	4.83%	5.80%
FLORA	2.80%	4.72%	6.19%	1.96%	65.47%	10.36%	8.50%
ICBINB	2.12%	3.26%	6.31%	1.72%	17.08%	56.90%	12.61%
STORE BRAND	2.16%	4.70%	5.17%	2.01%	11.93%	12.15%	61.89%

Note: Frequencies based on a sample of 569,338 individual purchases between 01/2009 and 10/2012. Store brand here is a composite generic good including Asda, Morrisons, Sainsbury's and Tesco own brand products. The highlighted entries on the diagonal denote the percentage of loyalty-driven purchases.

Table 11: Frequency of price changes.

	Mean	Std. Dev.	%(1)	%(2)
		Asda		
Arla	0.347	0.527	29.65%	2.51%
Dairy Crest	0.357	0.521	31.66%	2.01%
Unilever	0.271	0.493	22.65%	2.21%
		Morrisons		
Arla	0.412	0.560	34.17%	3.52%
Dairy Crest	0.342	0.545	27.14%	2.01%
Unilever	0.277	0.461	26.55%	0.56%
		Sainsbury's		
Arla	0.472	0.687	25.13%	11.06%
Dairy Crest	0.317	0.591	18.59%	6.53%
Unilever	0.281	0.483	25.13%	1.51%
		Tesco		
Arla	0.533	0.695	30.15%	11.56%
Dairy Crest	0.437	0.631	28.64%	7.54%
Unilever	0.469	0.673	26.77%	10.10%

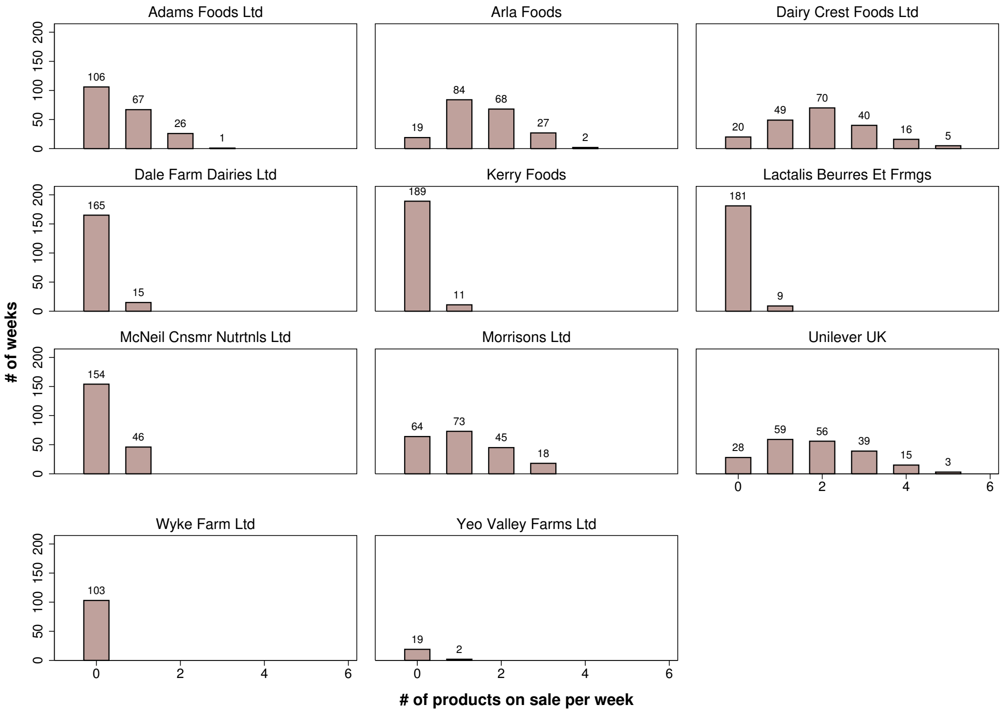
Note: Table presents average number of per-firm weekly price changes (without specifying direction) in each of the supermarket chains. Fourth and fifth column show the percentage of weeks with 1 and 2 price changes, respectively.

Table 12: Annual market shares by manufacturer and product for selected products in the 500g spreadable segment.

	Year				
PRODUCTS BY MANUFACTURER	2009	2010	2011	2012	2009-2012
ASDA					
Asda Store Brand	**10.0%**	**9.3%**	**6.4%**	**5.8%**	**7.7%**
Arla	**35.6%**	**42.3%**	**39.5%**	**50.6%**	**42.1%**
ANCHOR	10.7%	11.0%	10.8%	13.9%	11.6%
LURPAK	24.9%	31.3%	28.7%	36.7%	30.5%
Dairy Crest	**21.0%**	**14.9%**	**16.6%**	**21.3%**	**18.3%**
CLOVER	6.4%	6.6%	7.2%	11.3%	7.9%
COUNTRY LIFE	14.6%	8.3%	9.4%	10.0%	10.4%
Unilever	**33.4%**	**33.5%**	**37.5%**	**22.3%**	**31.8%**
FLORA	16.4%	14.1%	15.2%	21.6%	16.8%
ICBINB	17.1%	19.5%	22.2%	0.7%	15.0%
MORRISONS					
Morrisons Store Brand	**9.9%**	**11.3%**	**9.0%**	**5.9%**	**9.0%**
Arla	**35.2%**	**36.2%**	**35.8%**	**37.0%**	**36.0%**
ANCHOR	9.2%	8.8%	8.4%	10.1%	9.1%
LURPAK	26.0%	27.4%	27.3%	26.9%	26.9%
Dairy Crest	**20.2%**	**18.3%**	**21.8%**	**23.3%**	**21.0%**
CLOVER	12.0%	13.5%	14.2%	14.8%	13.7%
COUNTRY LIFE	8.2%	4.8%	7.5%	8.6%	7.3%
Unilever	**34.7%**	**34.2%**	**33.4%**	**33.7%**	**34.0%**
FLORA	26.9%	22.4%	21.6%	24.6%	23.8%
ICBINB	7.8%	11.8%	11.8%	9.1%	10.2%
SAINSBURY'S					
Sainsbury's Store Brand	**15.2%**	**16.4%**	**17.4%**	**14.9%**	**16.1%**
Arla	**35.3%**	**38.3%**	**37.3%**	**40.3%**	**37.9%**
ANCHOR	13.5%	14.3%	12.8%	14.1%	13.6%
LURPAK	21.9%	24.0%	24.5%	26.3%	24.3%
Dairy Crest	**17.5%**	**15.6%**	**19.5%**	**19.2%**	**18.0%**
CLOVER	8.1%	9.3%	11.2%	11.4%	10.1%
COUNTRY LIFE	9.3%	6.3%	8.3%	7.8%	7.9%
Unilever	**32.0%**	**29.6%**	**25.8%**	**25.6%**	**28.0%**
FLORA	21.5%	19.5%	15.9%	17.7%	18.5%
ICBINB	10.5%	10.1%	9.9%	7.8%	9.5%
TESCO					
Tesco Store Brand	**17.7%**	**12.9%**	**15.5%**	**13.5%**	**14.9%**
Arla	**33.8%**	**40.2%**	**40.0%**	**39.0%**	**38.4%**
ANCHOR	10.3%	13.7%	12.7%	11.2%	12.0%
LURPAK	23.6%	26.5%	27.3%	27.8%	26.4%
Dairy Crest	**16.1%**	**16.7%**	**16.6%**	**17.2%**	**16.6%**
CLOVER	9.1%	10.0%	9.3%	10.6%	9.7%
COUNTRY LIFE	7.0%	6.7%	7.3%	6.6%	6.9%
Unilever	**32.4%**	**30.2%**	**28.0%**	**30.4%**	**30.1%**
FLORA	24.3%	19.8%	16.1%	22.2%	20.4%
ICBINB	8.0%	10.4%	11.9%	8.1%	9.7%

Note: Calculations based on a subsample of products used to estimate the dynamic game. Source: own calculation using Kantar Worldpanel data.

Figure 2: Histograms of the number of products on sale by firm.



Note: Figure constructed using the universe of all 500g spreadable products by recording the promotional flags for each of the products. E.g. for Arla there were 19 weeks with no product on sale, 84 weeks with 1 brand on sale, 68 weeks with 2 brands on sale etc. If the numbers do not sum to 200 for certain manufacturers it is an indication that we did not observe any purchases their brands in the data in all weeks.

Table 13: Price levels.

	Means		Medians		Min/Max	
Products by manufacturer	p_H	p_L	p_H	p_L	p_H	p_L
Asda						
Asda Store Brand	1.02		1.00			
Arla						
Anchor	2.51	1.82	2.60	2.00	2.90	1.00
Lurpak	2.63	2.10	2.58	2.00	2.98	1.50
Dairy Crest						
Clover	1.73	1.30	1.75	1.38	2.00	1.00
Country Life	2.42	1.85	2.39	2.00	2.68	1.00
Unilever						
Flora	1.40	1.00	1.38	1.00	1.70	0.83
ICBINB	1.22	1.09	1.24	1.00	1.45	0.50
Morrisons						
Morrisons Store Brand	1.09		1.08			
Arla						
Anchor	2.55	1.92	2.60	2.00	2.90	1.50
Lurpak	2.71	2.11	2.80	2.00	3.00	1.50
Dairy Crest						
Clover	1.75	1.15	1.75	1.00	2.00	0.70
Country Life	2.45	1.83	2.39	2.00	2.85	1.10
Unilever						
Flora	1.47	0.94	1.40	1.00	1.70	0.70
ICBINB	1.21	0.82	1.25	1.00	1.45	0.50
Sainsbury's						
Sainsbury's Store Brand	1.13		1.10			
Arla						
Anchor	2.58	2.03	2.60	2.00	3.00	1.50
Lurpak	2.71	2.17	2.80	2.00	3.00	1.50
Dairy Crest						
Clover	1.75	1.22	1.75	1.00	2.00	0.85
Country Life	2.47	1.89	2.48	2.00	2.85	1.00
Unilever						
Flora	1.48	0.96	1.49	1.00	1.70	0.75
ICBINB	1.27	0.79	1.25	1.00	1.80	0.54
Tesco						
Tesco Store Brand	1.02		1.00			
Arla						
Anchor	2.59	1.84	2.60	2.00	2.90	1.00
Lurpak	2.73	1.95	2.80	2.00	2.98	1.40
Dairy Crest						
Clover	1.74	1.18	1.75	1.00	2.00	0.75
Country Life	2.42	1.76	2.40	2.00	2.85	1.10
Unilever						
Flora	1.49	1.01	1.46	1.00	1.70	0.75
ICBINB	1.24	0.88	1.24	1.00	1.80	0.54

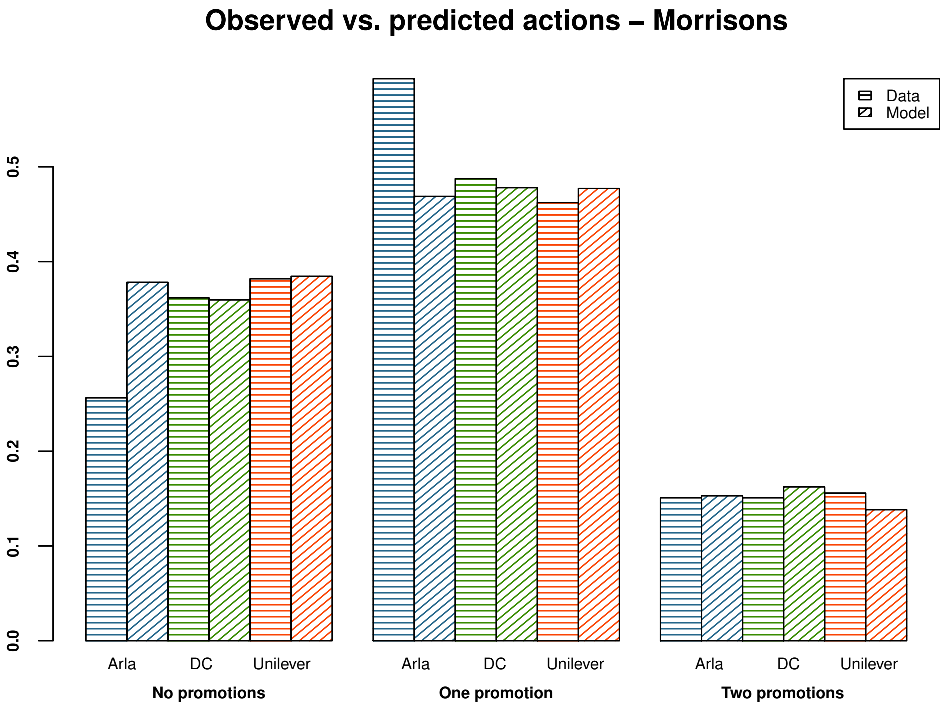
Note: All prices given in GBP. First four columns show prices calculated as 200-week averages/medians conditional on promotional status. For store brand there are no price promotions, so it is an unconditional mean/median. Prices in the last two columns are calculated as highest/lowest price observed in the sample period conditional on sale/no sale.

Table 14: Multinomial logit CCP estimates.

	Arla			Dairy Crest			Unilever		
	HL	LH	LL	HL	LH	LL	HL	LH	LL
$\mathbf{a}_{t-1}$									
Arla: HL	2.064***	0.592*	2.091***	-0.679	0.116	0.228	-0.001	0.333	-0.051
	(0.08)	(0.32)	(0.35)	(0.61)	(0.24)	(0.46)	(0.14)	(0.71)	(0.73)
Arla: LH	-0.032	2.385***	2.450***	-0.398	-0.452	-0.466	-0.232	0.495	-0.070
	(0.32)	(0.29)	(0.46)	(0.54)	(0.37)	(0.45)	(0.37)	(0.78)	(0.95)
Arla: LL	2.869***	3.018***	5.031***	0.124	-0.728	-0.219	-0.148	0.635	-0.059
	(0.83)	(0.65)	(0.79)	(0.46)	(0.56)	(0.70)	(0.32)	(0.64)	(0.58)
DC: HL	0.633	-0.107	-0.308	3.283***	0.805	2.668***	0.120	-0.005	-0.620
	(0.49)	(0.25)	(0.35)	(0.34)	(0.56)	(0.32)	(0.13)	(0.46)	(0.40)
DC: LH	0.133	-0.403	-0.087	0.846	2.732***	2.074***	0.146	-0.339	-0.720*
	(0.28)	(0.31)	(0.30)	(0.55)	(0.45)	(0.30)	(0.21)	(0.54)	(0.40)
DC: LL	-0.205	-0.569	-1.062**	2.312***	2.780***	4.387***	0.035	-0.221	-0.999
	(0.20)	(0.41)	(0.52)	(0.53)	(0.57)	(0.61)	(0.20)	(0.45)	(0.69)
Unilever: HL	-0.082	0.129	0.323*	-0.072	0.340	-0.948***	2.512***	-0.059	1.752***
	(0.27)	(0.15)	(0.19)	(0.35)	(0.38)	(0.35)	(0.28)	(0.87)	(0.28)
Unilever: LH	-0.313	-0.068	0.474*	0.087	-0.379	-0.404	0.583	3.023***	3.037***
	(0.58)	(0.28)	(0.27)	(0.26)	(0.39)	(0.40)	(0.40)	(0.15)	(0.23)
Unilever: LL	-0.812*	-0.122	-0.055	-0.548*	-0.077	-0.613	2.034*	1.487**	4.261***
	(0.48)	(0.11)	(0.59)	(0.32)	(0.42)	(0.51)	(1.14)	(0.59)	(0.83)
$\mathbf{s}_{t-1}$									
ANCHOR	46.893**	40.588	58.726	14.085	-14.866	-20.447**	-5.319	0.058	44.926*
	(18.32)	(32.63)	(37.59)	(25.40)	(17.11)	(9.74)	(19.72)	(24.10)	(26.81)
LURPAK	39.537***	19.496	19.526**	2.885	33.039***	19.656*	12.349	14.877*	33.932***
	(14.93)	(13.72)	(8.34)	(11.76)	(6.75)	(10.25)	(19.99)	(8.21)	(10.48)
CLOVER	-15.452*	5.741	10.781	8.741**	-12.049***	12.354*	-5.322	4.464	-4.045
	(8.95)	(5.75)	(6.90)	(4.28)	(4.59)	(6.58)	(6.03)	(3.40)	(6.78)
COUNTRY LIFE	-25.289***	6.071	-2.554	28.405*	28.989	42.215*	-57.456***	5.898	42.557**
	(7.41)	(11.71)	(17.65)	(16.15)	(21.78)	(22.18)	(6.57)	(15.09)	(20.47)
FLORA	3.161	3.139	2.408	-3.202	-13.367***	2.528	6.453	3.976	9.420*
	(4.54)	(5.75)	(3.84)	(6.58)	(4.69)	(8.63)	(5.80)	(9.42)	(5.67)
ICBINB	0.305	-4.137*	-1.185	-3.324	3.058	3.853	4.523	12.564***	13.773***
	(5.44)	(2.42)	(2.91)	(3.75)	(6.31)	(2.96)	(5.63)	(1.65)	(2.73)
STORE BRAND	-1.132	-2.270	-18.353	-6.775	-4.959	1.167	-2.047	-22.016***	-25.182***
	(6.05)	(8.26)	(14.07)	(15.52)	(4.18)	(10.09)	(5.64)	(7.62)	(8.39)
MORRISONS	-0.181	-0.519***	-0.457**	0.589***	-0.094	0.122	0.723***	-0.579***	-0.001
	(0.13)	(0.17)	(0.22)	(0.20)	(0.17)	(0.22)	(0.11)	(0.09)	(0.13)
SAINSBURY'S	-0.289*	-0.905**	-1.754***	0.223	-0.607**	-1.109***	0.707**	-0.574	-1.828***
	(0.17)	(0.38)	(0.61)	(0.45)	(0.29)	(0.33)	(0.29)	(0.48)	(0.52)
TESCO	1.135***	0.532	0.921**	0.509	-0.249*	0.184	1.086*	0.109	0.687***
	(0.18)	(0.37)	(0.42)	(0.42)	(0.13)	(0.34)	(0.20)	(0.34)	(0.20)
Constant	-2.042***	-1.223**	-3.031***	-2.114***	-1.155***	-3.488***	-2.303***	-1.712***	-4.349***
	(0.56)	(0.62)	(0.56)	(0.80)	(0.41)	(0.41)	(0.37)	(0.43)	(1.09)

Note: For all 3 players (Arla, Dairy Crest, Unilever) HH is the reference action. H stands for high and L low price, for the two products each firm is selling. Arla: Anchor and Lurpak, Dairy Crest: Clover and Country Life, Unilever: Flora and I Can't Believe It's Not Butter (ICBINB). Last panel of the table shows supermarket fixed effects to reflect the fact that different equilibrium strategies can be played in different markets. Asda is the reference market there. $N = 703$. Significance levels: *** 1%, ** 5%, * 10%.

Figure 3: Actions played by firms: model vs. data.



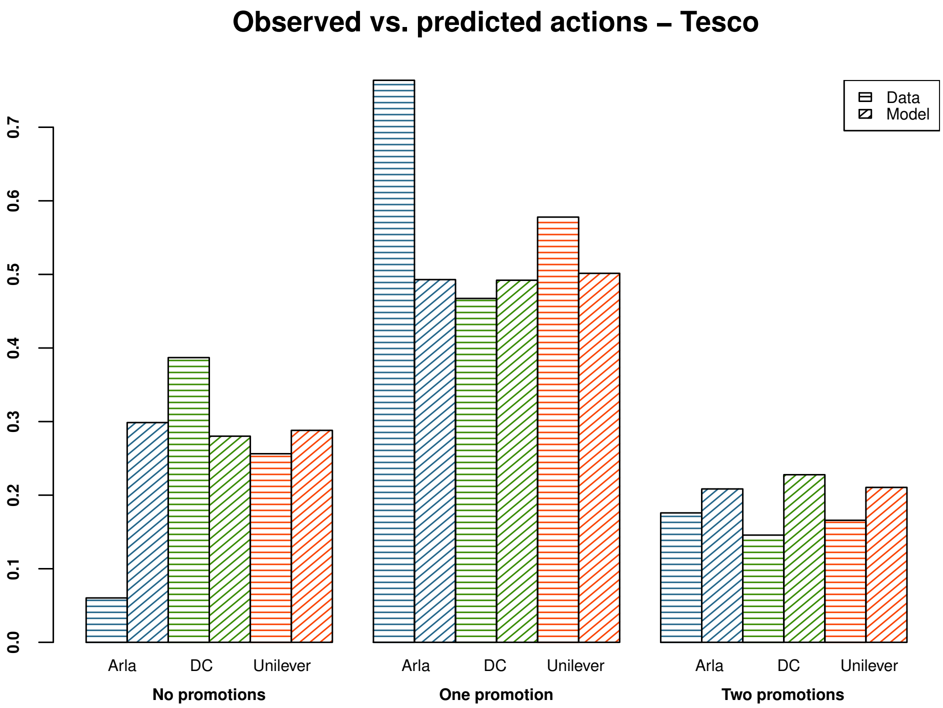
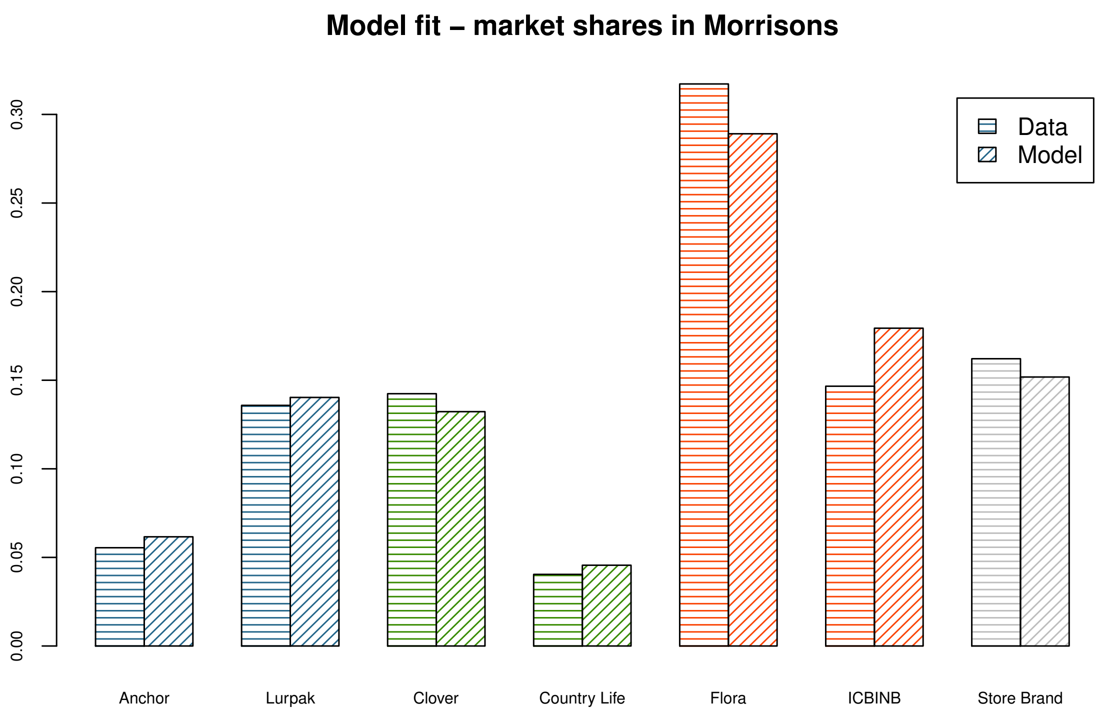
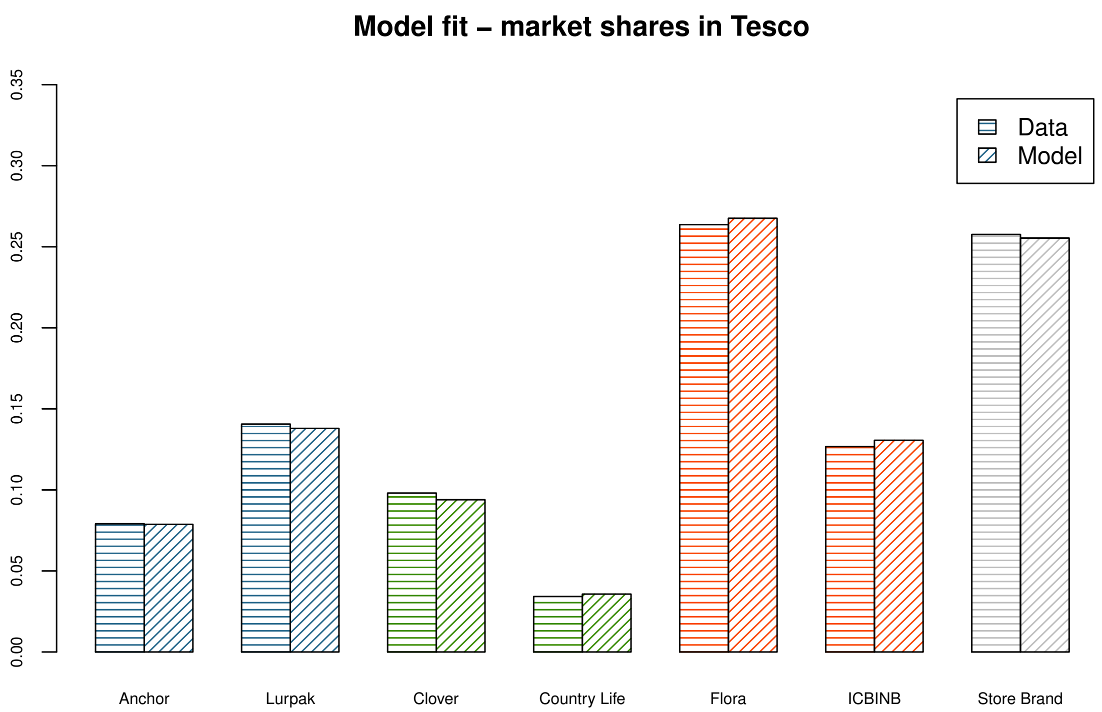


Figure 4: Market shares by brand: model vs. data.





Appendix D: Robustness checks

This appendix contains several robustness checks of our baseline model: different calibrations of the baseline model, results using a random coefficients demand model and different specification to price adjustment costs.

Robustness: Different calibrations

Table 15: Estimated discount factors.

H	MORRISONS β	TESCO β
0.50	0.9807*** (0.04)	0.9970*** (0.01)
1.00	0.9815*** (0.03)	0.9970*** (0.01)
2.00	0.9811*** (0.02)	0.9958*** (0.01)
3.00	0.9790*** (0.02)	0.9936*** (0.01)
4.00	0.9757*** (0.01)	0.9914*** (0.01)
5.00	0.9708*** (0.01)	0.9895*** (0.01)
6.00	0.9620*** (0.01)	0.9878*** (0.01)
7.00	0.9472*** (0.02)	0.9860*** (0.01)
8.00	0.9299*** (0.02)	0.9838*** (0.01)
9.00	0.9079*** (0.03)	0.9805*** (0.01)

Note: Results shown for different values of market size scaled by the variance of the shock, under the assumption that this value is the same for all firms, but potentially different across markets. Standard errors obtained using 100 bootstrap replications provided in parentheses below the point estimates. Significance levels: *** 1%, ** 5%, * 10%.

Table 16: Magnitude of adjustment costs.

H/ζ	MORRISONS Arla	MORRISONS DC	MORRISONS Uni	TESCO Arla	TESCO DC	TESCO Uni
0.10	35.03%	33.17%	31.30%	33.75%	33.62%	30.75%
0.20	34.94%	33.12%	31.17%	33.69%	33.58%	30.66%
0.30	34.85%	33.07%	31.05%	33.63%	33.54%	30.56%
0.40	34.77%	33.02%	30.93%	33.56%	33.50%	30.46%
0.50	34.69%	32.98%	30.80%	33.49%	33.46%	30.36%
1.00	34.36%	32.71%	30.23%	33.16%	33.26%	29.89%
2.00	33.78%	32.22%	29.22%	32.52%	32.93%	28.97%
3.00	33.29%	31.74%	28.30%	31.84%	32.61%	28.11%
4.00	32.79%	31.26%	27.48%	31.12%	32.27%	27.29%
5.00	32.35%	30.72%	26.73%	30.44%	31.94%	26.50%
6.00	32.09%	30.17%	26.07%	29.72%	31.62%	25.73%
7.00	31.99%	29.40%	25.50%	29.04%	31.29%	25.01%
8.00	31.80%	28.61%	24.94%	28.30%	30.96%	24.27%
9.00	31.61%	27.60%	24.33%	27.52%	30.66%	23.58%
10.00	31.43%	26.14%	23.90%	26.77%	30.38%	22.99%

Note: The numbers in the table are ratios of adjustment costs to variable profits for each firm in two different supermarkets. Both components of the payoff are calculated as average present values for 200 periods, averaged across 1000 simulated paths.

Table 17: Counterfactual results with $\mathbf{SC} = 0$ for different calibrations of H/ζ.

H/ζ		MORRISONS Arla	MORRISONS DC	MORRISONS Uni	TESCO Arla	TESCO DC	TESCO Uni
0.5	Δs	0.63%	0.59%	0.30%	0.08%	0.06%	0.04%
	$\Delta\Pi$	82.87%	75.38%	64.63%	78.88%	76.55%	63.41%
	ΔCS		0.44%			0.05%	
2.0	Δs	0.88%	0.72%	0.61%	0.30%	0.13%	0.14%
	$\Delta\Pi$	79.49%	72.99%	60.22%	75.64%	74.82%	72.89%
	ΔCS		0.70%			0.18%	
4.0	Δs	1.47%	1.14%	1.20%	0.63%	0.26%	0.27%
	$\Delta\Pi$	76.24%	70.01%	55.68%	71.49%	72.89%	55.08%
	ΔCS		1.25%			0.37%	
6.0	Δs	2.41%	2.14%	1.84%	0.95%	0.38%	0.38%
	$\Delta\Pi$	74.34%	67.16%	52.37%	67.55%	70.96%	51.14%
	ΔCS		2.04%			0.54%	
8.0	Δs	3.97%	3.80%	2.77%	1.25%	0.51%	0.48%
	$\Delta\Pi$	74.51%	64.16%	50.52%	63.80%	69.14%	47.67%
	ΔCS		3.27%			0.71%	

Note: Numbers in the table are percentage differences between the counterfactual scenario and the baseline model in: average market share (Δs), firm profits ($\Delta\Pi$) and consumer surplus (ΔCS). The figures were obtained by simulating the two models according to MPE choice probabilities 200 periods ahead, and averaging across 1,000 simulation paths.

Robustness: Random coefficients demand

Table 18: Demand estimates with heterogeneous brand fixed effects.

	ASDA	MORRISONS	SAINSBURY'S	TESCO
δ^h_{Anchor}	-3.301	-3.598	-3.861	-4.424
	2.044	*1.725*	*2.407*	*1.999*
δ^h_{Lurpak}	-2.778	-2.976	-3.552	-4.215
	2.491	*2.673*	*2.517*	*2.405*
δ^h_{Clover}	-3.724	-2.784	-3.929	-4.167
	1.712	*1.377*	*1.892*	*1.567*
$\delta^h_{Country\ Life}$	-3.667	-3.965	-4.320	-5.266
	2.102	*2.056*	*2.166*	*2.256*
δ^h_{Flora}	-2.473	-2.142	-2.729	-2.961
	1.327	*1.037*	*1.463*	*1.085*
δ^h_{ICBINB}	-2.646	-2.824	-3.537	-3.650
	1.264	*1.168*	*1.426*	*1.228*
δ^h_{SB}	-3.291	-3.269	-2.873	-3.235
	1.528	*1.574*	*1.216*	*1.332*
η	-0.924	-0.942	-0.677	-0.428
	$[-0.973; -0.876]$	$[-0.991; -0.893]$	$[-0.729; -0.625]$	$[-0.457; -0.399]$
γ	1.603	1.810	1.352	1.999
	$[1.568; 1.638]$	$[1.772; 1.848]$	$[1.313; 1.390]$	$[1.977; 2.022]$
N	104,946	71,294	102,939	280,828

Note: All means and sd's significantly different from 0 at 1% level. For brevity we suppress confidence intervals for the random coefficients. Each δ^h_j is assumed to be $\mathcal{N}(\mu_j, \zeta_j)$. For each brand/(super)market, the table displays the estimates of the mean and the corresponding standard errors (italicized). For η and γ, 95% confidence intervals reported in brackets.

Table 19: Measures of model fit – random coefficients demand.

H/ζ	MORRISONS		TESCO	
	Actions	Shares	Actions	Shares
0.1	0.635	0.021	0.989	0.011
0.5	0.631	0.021	**0.984**	**0.011**
1.0	0.633	0.022	0.984	0.011
2.0	0.653	0.022	0.990	0.011
3.0	0.683	0.022	0.995	0.011
4.0	0.705	0.023	0.999	0.011
5.0	0.698	0.023	1.002	0.012
6.0	0.680	0.023	1.009	0.012
7.0	0.656	0.024	1.028	0.012
8.0	0.641	0.024	1.059	0.013
9.0	**0.627**	**0.025**	1.096	0.013
10.0	0.661	0.025	1.146	0.013

Note: For both supermarkets, two measures of model fit are reported for different calibrations of H. The first one (second and fourth column) is the sum of absolute differences between the fractions of periods with a given action being played observed in the data and simulated from the equilibrium of the model. The second statistic, reported in columns 3 and 5, measures the absolute difference between observed and simulated market shares. Data from the equilibrium of the model were simulated 1,000 times, 199 periods ahead, using the state observed in week 1 of the data as initial conditions.

Table 20: Magnitude of adjustment costs with random coefficients demand.

H/ζ	MORRISONS			TESCO		
	Arla	DC	Uni	Arla	DC	Uni
0.10	37.22%	32.75%	33.10%	33.80%	33.62%	30.77%
0.20	37.21%	32.71%	33.03%	33.78%	33.61%	30.72%
0.30	37.19%	32.68%	32.94%	33.77%	33.59%	30.66%
0.40	37.17%	32.66%	32.86%	33.75%	33.58%	30.61%
0.50	37.15%	32.65%	32.77%	33.75%	33.56%	30.55%
1.00	36.99%	32.59%	32.32%	33.67%	33.47%	30.32%
2.00	36.45%	32.45%	31.26%	33.54%	33.32%	29.87%
3.00	35.87%	32.34%	30.20%	33.41%	33.18%	29.26%
4.00	35.37%	32.16%	29.26%	33.28%	33.06%	28.83%
5.00	35.21%	31.93%	28.59%	33.16%	32.94%	28.21%
6.00	35.25%	31.67%	28.10%	33.02%	32.83%	27.73%
7.00	35.27%	31.38%	27.69%	32.87%	32.70%	27.27%
8.00	35.38%	31.07%	27.25%	32.74%	32.58%	26.81%
9.00	35.54%	30.76%	26.89%	32.62%	32.46%	26.37%
10.00	35.93%	30.24%	26.64%	32.50%	32.34%	25.92%

Note: The numbers in the table are ratios of adjustment costs to variable profits for each firm in two different supermarkets. Both components of the payoff are calculated as average present values for 200 periods, averaged across 1000 simulated paths.

Table 21: Counterfactual results with $\mathbf{SC} = 0$ – random coefficients.

	MORRISONS			TESCO		
	Arla	DC	Uni	Arla	DC	Uni
Δs	3.14%	3.64%	2.46%	0.12%	0.16%	0.06%
$\Delta\Pi$	86.02%	69.25%	54.31%	79.77%	76.95%	64.00%
ΔCS		2.50%			0.06%	

Note: Numbers in the table are percentage differences between the counterfactual scenario and the baseline model in: average market share (Δs), firm profits ($\Delta\Pi$) and consumer surplus (ΔCS). The figures were obtained by simulating the two models according to MPE choice probabilities 200 periods ahead, and averaging across 1,000 simulation paths.

Table 22: Decomposition of main counterfactual results – random coefficients.

		MORRISONS		TESCO	
		Baseline	Counterfactual	Baseline	Counterfactual
Arla	No promotions				
	⋄ *Frequency*	31.9%	25.3%	25.8%	25.1%
	⋄ *Avg. duration*	2.80	1.34	2.52	1.34
	One promotion				
	⋄ *Frequency*	48.7%	50.0%	49.6%	50.0%
	⋄ *Avg. duration*	2.49	1.33	2.49	1.33
	Two promotions				
	⋄ *Frequency*	19.4%	24.8%	24.6%	24.9%
	⋄ *Avg. duration*	2.26	1.34	2.48	1.34
	$\overline{p}_{\text{Anchor}}$	£2.27	£2.24	£2.22	£2.22
	$\overline{p}_{\text{Lurpak}}$	£2.45	£2.41	£2.35	£2.34
Dairy Crest	No promotions				
	⋄ *Frequency*	31.9%	25.5%	26.1%	25.1%
	⋄ *Avg. duration*	2.69	1.34	2.42	1.34
	One promotion				
	⋄ *Frequency*	19.3%	24.5%	24.4%	24.9%
	⋄ *Avg. duration*	2.39	1.33	2.40	1.33
	Two promotions				
	⋄ *Frequency*	19.3%	24.5%	24.4%	24.9%
	⋄ *Avg. duration*	2.17	1.33	2.39	1.34
	$\overline{p}_{\text{Clover}}$	£1.50	£1.45	£1.47	£1.46
	$\overline{p}_{\text{Country Life}}$	£2.17	£2.14	£2.10	£2.09
Unilever	No promotions				
	⋄ *Frequency*	33.4%	26.7%	25.5%	25.1%
	⋄ *Avg. duration*	2.48	1.37	2.18	1.34
	One promotion				
	⋄ *Frequency*	49.3%	50.1%	50.5%	50.0%
	⋄ *Avg. duration*	2.15	1.34	2.17	1.33
	Two promotions				
	⋄ *Frequency*	17.3%	23.2%	24.0%	24.9%
	⋄ *Avg. duration*	1.90	1.31	2.15	1.34
	$\overline{p}_{\text{Flora}}$	£1.25	£1.22	£1.25	£1.25
	$\overline{p}_{\text{ICBINB}}$	£1.05	£1.02	£1.06	£1.06

Note: The table compares various summary statistics in the baseline scenario where price adjustment is costly and in the counterfactual with no promotional costs. For each firm, we present simulated frequency and duration of different actions (first six rows), and average long-run prices of each brand, weighted by market shares, denoted as $\overline{p}_*$.

Robustness: Different specification for price adjustment costs

Table 23: Fixed promotional costs. and discount factors.

	MORRISONS	TESCO
Arla		
SC_{Anchor}	0.48	1.36
	(1.06)	(0.79)
SC_{Lurpak}	0.80	1.43
	(0.95)	(0.89)
SC_{Both}	0.52	0.84
	(1.39)	(0.99)
DC		
SC_{Clover}	0.42	-0.09
	(0.56)	(0.31)
$SC_{Country\,Life}$	0.15	-0.14
	(0.52)	(0.34)
SC_{Both}	0.46	-0.21
	(0.86)	(0.49)
Unilever		
SC_{Flora}	0.89	0.27
	(0.41)	(0.29)
SC_{ICBINB}	0.09	0.07
	(0.67)	(0.40)
SC_{Both}	0.98	0.01
	(0.80)	(0.53)
β	0.94***	0.98***
	(0.41)	(0.20)

Note: Table presents estimates of *fixed promotional costs*, i.e. costs incurred whenever a given product is on promotion, scaled by the variance of to the distribution of ε, which is assumed type-I extreme value with mean 0, as well as the discount factors. Standard errors obtained using 100 bootstrap replications given in parentheses below the point estimates. Significance levels: *** 1%, ** 5%, * 10%.