# 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, in line with previous evidence in the literature, we find that price adjustment costs are substantial and represent between 24-34% of manufacturers' net margins. Second, our model predicts that the removal of these costs reduces persistence in prices, increases firms' profits but has little effect on consumer surplus. Third, 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 is able to provide equilibrium predictions for highly stylised settings, it is important to understand the mechanisms generating price patterns observed in actual market situations. In this paper we propose a tractable dynamic game model to bridge the gap between economic theory and practical pricing problems. We structurally estimate the 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 costs when they adjust prices[1] and consumers exhibit some degree of inertia[2] in their choices. The demand side friction creates two countervailing effects on firms' pricing decisions: *investing* and *harvesting*. The investing motive acts as an incentive for firms to temporarily lower their prices in order to build up a larger base of loyal consumers. Subsequently, after acquiring a number of loyal consumers, firms can increase their prices and harvest the investments made in the previous periods. 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] Hence, differently from the IO literature on dynamic pricing, we model prices as discrete choices from a predetermined set.[4] Under this assumption, our model turns out to be a particular instance of the dynamic oligopoly framework of Ericson and Pakes (1995) that can be estimated using recent methods developed for dynamic discrete games.

We use the model and scanner data to study pricing in the UK butter and margarine industry. 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 channels are national retail chains. We treat each of the four largest UK supermarket chains (known as *the big four*[5]) as a separate market. 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.

[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), as well as Conlon and Rao (2019) and Williams (2022) for recent examples of departures from continuous models of pricing.

[5] It consists of Asda, Morrisons, Sainsbury's and Tesco.

The costs that firms incur in our model when lowering product prices represent the fees manufacturers pay to the supermarkets – also known as promotional or commercial fees[6] – that are used to cover the costs of the promotional campaigns. These costs account for relocation of products to shelves with more visibility, leaflets printing, production of TV commercials as well as possible compensations a firm may have to pay for markup reductions or increased competition against retailers own products during promotional periods. In the same spirit as how costs are typically modelled in entry games, we consider two types of costs. One is paid upfront when promotion begins. The other is paid throughout the duration of the promotion periods. The former, which we will refer to as an adjustment cost, and the latter play analogous roles to entry and fixed operating costs, respectively, in a classic entry game. These costs are nonparametrically identified using recent results from the empirical dynamic game literature.[7]

Following the above arguments, the empirical analysis in this paper is informative about the implications of promotional fees in retailing markets. This is particularly 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.[8] Our counterfactual studies will focus on the adjustment costs component of the fees as our structural estimates find them to be crucial (in absolute terms and statistically) while the contributions from the operating costs are negligible.

In this paper we are interested in understanding how supply and demand frictions affect prices, consumer welfare and firms' profits. Specifically, we ask: (i) what are the magnitudes and the effects of price adjustment costs on prices, consumer welfare and firms' profits? (ii) what are the effects of consumer inertia on prices when price adjustments are costly?

Our estimates of price adjustment costs are substantial in magnitude and constitute between 24% and 34% of firms' variable profits.[9] In absolute terms, these estimates are very similar

[6]The existence and relevance of these fees for pricing decisions have been extensively documented in the marketing literature (Kadiyali et al. (2000), Chintagunta (2002)) as well as in the media; Appendix A provides a series of anecdotal evidence on the importance of promotional fees.

[7]Formally, we are assuming that: (i) there are no fees to be paid for returning prices from promotion back to regular; and, (ii) there are no operating costs at regular prices in the dynamic model. The first assumption is quite natural. The second assumption does not actually mean there are no associated operating costs on the retailer's side but rather such costs do not enter manufacturers' dynamic pricing decisions. These restrictions can be interpreted as normalisations because a fully flexible model is not identified. Specifically, our model generalizes entry games where it is well-known that entry and operating costs cannot be identified together with the scrap value and the cost of staying out, but identification is possible once scrap value and the cost of staying out are normalised. We refer the reader to Aguirregabiria and Suzuki (2014) and Komarova et al. (2018) for further discussions.

[8]*"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.

[9]These estimates are in line with existing evidence in the macro literature – despite the fact that, as explained before, the nature of price adjustment costs in this paper is different from the nature of price adjustment costs in

across firms 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.[10]

Our counterfactual study considers the implications of price adjustment costs for firm profits and consumer surplus. We find that when firms can change prices without any costs, their profits increase substantially, between 50-70%, but consumer surplus goes up by only 0.4-3.3%. For firms, the benefit of price adjustment costs reduction outweighs the increase in price competition. Our model predicts promotions would have shorter durations but occur more frequently, than when price adjustment costs are present. The welfare improvement for consumers, on the other hand, is much smaller. This is because, when consumers switch brands, the absence of inertia diminishes the gain from price reduction. Thus, our model suggests suggest that a ban of promotional fees would benefit producers but have little effect on consumers.[11]

Finally, our demand estimates also indicate that inertia plays a key role to explain consumer choices in this industry. We provide evidence suggesting that inertia arises out of a behavioral relation between past and current purchases rather than from unobserved consumer heterogeneity. Following the literature (Dubé et al., 2009, 2008, 2010; Pavlidis and Ellickson, 2017), in our application we interpret consumer inertia as the result of brand loyalty – rather than other sources such as consumer learning or search costs. To investigate whether consumer inertia has implications for price dynamics, we perform a comparative statics exercise that compares equilibrium prices across different levels of consumer inertia. Our model predicts that increases in inertia result in higher equilibrium prices. Interestingly, we also observe this effect to be more pronounced in the model with price adjustment costs than without. 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 indicates that equilibrium prices are affected by the complementarity between demand and supply frictions. More broadly, this result sug-

the macro literature. See, for example, Levy et al. (1997), Dutta et al. (1999) and Zbaracki et al. (2004).

[10]Our results also complement findings from the marketing literature indicating that market shares are positively correlated with the frequency of temporary price cuts. 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.

[11]This is a partial equilibrium effect because it does not take into account reactions from supermarkets that, in this scenario, would lose a considerable source of revenues. We also computed variations in profits and consumer surplus assuming that after the counterfactual changes prices would increase in 20% to restore retailers' revenues. As in our baseline results (assuming prices fixed at current levels), after the counterfactual change profits would increase substantially. The difference is that considering also changes in prices, market shares and consumer surplus would fall considerably indicating that the ban of promotional fees may have, in this scenario, a perverse effects on consumers.

gests models that do not account for price adjustment costs may substantially underestimate the negative effects of consumer inertia on prices and consumer welfare.

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. We use the identifying strategy recently developed by Komarova, Sanches, Silva Jr., and Srisuma (2018) to estimate the other parameters of the game. Particularly, the adjustment costs in our model, which are heterogeneous across brands and supermarkets, are examples of what Komarova et al. (2018) generically call switching costs in a dynamic decision problem. They show these costs can be estimated in closed form with a robustness property against misspecification of the profit function and the discount factor. The same authors also show the discount factor can be identified and estimated along with any other parameters that enter the period payoffs linearly as is the case in most applications including ours.

Unlike some entry or investment game applications where borrowing rates may be natural candidates for discounting, the relevant range for the discount factor in a temporary pricing decision problem is less obvious *a priori*.[12] Based on the identification results in Komarova et al. (2018) we estimate the discount factor and show dynamics matter in our application empirically. We find the firms' weekly discount factors ranging between 0.92 and 0.99. As a part of our robustness analysis, we also performed our counterfactual exercises using higher discount rates than what we estimated. Our main conclusions are robust to different discount rates.

We will end this section by describing related literature and summarising our contributions. The rest of the paper is organised as follows. Section 2 discusses the industry background and our 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 presents several robustness checks of our main conclusions. Finally, Section 8 concludes the paper. In the Appendices we provide anecdotal evidence and related mathematical details used to identify price adjustment costs, computational particulars we used to estimate and solve the dynamic game, additional tables and results to support our empirical studies and the tables with the results of our robustness exercises.

[12]For instance, Slade (1998) and Aguirregabiria (1999) interpret the discount rates in their applications as *manager's discount rates*, and they set their discount rates to be 0.99 (weekly) and 0.985 (monthly), respectively. These rates are much lower than the 0.9 (or higher) annual rates typically employed in entry and investment game applications. We refer the reader to Nair (2019) for a recent discussion relating to the discount factor in the context of dynamic pricing games. There are also other applications in economics that estimate discount factors to be much lower than conventional borrowing rates, for examples, see De Groote and Verboven (2019), Kaplan (2012), Shen et al. (2020) and Bajari et al. (2016).

## Related literature and contributions

■ **Literature.** This paper is related to several strands of the literature. First, our model fits into a large literature explaining temporary sales in different markets. Early theoretical contributions typically considered sellers of a homogeneous good who offered temporarily lower prices to discriminate between informed and uninformed (Varian, 1980) or high- and low-valuation consumers (Conlisk et al., 1984). Sobel (1984) extended the model in the latter paper to an oligopolistic setting to find that there are equilibria in which firms act as monopolists to their loyal consumers and cut their prices only to compete for the price-sensitive consumers. Aguirregabiria (1999) provides an alternative explanation for cyclical pricing based on retailers' inventory dynamics and costs associated with placing orders and changing prices. Pesendorfer (2002) attempts to explain pricing patterns of two ketchup brands using a model of intertemporal pricing. As in our paper, Pesendorfer (2002) models retailers' pricing decisions using binary variables (regular/promotional). The main source of price dynamics in his paper, however, is demand accumulation due to consumer stockpiling and purchase acceleration in the low-price periods. Another paper exploring the stockpiling side of the story is Hendel and Nevo (2013), who are able to quantify the welfare effects of sales in the market for soft drinks. Some recent papers have also tried to broaden the scope of potential explanations for sales by including sellers' rational inattention (Matějka, 2015) and consumers' loss aversion (Heidhues and Kőszegi, 2014). Both aforementioned papers develop theories to rationalise discreteness in equilibrium prices observed in the data (i.e. coexistence of disconnected regular and sale price regimes).

For our application, instead, price promotions appear as the result of consumer switching costs (Beggs and Klemperer, 1992; Dubé et al., 2009, 2008, 2010). The existence of consumer switching costs creates two countervailing effects for firms' pricing decisions: *investing* and *harvesting*, which is widely accepted in the literature to induce dynamic pricing for firms. Villas-Boas (2015) surveyed vast theoretical and empirical literature to conclude that depending on the assumptions about firms' and consumers' planning horizons, switching costs might result in higher (Beggs and Klemperer, 1992) or lower (Dubé et al., 2009) profits and equilibrium prices. Dubé et al. (2008) and Dubé et al. (2009) empirically analyse the implications of switching costs for monopolist's and oligopolists' pricing strategies, respectively, in the orange juice and margarine industry. The main finding of the second paper is that oligopoly profits can be lower by more than 10% in the presence of brand loyalty, since the investing motive tends to prevail. Arie and Grieco (2014) and Pearcy (2014) establish theoretical properties of pricing equilibria under logit demand and switching costs, mostly confirming the empirical findings of Dubé et al. (2009).

A new feature we introduce to a model with consumer-side switching cost are supply side frictions in the form of costs of adjusting prices. Slade (1998) quantifies the magnitude of fixed and variable cost of adjusting prices of saltine crackers assuming the industry is monopolistically competitive. Similarily to us, she treats the pricing decision as discrete and structurally estimates a dynamic discrete choice model. In that sense, our model extends her approach to strategic, multiproduct firms.[13] Her results suggest that adjustment costs are important and vary across products and supermarket chains. Kano (2013) also estimates a dynamic game with price adjustment costs for the market of (graham) crackers assuming two different market structures: monopolist competition and oligopoly. She shows that estimates of price adjustment costs under monopolistic competition are biased upwards because in oligopoly models prices are typically more rigid than under monopolistic competition.

Methodologically, how one would estimate and simulate a game with discrete action space differ from a game where action is a continuous variable. The game we use in this paper belongs to the class of dynamic discrete games studied by Aguirregabiria and Mira (2007) and Pesendorfer and Schmidt-Dengler (2008).[14] These authors show pure strategy Markov perfect equilibria for such games generally exist. They characterise the equilibria as fixed points of a system of linear equations that can be used to solve the game, and they propose estimators for the games (also see Pakes et al. (2008) and Sanches et al. (2016) for alternative estimation methods). A well-known way to model and estimate dynamic games with continuous actions is proposed by Bajari et al. (2007). E.g., in a related context, see Pavlidis and Ellickson (2017) who used it to study oligopolists' dynamic pricing strategies in the yoghurt industry. Pure strategy Markov perfect equilibrium has also been shown to exist for this class of continuous action games. We refer the reader to Srisuma (2013) for the equilibrium existence and characterisation results, as well as an alternate estimation method.

■ **Contributions.** To the best of our knowledge, this paper is the first to estimate a model with multiproduct, forward-looking firms in an oligopoly setting in which consumers exhibit inertia in their choices and firms pay a cost to adjust prices. Our counterfactual results contribute directly to the literature summarised in the paragraphs above. Related to the literature on consumer switching costs, our results indicate that if price adjustment costs are relevant, the effects of consumer inertia on prices can be much more substantial than a model where firms can adjust prices freely. Under this setting, we also compute the welfare effects of price adjustment costs and show that they have a negative and relevant impact on firms profits but little effect on consumer welfare. Considering that these price adjustment costs are mainly associated with promotional fees imposed by retailers on manufacturers, the latter result suggests that a ban of these fees would lead to a relevant increase in firms profits but would have little effect on consumer surplus.[15]

[13]The other important difference is that she does not model consumer behavior at the micro level, but uses aggregate demand estimates to construct a *goodwill* state variable.

[14]See the surveys by Arcidiacono and Ellickson (2011) or Aguirregabiria and Nevo (2013) for more details.

[15]We also show that if, after the policy change, supermarkets force an increase in prices to recover potential

# 2 Data and industry background

### Data

The data used in this paper come from Kantar Worldpanel, which is a representative, rolling survey of UK households documenting their daily grocery purchases. 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.[16] To ensure that we have sufficient amount of data to precisely estimate the dynamic game, we use a 200-week subsample from 2009 to 2012 as a period with relatively little changes in market structure and stable set of firms and products.[17]

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,[18] 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 restrict our attention only to purchases of butter and margarine observed in those chains.

losses, the ban of promotional fees can have a negative effect on consumers surplus – see Section 7 for details.

[16] 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.

[17] We are not attempting to analyse long-run industry dynamics but rather short-run competition in prices, at the same time wanting the set of main firms, products and pricing strategies to be relatively constant over the period in question. This is shown, e.g. in Table B.5, where we compare yearly market shares to their 4-year averages and see little differences despite large week-to-week movements. Thus, it is reasonable we assume away structural changes in the sample and focus on stationary equilibria.

[18] The annual value of UK butter and margarine industry in 2014 is estimated to be £1.35bn.[19] 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. The 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.

### Producers

The product 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-firm concentration ratio, $CR_4$ exceeds 90%.[20] 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.[21] Two of the three market leaders, Arla and Dairy Crest, are also major manufacturers of other dairy products (milk, cheese and yoghurt), 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.[22]

### 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

[20] 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.

[21] 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.

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

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 margarines. 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.[23] 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 B.1), and, alternatively on two subsequent purchase occasions (if they do not coincide with two consecutive weeks, see table B.2). 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 B.5 in Appendix B 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 recommended that the UK chain stores follow national pricing rules.[24] This also means we do not have to

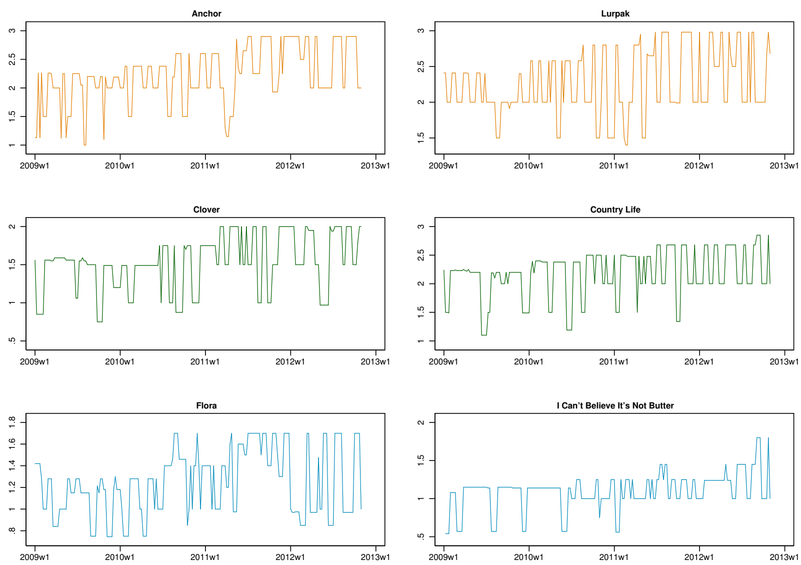
[23]To check that by selecting a subset of products we do not distort the market structure, we computed expenditure- and volume-based market shares using the selected sample. Compared to the entire market, firm- and brand-level market shares in the 500g spreadable segment are quantitatively proportionate, 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 industry. In Section 7 we discuss results of a demand estimation exercise with a larger set of products.

[24]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 week-chain-product combinations, we observe very small degree of deviation from a national price, which we primarily attribute to reporting mistakes. To mitigate measurement error, we therefore we treat

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. 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 B.3 in Appendix B 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. For our six products we observe between 20 and 29 distinct sale spells in the 200-week sample (see Table B.4 in Appendix B). Average duration of a single spell is around 3-4 weeks, depending on the brand. However, we also witness much shorter and much longer periods of reduced prices, varying from one to as many as 10 weeks. Periods of regular prices are on average longer, but promotions in this market are much more frequent than in many other datasets (cf. Pesendorfer (2002) or Hendel and Nevo (2006)). 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.

the weekly median as the national price.

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 B.6 in Appendix B. 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 a 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-week sample. Virtually all of the price movements are between regular and sale prices. Store brands are also important in the industry and their prices 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 propose in the following section to quantify the effects of supply and demand frictions on welfare, prices and profits.

# 3 Model

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

## 3.1 Preliminaries

We assume firms compete in a dynamic pricing game with adjustment costs, which falls into the class of Markovian games developed in the empirical IO literature (Arcidiacono and Ellickson (2011), Aguirregabiria and Nevo (2013)). 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. We treat each supermarket as an independent market but allow markups, price adjustment costs and demand parameters to vary across supermarket chains.

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.[25] 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.

## 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 $\boldsymbol{\mathcal{J}} = \bigcup_{i=1}^{N} \mathcal{J}_i$, with $\mathcal{J}_i$ denoting the set of products produced by firm $i$. Let $\mathcal{A}_i$ denote the set of actions available to firm $i$. 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, each firm has two products, $|\mathcal{J}_i| = 2$, so firm $i$ can choose among 4 actions and $\mathcal{A}_i = \{(p_{i1}^H, p_{i2}^H), (p_{i1}^H, p_{i2}^L), (p_{i1}^L, p_{i2}^H), (p_{i1}^L, p_{i2}^L)\}$, where $p^H$ and $p^L$ denote high and low price, respectively.

The decision problem of Firm $i$'s pricing manager 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 manager's 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 firms. Occasionally we will abuse the notation and write $\mathbf{a}_t = (a_{it}, \mathbf{a}_{-it})$, where $\mathbf{a}_{-it}$ denotes the actions of all firms other than firm $i$. $\mathbf{z}_t \in \boldsymbol{\mathcal{Z}}$ is the vector of publicly observed, payoff-relevant state variables, which in our model contains last period's market shares and actions, $\mathbf{z}_t = (\mathbf{s}_{t-1}, \mathbf{a}_{t-1})$, and $\boldsymbol{\varepsilon}_{it} = (\varepsilon_{it}(a_{it}))_{a_{it} \in \mathcal{A}_i}$ 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 firms' actions, next period's draws of $\varepsilon$, and the future evolution of state variables.

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

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

[25] We will provide further details on this cost in Section 4.

where $\mathbf{1}(\cdot)$ is the indicator function, $AC_i^{\ell' \to \ell}$ is the adjustment cost of switching from action $\ell'$ to $\ell$ and $FC_i^{\ell}$ is any fixed cost associated with choosing action $\ell$. 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, $s_{jt}$ is the market share derived from the consumers' problem, and $H$ represents the potential number of consumers in the market.[26] $\zeta$ is the standard deviation of the unobserved shocks.

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

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

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 $\mathbf{a}_{-it}$; $G(\mathbf{z}_{t+1}|\mathbf{z}_t, \mathbf{a}_t)$ gives the probability that state $\mathbf{z}_{t+1}$ is reached when the state and action profile are $\mathbf{z}_t$ and $\mathbf{a}_t$; $Q(.)$ is the cumulative distribution function of the vector of shocks $\boldsymbol{\varepsilon}_{it+1}$.
If $\mathbf{a}_{-it} = (\ell_1, \ldots, \ell_{i-1}, \ell_{i+1}, \ldots, \ell_N)$, 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 (CCPs). 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)).

[26]To check whether the assumption of constant marginal costs during this period is reasonable we checked the variation of milk prices during 2009-12. Figure B.1 in Appendix B (a) shows the price of a pint of pasteurised milk in pence and (b) the price index (January 2009 equal to 100) of fresh milk (recently extracted unprocessed milk) – we looked at the prices of whole/fat milk but the time series of these products starts only in 2015. The numbers were collected from the UK Office of National Statistics and are used to compute consumer inflation indexes in the UK. Both graphs show that prices of pasteurised and fresh milk were relatively constant over 2009-12.

## 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 $\mathcal{J}$ or 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 their previous choice, 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. We formalize the structure of our demand model in the next paragraphs. For our baseline model, we keep a more parsimonious specification. In Appendix C we show the estimates and results of counterfactual exercises using a random coefficients model. We discuss these results in Section 7. Essentially, all our main findings are maintained under this alternative demand model.

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

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

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

$\delta_j$ are alternative-specific intercepts, fixed over time.[27] $\mathbf{1}(y^h_{t-1} = j)$ equals one if household $h$'s purchase at $t-1$ was the same as the one in the current period. $\gamma$ is a parameter measuring the degree of consumer loyalty (if $\gamma > 0$).[28] Under the assumption that $\xi$'s are independent type-I extreme value, the probability that household $h$ will purchase good $j$ at time $t$ is:

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

Since we are ultimately interested in aggregate market shares, we can use the law of total

[27] In principle, we could allow these alternative-specific intercepts to vary over time. In Online Appendix A, we show a number of exercises suggesting that these intercepts are not varying significantly over time. This is expected in a industry with relatively little innovation and where the characteristics of products/brands are very well-known by the consumers – see also Griffith et al. (2017). Hence, we adopted a more parsimonious specification with alternative-specific intercepts that are fixed over time.

[28] 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.

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 the same strategies upon observing the same realisation of $(\mathbf{z}, \boldsymbol{\varepsilon})$. 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 firms – for every possible realisation of the state vector $(\mathbf{z}, \boldsymbol{\varepsilon})$. 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. We examine key assumptions behind our model and illustrate the plausibility of these assumptions in light of the literature, industry background and our data. In Section 7 we present various robustness checks of the model relaxing many assumptions discussed in this section.

■ **Manufacturers make price decisions.** As in most papers within the IO/marketing literature (Nevo, 2001; Slade, 1998; Kano, 2013; Dubé et al., 2009, 2008, 2010; Chintagunta et al., 2003; Pavlidis and Ellickson, 2017) we assume the manufacturers set the price and therefore are the players in the game. Particularly for our setting, this also seems to be reasonable because the manufacturers in our application are market leaders with substantial bargaining power. We provide additional arguments to support our choice here: (i) given the existence of private labels (supermarket store brands) that are known to yield higher margins for the retailers, supermarkets should have no incentives to price national brands aggressively (Meza and Sudhir, 2010); (ii) Lal (1990) argues that manufacturers invest in price promotions to limit store brand's encroachment into the market; (iii) 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; (iv) 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.

■ **Pricing decisions of butter/margarine independently of other products.** The assumption discussed in the previous paragraph is also consistent with independence of pricing decisions across categories – another assumption adopted by virtually all papers within the dynamic pricing literature (Dubé et al., 2009, 2008, 2010; Pavlidis and Ellickson, 2017; Slade, 1998; Kano, 2013). We also note that, in our model (as in other papers within this literature), consumers choice set have already an "outside option", which captures, at least partially, substitutions between the butter/margarine brands that are explicitly modelled and other products. This feature of the model certainly helps to mitigate potential biases in the demand estimates arising from this modelling choice. Finally, experimental evidence in the literature suggests that substitutability between products of different categories seems to be limited Hoch et al. (1994).

■ **Retailing chains as separate markets.** We treat the four retailing chains as separate markets, in which the pricing games are played independently. This assumption seems to be corroborated by our data and the literature. For example, from the consumers' side, we find that 80% of the households in the sample made all their purchases at the same store within a 30 days period and 75% shop in at most 2 supermarkets during a calendar year. We expect many households that purchased from different stores did so coincidentally rather than them shopping for the cheapest price (i.e. they are "shoppers"), because promotions occurred frequently at different supermarkets in a highly uncoordinated manner within for all brands throughout the sample period (see Figure B.2 in Appendix B). This line of thinking is supported by informal evidence given in related papers on how supermarkets view intra versus inter store competition. For examples, Slade (1998) and Chintagunta et al. (2003) interviewed supermarket managers in the US; they suggest that the fractions of shoppers are very small and the relevant competition dimension is among brands at the same store and not between stores. There is also a related result, where a pricing experiment ran by Hoch et al. (1994), which found that increases in prices of different product categories had no effect on store traffic, supports this view. It is worth emphasising that 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.[29]

■ **Myopic consumers.** 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 forward looking. However, this requires us to make non-trivial modelling assumptions that will substantially alter how to estimate and simulate the model. Firstly, we would need to refine our notion of equilibrium. If we assume consumers and firms have the same information set (net of private shocks) and rational expectations, then we can define Markov perfect equilibrium as done in Goettler and Gordon (2011). Alternatively, Fershtman and Pakes (2012) proposed a different notion of equilibrium that explicitly allows for asymmetric information between firms and consumers. In both cases, we would need to be explicit about how many periods ahead consumers are preparing for the future, as well as how they use state variables to form expectations of future prices across brands. By treating consumers as myopic, we can remain agnostic about expectations of future prices and can make more realistic behavioural assumptions on the demand side (e.g. that consumers only know the prices and what they bought last period, rather than the entire distribution of market shares and past prices). From the computational stand point, solving the game with forward looking consumers would also become much more complicated as we would need to jointly solve the coupled dynamic programming problems of the firms and consumers.

■ **Consumer heterogeneity.** We later explore different models of consumer behaviour as part 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

[29]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.

on this demand model in Section 7. Results of our structural estimates and counterfactuals are close to those we obtained using our baseline formulation.

■ **Loyalty definition.** Finally, the approach we have described in Section 3.3, 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 would 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 supply side, particularly on the dynamic parameters.

## 4.1 Identification strategy

The primitives of the game are $\{H, \boldsymbol{\delta}, \gamma, \eta, \{\mathbf{mc}_i\}_{i=1}^N, \{\mathbf{AC}_i\}_{i=1}^N, \{\mathbf{FC}_i\}_{i=1}^N, \zeta, \beta\ , Q, G\}$. The demand model identifies $(\boldsymbol{\delta}, \gamma, \eta)$. We assume type-I extreme value distributional assumption for $Q$, identify the transition law, $G$, directly from the data and treat them to be known for identification. This is, however, not enough to identify the remaining primitives without further restrictions. For example, even if $\beta$ is known, we can see from the expressions in (1) and (3) that $\zeta$ cannot be separately identified from $H$, $\mathbf{AC}_i$ and $\mathbf{FC}_i$. We therefore consider the reduced set of primitives: $\{H', \{\mathbf{mc}_i\}_{i=1}^N, \{\mathbf{AC}'_i\}_{i=1}^N, \{\mathbf{FC}'_i\}_{i=1}^N, \beta\}$, where $H' := H/\zeta$, $\mathbf{AC}'_i := \mathbf{AC}_i/\zeta$ and $\mathbf{FC}'_i := \mathbf{FC}_i/\zeta$. For notational simplicity, in what follows, we use $\mathbf{AC}$ and $\mathbf{FC}$ to denote the vectors of adjustment and fixed costs respectively that have been stacked across firms and products.

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, assuming the knowledge of the discount factor. We follow Komarova, Sanches, Silva Jr., and Srisuma (2018) who show that $\mathbf{AC}'$ can be identified in closed form independently of all the other primitives 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. We motivate this restriction by interpreting the price adjustment costs as covering promotional expenses, as documented in the literature (e.g. see Kadiyali et al. (2000), Chintagunta (2002)) and media (see Appendix A). Further technical details on the identification strategy of $\mathbf{AC}'$ can be found in Online Appendix B.1.

Our baseline model assumes that the fixed cost for each player is a constant. Note that these fixed costs cannot be identified when they are the same for every pricing decision. This can be seen by inspecting (1), where the fixed costs become an intercept term that does not affect the pricing decision. We set this value to be zero in the baseline model. The assumption of a constant fixed cost can be interpreted as the cost of basic services that a supermarket provides whether any products go on promotion. If components of $\mathbf{FC}'$ vary, then a fixed cost can be thought of as a variable cost of promotions. E.g., this allows promotional fees to be a function of the duration of promotional spells or, indirectly, of quantities sold during promotions.

The assumptions we make on $\mathbf{AC}'$ and $\mathbf{FC}'$ can also be thought of as normalisations. Some normalisations are necessary as dynamic games are not identified (Pesendorfer and Schmidt-Dengler (2008)). Comparing to a classic entry game, our restriction on the fixed costs corresponds to the common normalisation of a zero operating costs for active firms. Correspondingly, the restriction we impose on the price adjustment costs is analogous to setting the scrap value of exiting to zero. See Aguirregabiria and Suzuki (2014) and Komarova, Sanches, Silva Jr., and Srisuma (2018) for a discussion on identifying components of the profit function that includes our adjustment costs as a special case.

In practice, following Komarova, Sanches, Silva Jr., and Srisuma (2018), we can first estimate $\mathbf{AC}'$ that is robust against possible misspecification of static profits and fixed costs. Then, for any given $H'$ and $\mathbf{mc}$ we can estimate $\beta$ and $\mathbf{FC}'$. Our baseline model sets $\mathbf{FC}'$ to be zero to focus on the roles of $\mathbf{AC}'$ and $\beta$.[30] In our application we estimate demand-side parameters outside of the dynamic game, calibrate $H'$ and use marginal costs estimates that are based on a subsample of our data set from Griffith et al. (2017). High and low price levels for each brand in each supermarket are assumed to be equal to the median regular and promotional prices observed during the whole period (see Table B.6 in Appendix B). In Section 7 we also discuss robustness of our counterfactual results assuming different levels for high and low prices.

[30]We in fact do not have to normalise $\mathbf{FC}'$ because the normalisation we make on $\mathbf{AC}'$ is sufficient to identify the model. When we estimate $\mathbf{FC}'$, we find that they are small in magnitude and not statistically significant. The results from estimating the model with non-zero fixed costs can be found in Table C.14 and we provide a discussion on related findings in Section 7 as a part of our robustness checks.

## 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' conditional choice probabilities (CCPs), i.e. obtain $\widehat{\Pr}_i(a_i = \ell|\mathbf{z})$ for all $i$ and $\mathbf{z}$.
4. Use CCPs to get $\widehat{\mathbf{AC}}'$ in closed form.
5. Plug the demand and $\widehat{\mathbf{AC}}'$ estimates into the conditional value functions and estimate the discount factor by minimising a nonlinear least squares criterion for each $H'$ and choose $H'$ providing best fit.

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 $\widehat{\mathbf{AC}}'$ can be computed in closed-form following expression (B.9) derived in Online Appendix B.1. A candidate for the estimate of $\beta$ in Step 5 can be computed for each calibration of $H'$. 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 in Online Appendix B.2.

### Conditional choice probabilities

We identify structural parameters based on estimated conditional choice probabilities. 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, geographical 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 firm 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 firm 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. The estimates can be found in Table B.7 in Appendix B.

**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 depend on the calibration discussed previously. This section also explains how to use model fit criteria to guide calibration. In Section 7 we present sensitivity analyses of our results to these choices and a battery of robustness checks of our main results.

## 5.1 Demand estimation

Table 2 contains demand estimates for the model described in Subsection 3.3. We find consumer loyalty (measured by $\gamma$) 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, $\eta$, are negative in all cases and the differences between them reflect possible differences in the composition of each supermarket's clientele, e.g. due to differences in store format or geographic locations.

A potential concern with the estimates in Table 2 is the magnitude of $\gamma$ (compared to $\eta$). It is well known that (persistent) unobserved consumer heterogeneity may inflate $\gamma$ and have consequences for the interpretation of our model.[31] In the limit, if the coefficient $\gamma$ 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

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

Table 2: Demand estimates

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

formulation that controls for more flexible forms of consumer heterogeneity. Succinctly, even controlling for consumer heterogeneity we still observe that the estimates of $\gamma$ are relatively large and significant at $1\%$, suggesting that consumer inertia in this market is consistent with brand loyalty. We give a more detailed perspective of these results in Section 7.

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.[32] This is because we do not expect product characteristics not observed by the consumers, which are not captured by product-specific intercepts, to be correlated with prices 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

[32]More formally, in Online Appendix A we present evidence showing that time-varying unobserved heterogeneity is not a first order issue in our setting.

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 $\zeta$, i.e. $\{\widehat{\mathbf{AC}_i'}\}_{i=1}^N$. 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.[33]

**Table 3:** Price adjustment costs.

| | Asda | Morrisons | Sainsbury's | Tesco |
|---|---|---|---|---|
| **Arla** | | | | |
| $AC_{Anchor}$ | 2.177 | 2.508 | 2.511 | 2.497 |
| | (2.15) | (2.56) | (2.72) | (2.33) |
| $AC_{Lurpak}$ | 2.388 | 2.438 | 2.451 | 2.441 |
| | (2.05) | (2.50) | (2.6) | (2.25) |
| $AC_{Both}$ | 4.430 | 4.746 | 4.765 | 4.745 |
| | (3.00) | (3.52) | (3.60) | (3.25) |
| **DC** | | | | |
| $AC_{Clover}$ | 2.589*** | 2.584*** | 2.583*** | 2.582*** |
| | (0.68) | (0.78) | (0.88) | (0.83) |
| $AC_{Country\,Life}$ | 2.149*** | 2.154*** | 2.131*** | 2.155*** |
| | (0.64) | (0.79) | (0.9) | (0.85) |
| $AC_{Both}$ | 4.536*** | 4.544*** | 4.547*** | 4.557*** |
| | (0.84) | (0.95) | (1.06) | (1.01) |
| **Unilever** | | | | |
| $AC_{Flora}$ | 1.526** | 1.612** | 1.633** | 1.627** |
| | (0.50) | (0.52) | (0.51) | (0.51) |
| $AC_{ICBINB}$ | 2.251*** | 2.445*** | 2.446*** | 2.451*** |
| | (0.63) | (0.61) | (0.6) | (0.6) |
| $AC_{Both}$ | 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 $\varepsilon$, which is assumed type-I extreme value with location parameter 0 and scaling parameter $\zeta^2$. Standard errors obtained using 100 bootstrap replications given in parentheses below the point estimates. Significance levels: *** 1%, ** 5%, * 10%.

While it is easy to estimate $\{\mathbf{AC}_i'\}_{i=1}^N$, its economic interpretation is limited by the unknown scaling of $\zeta$. 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.

[33] 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.

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 suggests that discount rates are relatively small when annualised compared to a figure of 0.9 or higher that are often assumed in entry or investment game applications, which is reasonable given the latter involves costly long-run investments that are not easily reversible compared to temporary price promotions. Indeed, analogously to Slade (1998) and Aguirregabiria (1999) for example, we interpret the discount factor as the manager's discount rate that has a broader composition than borrowing rates. Nevertheless, the estimates of the discount factors and the corresponding standard errors clearly indicate that short-run expectations matter for pricing decisions. 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. These estimates are also consistent with evidence from the macro literature – despite the differences between the nature of price adjustment costs estimated in this paper and menu costs estimated in the macro literature. 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.

**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% |
| $\beta$ | 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.

We can then summarise the game estimates as follows:

1. Adjustment costs represent a large fraction of manufacturers' payoffs. The magnitudes of

our estimates are in line with anecdotal evidence[34] and, judging by their relative importance on manufacturers' payoffs, it is likely that price adjustment costs have implications for the structure of this market.

2. The estimates of the discount factor indicate that short-run expectations matter for pricing decisions of retailing products.

### 5.3 Model fit

Results in Table 4 depend on the scaled market size, $H' = H/\zeta$. 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 higher than 9 yielded much worse fit. Moreover, the expected payoffs quickly reach (numerical) infinity as $H'$ increases making the computation of counterfactual equilibrium infeasible. For the values of $H' \in \{0.1, \dots, 10\}$, 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 B.4 and B.5 in Appendix B). 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.

## 6 Counterfactual studies

We now turn to our two counterfactual studies. Our 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.

[34] See Appendix A.

**Table 5:** Measures of model fit.

| $H/\zeta$ | 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.

■ **Price adjustment costs, profits and consumer surplus.** We start with an analysis of the effects of price adjustment costs 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.[35] To compute equilibrium profits, shares and consumer welfare we solve the model using the value function approximation method described in Online Appendix B.3. Starting from the state vector observed in the first week in our sample we simulate the model 199 periods ahead 1000 times and compute average shares, 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

[35]While we focus on the results for the calibration based on the best fit of the model, Appendix C Table C.3 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 C.12 and C.13 in Appendix C.

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 $\mathbf{AC} = 0$.

| | MORRISONS | | | TESCO | | |
|---|---|---|---|---|---|---|
| | **Arla** | **DC** | **Uni** | **Arla** | **DC** | **Uni** |
| $\Delta$s | 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% |
| $\Delta CS$ | | 3.27% | | | 0.29% | |

**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 ($\Delta CS$). 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. 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 with price changes. In the next section, we discuss the results of alternative counterfactual exercises that try to address these concerns.

■ **Consumer loyalty under price adjustment costs.** To examine the effects of consumer

**Table 7:** Decomposition of main counterfactual results.

| | | Morrisons Baseline | Morrisons Counterfactual | Tesco Baseline | Tesco 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 $\overline{p}_*$.

loyalty in the presence of price adjustment costs we simulate the pricing game using the estimated parameters and different values for the inertia parameter, $\gamma$. We redo the same exercise setting $\mathbf{AC} = 0$ 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 contains the factor that we use to scale the parameter capturing consumer loyalty ($\gamma$ 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 is the price ratio between the models with and without price adjustment costs.

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

| Scaling factor | AC= 0 | | Estimated AC | | $\frac{\text{Price AC}}{\text{Price AC=0}}$ |
|---|---|---|---|---|---|
| | 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.

The results in the table are to be interpreted as follows: first, increases in consumer inertia are associated with increases in average 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 $\gamma$ on prices are relatively small (but still positive). When the levels of inertia are already high, increases in the loyalty factor lead to an 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 leads to a price increase of 1.62% in the model where price adjustment costs are zero and increase of 5.63% in the model with price adjustment costs. Analogous findings hold 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 results suggest that price exhibits supermodularity in consumer switching costs and price adjustment costs.[36] Intuitively, supermodularity means there is a complementarity between the effects price adjustment costs and consumer switching costs on reducing price competition. Therefore firms' ability to extract rents from consumer inertia is greater when price adjustment costs are non-negligible.

Finally, adjustment costs appear to be a more important factor affecting equilibrium prices than consumer loyalty. 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. In the model with price adjustment costs, an increase in the loyalty factor from zero (no consumer loyalty) to one (baseline estimates of consumer loyalty) leads to a price increase of approximately 0.4% in Morrisons and of 0.2% in Tesco.

# 7 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 C shows the main results of these robustness exercises.

■ **Market size calibration.** In Appendix C, tables C.1 and C.2 respectively show the estimates of the discount factors and adjustment cost magnitudes for different values of $H/\zeta$. Over the entire range under consideration, the discount factors are significant and average price adjustment costs, while decreasing in market size, remain close to 30% of average profits. Table C.3 shows the results of the counterfactual in which we compute the effects of price adjustment costs on shares, profits and consumer surplus – see Table 6 – for different calibrations of $H/\zeta$. Results also indicate that, regardless of the calibration of this parameter, the exclusion of $AC$ from our model would lead, mainly, to a substantial increase in profits.

■ **Consumer heterogeneity.** To allow for persistent taste heterogeneity, we treat the brand

[36] More formally, let $p\left(\gamma, \mathbf{AC}=\mathbf{1}\right)$ be the average equilibrium price of butter/margarine when consumer switching costs are equal to $\gamma$ and price adjustment costs are equal to the estimated levels. Analogously, let $p\left(\gamma, \mathbf{AC}=\mathbf{0}\right)$ be the average price of butter/margarine when consumer switching costs are equal to $\gamma$ and price adjustment costs are equal to zero. $p\left(\cdot,\cdot\right)$ is supermodular in consumer switching costs and price adjustment costs means:

$$\left(p\left(\gamma', \mathbf{AC}=\mathbf{1}\right) - p\left(\gamma, \mathbf{AC}=\mathbf{1}\right)\right) - \left(p\left(\gamma', \mathbf{AC}=\mathbf{0}\right) - p\left(\gamma, \mathbf{AC}=\mathbf{0}\right)\right) \geq 0$$

for any $\gamma' > \gamma$. This is what we observe in Table 8.

fixed effects as random coefficients (see Table C.8 in Appendix C for results).[37] Unsurprisingly, heterogeneous brand fixed effects absorb persistent differences in tastes, which in the baseline specification are captured by $\gamma$ together with any loyalty effect. The results indicate that, even when controlling for more flexible forms of consumer heterogeneity, the parameter $\gamma$ is still large. This suggests that inertia in consumer choices may be due to some form of brand loyalty, and not only unobserved taste differences. Instead of assuming firms anticipate infinitely many consumer types, which would make the analysis computationally infeasible[38], 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 C.10 in Appendix C 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 C.11 shows that in absolute terms the price adjustment costs are also almost unchanged relative to the baseline model.

■ **Larger choice set.** To make sure that our market definition is not too narrow and induces biases in the substitution patterns implied by our demand estimates, we reestimated the demand model with an expanded choice set including smaller (250g) packsize where possible (i.e. all brands other than two where 500g is the only available size). We considered four specifications:

1. Fixed effects $\delta_j$ vary by brand-size. Loyalty is to exactly the same product (brand and size). This is the most narrow definition of loyalty.

2. Same as 1 but loyalty to brand (size doesn't matter).

3. Same as 2 but only brand constants ($\delta_j$ is the same for a given brand but differ with pack sizes).

4. Nested logit with first level of nesting being the choice between 250g/500g/outside option, second level with brands.

The results are shown in Table C.9 in Appendix C. Our conclusion is that including additional products does not drastically change the estimates of the two main parameters governing substitution patterns - $\eta$ and $\gamma$ relative to our main benchmark. Unlike a static logit model, it is quite difficult to compute the cross price elasticity with state dependent consumers that have to be aggregated over the distribution of past loyalty and over time. We believe that comparing the estimates of $\eta$ and $\gamma$ is sufficient to conclude that substitution patterns are not seriously biased

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

[38] 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.

when we restrict the choice set to only 500g products (assuming that prices and market shares are taken directly from the data and hence do not depend on the choice set, as typically done in practice).

The definition of loyalty in (2)-(4) naturally follows from our interpretation of state dependence stemming from attachment to brands. We do not see a clear reason why loyalty should be defined as narrowly as in (1), i.e. if someone purchased a smaller pack of the same product before, she is still considered loyal when buying a bigger pack now. The results in (3) can differ quite a bit (especially for Tesco $\eta$ is twice as large in absolute terms), but we see this as an omitted variable problem - this specification does not control for pack size at all. Finally, the results from (4) are particularly reassuring and most similar to our benchmark estimates. The nested logit specification allows for substitution patterns to be different between and within nests, as long as the dissimilarity/nesting parameter is different from 1. Our estimates range from 1.034 (Asda) to 1.125 (Morrisons), so any bias stemming from the violation of the IIA assumption should be of negligible magnitude. In particular, for Morrisons, $\hat{\eta} = -0.615$ compared to $\hat{\eta} = -0.655$ in our baseline specification, while for Tesco the difference is as small as 0.001 (-0.159 vs. -0.158).

■ **Fixed costs as part of promotional costs.** We mentioned previously that the normalisation $\mathbf{FC} = 0$ is not necessary once normalisations on $\mathbf{AC} = 0$ have been made, i.e. $\mathbf{FC}$ can be identified. Table C.14 provides the estimates for $\mathbf{FC}$. It shows that fixed costs are not significantly different from zero for neither supermarkets and none of the products. This result is consistent with the estimates in Slade (1998), who finds that the lump-sum cost incurred at the instant of changing prices dominates any other variable costs which depend on the absolute difference between the old and new price. Additionally, the bottom row of that table shows that the estimated $\beta$'s are quite robust to whether $\mathbf{FC}$ is assumed to be zero a priori or not.

■ **Changes of price levels when $\mathbf{AC} = \mathbf{0}$.** To compute our baseline counterfactual results, we have assumed that after the counterfactual change – i.e. after recomputing the equilibrium of our model with $\mathbf{AC} = 0$ – price levels are fixed. On the other hand, it is reasonable to think that retailers would force an increase in final prices of butter and margarine to recover part of the resources lost with the ban of promotional fees (that may respond to an important fraction of $\mathbf{AC}$). That said, we also estimate the effects of price adjustment costs on prices, profits and welfare, considering that, *after* the counterfactual change – i.e. after recomputing the equilibrium of the model with $\mathbf{AC} = 0$ –, high and low price levels would increase in $20\%$. Table C.5 in the Appendix shows the effects of price adjustment costs on market shares, profits and consumer surplus under this scenario. Overall, the results are close to our baseline results. There is an important difference, however: with the price increase, consumer welfare and market shares would fall significantly. In other words, this implies that if, after the ban of promotional fees, supermarkets increase final prices, the policy change may lead to welfare losses to consumers.

■ **Different discount rates.** As discussed before, estimated weekly discount rates are relatively low compared to those assumed in the literature. To see whether our main results are sensitive to the choice of the discount factor, we recomputed the results in Table 6 using different values for the discount factor. Table C.4 shows the variation in market shares, profits and consumer surplus for both supermarkets and $\beta \in [0.980; 0.996]$ when we fix $\mathbf{AC} = 0$.[39] The results are quite close to our baseline results. Succinctly, regardless of the discount rates, the exclusion of the $\mathbf{AC}$ component from our models implies a significant increase in profits but little changes in market shares and consumer surplus.

■ **Different price levels.**[40] We also examine the behavior of our counterfactuals assuming different high and low price levels. Precisely, we increase and decrease high and low price levels of each brand[41] in 10% and recomputed the effects of price adjustment costs on market shares, consumer surplus and firms profits. The results for both supermarkets are in Table C.6. It shows the % variation in market shares, consumer surplus and profits between the baseline scenario and the scenario where price adjustment costs are fixed at zero but assuming an increase and a decrease of 10% in price levels. The results are very close to our baseline results. We also recompute the counterfactuals shown in Table 6 assuming an increase of 10% in high and low price levels. Results are in Table C.7 in Appendix C. Again, they appear to be quite close to the baseline results.

# 8 Summary and conclusions

This paper propose a new dynamic multiproduct pricing game with supply (price adjustment costs) and demand (consumer switching costs) frictions. We use it to study the effects of frictions on price dynamics, profits and consumer welfare for the UK butter and margarine industry. Following an empirical regularity documented in data and the related literature, we assume that price competition occurs through temporary price cuts (sales). We therefore model firms' decisions as a discrete choice between regular and sales prices. In our model, temporary

[39]For $\beta > 0.996$ we could not solve the counterfactual models (with $\mathbf{AC} = 0$). The reason is that, when the discount factor is relatively high and $\mathbf{AC} = 0$, the exponential of the sum of discounted profits in the counterfactual scenario gets very large and equilibrium probabilities are not defined.

[40]Keep in mind that the results reported in this paragraph are different from the results reported in the paragraph "Changes of price levels when $\mathbf{AC} = 0$". Here the counterfactual is computed assuming higher markups *after* and *before* the counterfactual change. In the previous paragraph, we increased markups only *after* the counterfactual change.

[41]Which, as explained before, were computed as the average regular and average promotional price of each brand in each supermarket across all periods covered by our sample.

price cuts are rationalised by consumer switching costs (e.g. due to brand loyalty). This type of consumer behavior creates two countervailing effects for firms' pricing decisions: *investing* and *harvesting*. The first motive acts as an incentive for firms to temporarily lower prices in order to build up a larger base of loyal consumers. Subsequently, after acquiring a number of loyal consumers, firms may increase their prices and *harvest* the investments made in the previous periods (Beggs and Klemperer, 1992; Dubé et al., 2009, 2008, 2010). We estimate the structural parameters of the model – including firms discount factor – using scanner data. We solve the model and analyse the effects of price adjustment costs and consumer inertia on prices, consumer welfare and firms' profits. To the best of our knowledge this is the first paper to estimate a dynamic pricing model with multiproduct, forward-looking firms in an oligopoly setting in which consumers exhibit inertia in their choices and firms pay a cost to adjust prices.

The main findings of our empirical analysis are as follows. First, 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 leads to a significant increase in profits but has little effect on prices and consumer welfare. Considering that these price adjustment costs are mainly associated with fees charged by retailers on manufacturers to cover the expenses of promotional campaigns, the latter result suggests that a ban of these fees would lead to increases in firms' profits but have modest impact on consumers. Second, we also study how consumer inertia affects prices when price adjustment is costly. We show that when adjustment costs are at the estimated levels, higher consumer switching costs lead to a more pronounced increase in prices than in the model where price adjustment costs are normalised to zero, suggesting that the effects of consumer loyalty on prices may be underestimated if researchers neglect the existence of price adjustment costs. This finding is another contribution of our work as interactions of consumer switching costs and price adjustment costs and their effects on prices have not been previously considered simultaneously in the marketing/IO literature (Dubé et al., 2009, 2008, 2010; Pavlidis and Ellickson, 2017).

Finally, beyond our structural analysis, based on the magnitudes of our estimates, it seems price adjustment costs could play a non-trivial role in determining market structure in the UK butter and margarine market. Particularly, 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.

# References

AGRAWAL, D. (1996): "Effect of Brand Loyalty on Advertising and Trade Promotions: A Game Theoretic Analysis with Empirical Evidence," *Marketing Science*, 15, 86–108.

AGUIRREGABIRIA, V. (1999): "The Dynamics of Markups and Inventories in Retailing Firms," *Review of Economic Studies*, 66, 275–308.

AGUIRREGABIRIA, V. AND P. MIRA (2007): "Sequential Estimation of Dynamic Discrete Games," *Econometrica*, 75, 1–53.

AGUIRREGABIRIA, V. AND A. NEVO (2013): "Recent Developments in Empirical IO: Dynamic Demand and Dynamic Games," in *Advances in Economics and Econometrics: Tenth World Congress*, ed. by D. Acemoglu, M. Arellano, and E. Dekel, Cambridge University Press, vol. 3: Econometrics, 53–122.

AGUIRREGABIRIA, V. AND J. SUZUKI (2014): "Identification and Counterfactuals in Dynamic Models of Market Entry and Exit," *Quantitative Marketing and Economics*, 12, 267–304.

AILAWADI, K. L., B. A. HARLAM, J. CÉSAR, AND D. TROUNCE (2006): "Promotion Profitability for a Retailer: The Role of Promotion, Brand, Category and Store Characteristics," *Journal of Marketing Research*, 43, 518–535.

ALVAREZ, F. AND F. LIPPI (2014): "Price Setting with Menu Cost for Multiproduct Firms," *Econometrica*, 82, 89–135.

ANDERSON, E., B. A. MALIN, E. NAKAMURA, D. SIMESTER, AND J. STEINSSON (2017): "Informational Rigidities and the Stickiness of Temporary Sales," *Journal of Monetary Economics*, 90, 64–83.

ARCIDIACONO, P. AND P. B. ELLICKSON (2011): "Practical Methods for Estimation of Dynamic Discrete Choice Models," *Annual Review of Economics*, 3, 363–394.

ARIE, G. AND P. L. E. GRIECO (2014): "Who pays for switching costs?" *Quantitative Marketing and Economics*, 12, 379–419.

BAJARI, P., C. L. BENKARD, AND J. LEVIN (2007): "Estimating Dynamic Models of Imperfect Competition," *Econometrica*, 75, 1331–1370.

BAJARI, P., C. S. CHU, D. NEKIPELOV, AND M. PARK (2016): "Identification and semiparametric estimation of a finite horizon dynamic discrete choice model with a terminating action," *Quantitative Marketing and Economics*, 14, 271–323.

BARWICK, P. J. AND P. A. PATHAK (2015): "The Costs of Free Entry: An Empirical Study of Real Estate Agents in Greater Boston," *RAND Journal of Economics*, 46, 103–145.

BEGGS, A. AND P. KLEMPERER (1992): "Multi-Period Competition with Switching Costs," *Econometrica*, 60, 651–66.

BERRY, S., J. LEVINSOHN, AND A. PAKES (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63, 841–890.

BLOOM, P. N., G. T. GUNDLACH, AND J. P. CANNON (2000): "Slotting Allowances and Fees: Schools of Thought and the Views of Practicing Managers," *Journal of Marketing*, 64, 92–108.

CHINTAGUNTA, P. (2002): "Investigating Category Pricing Behavior at a Retail Chain," *Journal of Marketing Research*, 39, 141–154.

CHINTAGUNTA, P. K., J.-P. DUBÉ, AND V. SINGH (2003): "Balancing profitability and customer welfare in a supermarket chain," *Quantitative Marketing and Economics*, 1, 111–147.

COMPETITION COMMISSION (2000): "Supermarkets: A Report on the Supply of Groceries from Multiple Stories in the United Kingdom," Tech. Rep. CM 4882.

CONLISK, J., E. GERSTNER, AND J. SOBEL (1984): "Cyclic Pricing by a Durable Goods Monopolist," *Quarterly Journal of Economics*, 99, 489–505.

CONLON, C. T. AND N. L. RAO (2019): "Discrete Prices and the Incidence and Efficiency of Excise Taxes," *American Economic Journal: Policy*, forthcoming.

DE GROOTE, O. AND F. VERBOVEN (2019): "Subsidies and time discounting in new technology adoption: Evidence from solar photovoltaic systems," *American Economic Review*, 109, 2137–72.

DELLAVIGNA, S. AND M. GENTZKOW (2019): "Uniform Pricing in US Retail Chains," *Quarterly Journal of Economics*, 134, 2011–84.

DORASZELSKI, U. AND M. SATTERTHWAITE (2010): "Computable Markov-Perfect Industry Dynamics," *RAND Journal of Economics*, 41, 215–243.

DUBÉ, J.-P., G. J. HITSCH, AND P. E. ROSSI (2009): "Do Switching Costs Make Markets Less Competitive?" *Journal of Marketing Research*, 46, 435–445.

——— (2010): "State dependence and alternative explanations for consumer inertia," *RAND Journal of Economics*, 41, 417–445.

DUBÉ, J.-P., G. J. HITSCH, P. E. ROSSI, AND M. A. VITORINO (2008): "Category Pricing with State-Dependent Utility," *Marketing Science*, 27, 417–429.

DUBOIS, P., R. GRIFFITH, AND A. NEVO (2014): "Do Prices and Attributes Explain International Differences in Food Purchases?" *American Economic Review*, 104, 832–867.

DUTTA, S., M. BERGEN, D. LEVY, AND R. VENABLE (1999): "Menu Costs, Posted Prices, and Multiproduct Retailers," *Journal of Money, Credit and Banking*, 31, 683–703.

EIZENBERG, A. AND A. SALVO (2015): "The Rise of Fringe Competitors in the Wake of an Emerging Middle Class: An Empirical Analysis," *American Economic Journal: Applied Economics*, 7, 85–122.

ELLISON, S. F., C. M. SNYDER, AND H. ZHANG (2015): "Costs of Managerial Attention and Activity as a Source of Sticky Prices: Structural Estimates from an Online Market," Working Paper, MIT.

ERICSON, R. AND A. PAKES (1995): "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, 62, 53–82.

FERSHTMAN, C. AND A. PAKES (2012): "Dynamic Games with Asymmetric Information: A Framework for Empirical Work," *Quarterly Journal of Economics*, 127, 1611–61.

FOWLIE, M., M. REGUANT, AND S. P. RYAN (2016): "Market-Based Emissions Regulation and Industry Dynamics," *Journal of Political Economy*, 124, 249–302.

GOETTLER, R. L. AND B. R. GORDON (2011): "Does AMD Spur Intel to Innovate More?" *Journal of Political Economy*, 119, 1141–1200.

GOLDBERG, P. K. AND R. HELLERSTEIN (2013): "A Structural Approach to Identifying the Sources of Local-Currency Price Stability," *Review of Economic Studies*, 80, 175–210.

GRIFFITH, R., E. LEIBTAG, A. LEICESTER, AND A. NEVO (2009): "Consumer Shopping Behavior: How Much Do Consumers Save?" *Journal of Economic Perspectives*, 23, 99–120.

GRIFFITH, R., L. NESHEIM, AND M. O'CONNELL (2017): "Income effects and the welfare consequences of tax in differentiated product oligopoly," *Quantitative Economics*, forthcoming.

HEIDHUES, P. AND B. KŐSZEGI (2014): "Regular prices and sales," *Theoretical Economics*, 9, 217–251.

HENDEL, I. AND A. NEVO (2006): "Measuring the Implications of Sales and Consumer Inventory Behavior," *Econometrica*, 74, 1637–1673.

——— (2013): "Intertemporal Price Discrimination in Storable Goods Markets," *American Economic Review*, 103, 2722–2751.

HOCH, S. J., X. DREZE, AND M. E. PURK (1994): "EDLP, Hi-Lo, and margin arithmetic," *Journal of Marketing*, 58, 16–27.

HORSKY, D., P. PAVLIDIS, AND M. SONG (2012): "Incorporating State Dependence in Aggregate Brand-level Demand Models," Working Paper, Simon Graduate School of Business, University of Rochester.

HOSKEN, D. AND D. REIFFEN (2004): "Patterns of Retail Price Variation," *RAND Journal of Economics*, 35, 128–146.

HOTZ, V. J. AND R. A. MILLER (1993): "Conditional Choice Probabilities and the Estimation of Dynamic Models," *Review of Economic Studies*, 60, 497–529.

HOTZ, V. J., R. A. MILLER, S. SANDERS, AND J. SMITH (1994): "A Simulation Estimator for Dynamic Models of Discrete Choice," *Review of Economic Studies*, 61, 265–289.

KADIYALI, V., P. CHINTAGUNTA, AND N. VILCASSIM (2000): "Manufacturer-Retailer Channel Interactions and Implications for Channel Power: An Empirical Investigation of Pricing in a Local Market," *Marketing Science*, 19, 127–248.

KANO, K. (2013): "Menu Costs and Dynamic Duopoly," *International Journal of Industrial Organization*, 31, 102–118.

KAPLAN, G. (2012): "Moving back home: Insurance against labor market risk," *Journal of Political Economy*, 120, 446–512.

KOMAROVA, T., F. A. M. SANCHES, D. SILVA JR., AND S. SRISUMA (2018): "Joint Analysis of the Discount Factor and Payoff Parameters in Dynamic Discrete Choice Models," *Quantitative Economics*, 9, 1153–94.

LAL, R. (1990): "Price Promotions: Limiting Competitive Encroachment," *Marketing Science*, 9, 247–262.

LEVY, D., M. BERGEN, S. DUTTA, AND R. VENABLE (1997): "The Magnitude of Menu Costs: Direct Evidence from Large U.S. Supermarket Chains," *Quarterly Journal of Economics*, 112, 791–825.

MATĚJKA, F. (2015): "Rationally Inattentive Seller: Sales and Discrete Pricing," *The Review of Economic Studies*, 83, 1125–1155.

MEZA, S. AND K. SUDHIR (2010): "Do private labels increase retailer bargaining power?" *Quantitative Marketing and Economics*, 8, 333–363.

NAIR, H. S. (2019): "Diffusion and pricing over the product life cycle," in *Handbook of the Economics of Marketing*, Elsevier, vol. 1, 359–439.

NEVO, A. (2001): "Measuring Market Power in the Ready-To-Eat Cereal Industry," *Econometrica*, 69, 307–342.

PAKES, A., M. OSTROVSKY, AND S. BERRY (2008): "Simple estimators for the parameters of discrete dynamic games (with entry/exit examples)," *The RAND Journal of Economics*, 38, 373–399.

PAVLIDIS, P. AND P. ELLICKSON (2017): "Implications of Parent Brand Inertia for Multiproduct Pricing," *Quantitative Marketing and Economics*, 15, 188–227.

PEARCY, J. (2014): "Bargains Followed by Bargains: When Switching Costs Make Markets More Competitive," Working Paper, Montana State University.

PESENDORFER, M. (2002): "Retail Sales: A Study of Pricing Behavior in Supermarkets," *Journal of Business*, 75, 33–66.

PESENDORFER, M. AND P. SCHMIDT-DENGLER (2008): "Asymptotic Least Squares Estimators for Dynamic Games," *Review of Economic Studies*, 75, 901–928.

SANCHES, F. A., D. J. SILVA, AND S. SRISUMA (2016): "Ordinary Least Squares Estimation of a Dynamic Game Model," *International Economic Review*, 57, 623–634.

SEILER, S. (2013): "The impact of search costs on consumer behavior: A dynamic approach," *Quantitative Marketing and Economics*, 11, 155–203.

SHEN, Y., C. CHAN, F. ZHENG, AND G. J. ESCOBAR (2020): "Structural Estimation of Intertemporal Externalities on ICU Admission Decisions," *Available at SSRN 3564776*.

SLADE, M. E. (1998): "Optimal Pricing with Costly Adjustment: Evidence from Retail Grocery Prices," *Review of Economic Studies*, 65, 87–107.

SOBEL, J. (1984): "The Timing of Sales," *Review of Economic Studies*, 51, 353–368.

SRINIVASAN, S., K. PAUWELS, D. M. HANSSENS, AND M. G. DEKIMPE (2004): "Do Promotions Benefit Manufacturers, Retailers, or Both?" *Management Science*, 50, 617–629.

SRISUMA, S. (2013): "Minimum distance estimators for dynamic games: Minimum distance estimators for dynamic games," *Quantitative Economics*, 4, 549–583.

STELLA, A. (2019): "Economies of Scope in Price Setting: A Moment Inequalities Estimation," *Journal of Monetary Economics*, forthcoming.

SWEETING, A. (2013): "Dynamic Product Positioning in Differentiated Product Markets: The Effect of Fees for Musical Performance Rights on the Commercial Radio Industry," *Econometrica*, 81, 1763–1803.

VARIAN, H. R. (1980): "A Model of Sales," *American Economic Review*, 70, 651–659.

VILLAS-BOAS, J. M. (2015): "A Short Survey on Switching Costs and Dynamic Competition," *International Journal of Research in Marketing*, forthcoming.

WILLIAMS, K. R. (2022): "The Welfare Effects of Dynamic Pricing: Evidence From Airline Markets," *Econometrica*, 90, 831–858.

ZBARACKI, M. J., M. RITSON, D. LEVY, S. DUTTA, AND M. BERGEN (2004): "Managerial and customer costs of price adjustment: direct evidence from industrial markets," *Review of Economics and Statistics*, 86, 514–533.

# 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".*[42]
  2. "*Terms are commercially sensitive but in general the payments, (...), are made for various activities (...)".*[43]

- 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(...)".* [44]
  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".*[45]

- Promotional fees are a very important source of revenues to supermarkets[46]:

  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".*[47]

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

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

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

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

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

[47] 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".*[48]
  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****".*[49]

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

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

# B Additional tables and figures

**Table B.1:** 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 B.2:** 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 B.3:** 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 B.4:** Durations of promotions and periods of regular prices in one chain (Tesco).

| PRODUCTS BY MANUFACTURER | # PERIODS | AVG DUR. | STD. DEV. | MIN | MAX |
|---|---|---|---|---|---|
| **Promotional prices** | | | | | |
| **Arla** | | | | | |
| ANCHOR | 25 | 3.64 | 2.08 | 1 | 10 |
| LURPAK | 29 | 3.93 | 2.12 | 1 | 9 |
| **Dairy Crest** | | | | | |
| CLOVER | 20 | 3.80 | 2.04 | 1 | 9 |
| COUNTRY LIFE | 22 | 3.32 | 1.29 | 1 | 6 |
| **Unilever** | | | | | |
| FLORA | 25 | 4.44 | 3.78 | 1 | 10 |
| ICBINB | 22 | 3.32 | 2.10 | 1 | 9 |
| **Regular prices** | | | | | |
| **Arla** | | | | | |
| ANCHOR | 24 | 4.54 | 2.57 | 1 | 11 |
| LURPAK | 30 | 2.87 | 1.72 | 1 | 7 |
| **Dairy Crest** | | | | | |
| CLOVER | 21 | 5.91 | 4.93 | 1 | 19 |
| COUNTRY LIFE | 22 | 5.77 | 4.93 | 1 | 21 |
| **Unilever** | | | | | |
| FLORA | 25 | 3.56 | 1.85 | 1 | 8 |
| ICBINB | 22 | 5.73 | 6.26 | 1 | 21 |

**Note**: # PERIODS denotes the number of distinct spells of promotional (top panel) and regular prices (bottom panel) in the 200-week sample.

**Table B.5:** 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.

**Table B.6:** 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.

**Figure B.1:** Pasteurised and fresh milk prices.

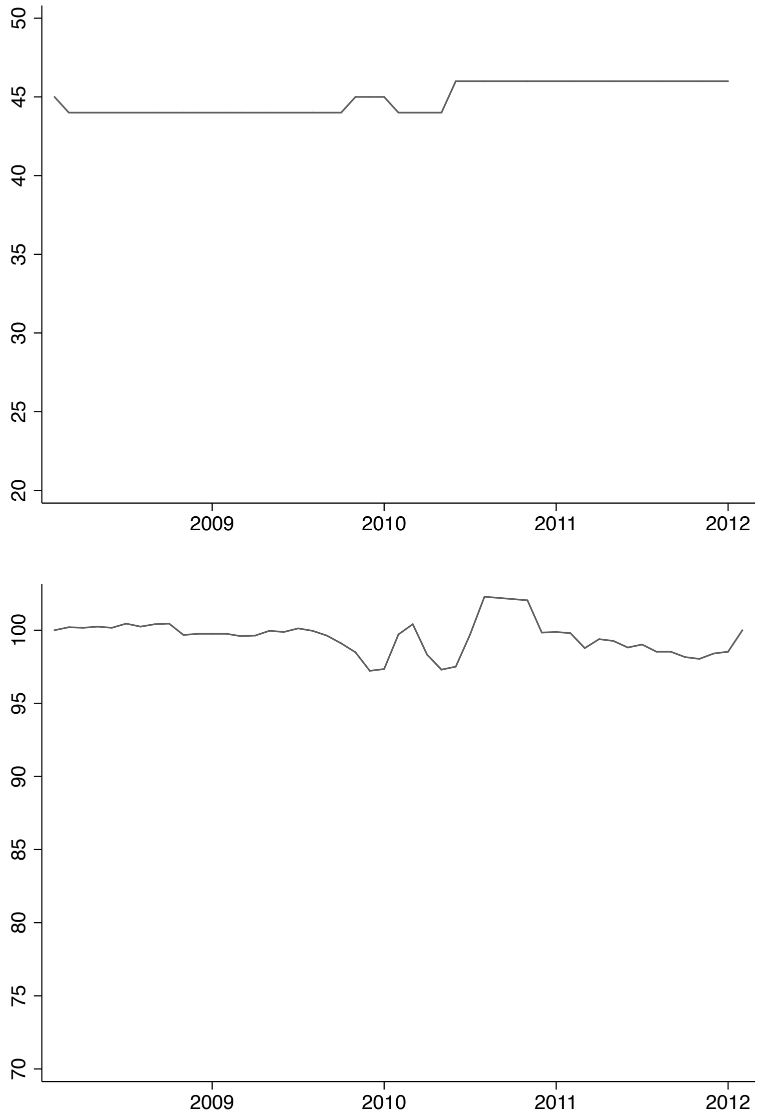


**Figure B.2:** Price dynamics across supermarket chains. Each graph shows time series of prices for 1 brand in 4 supermarket chains.

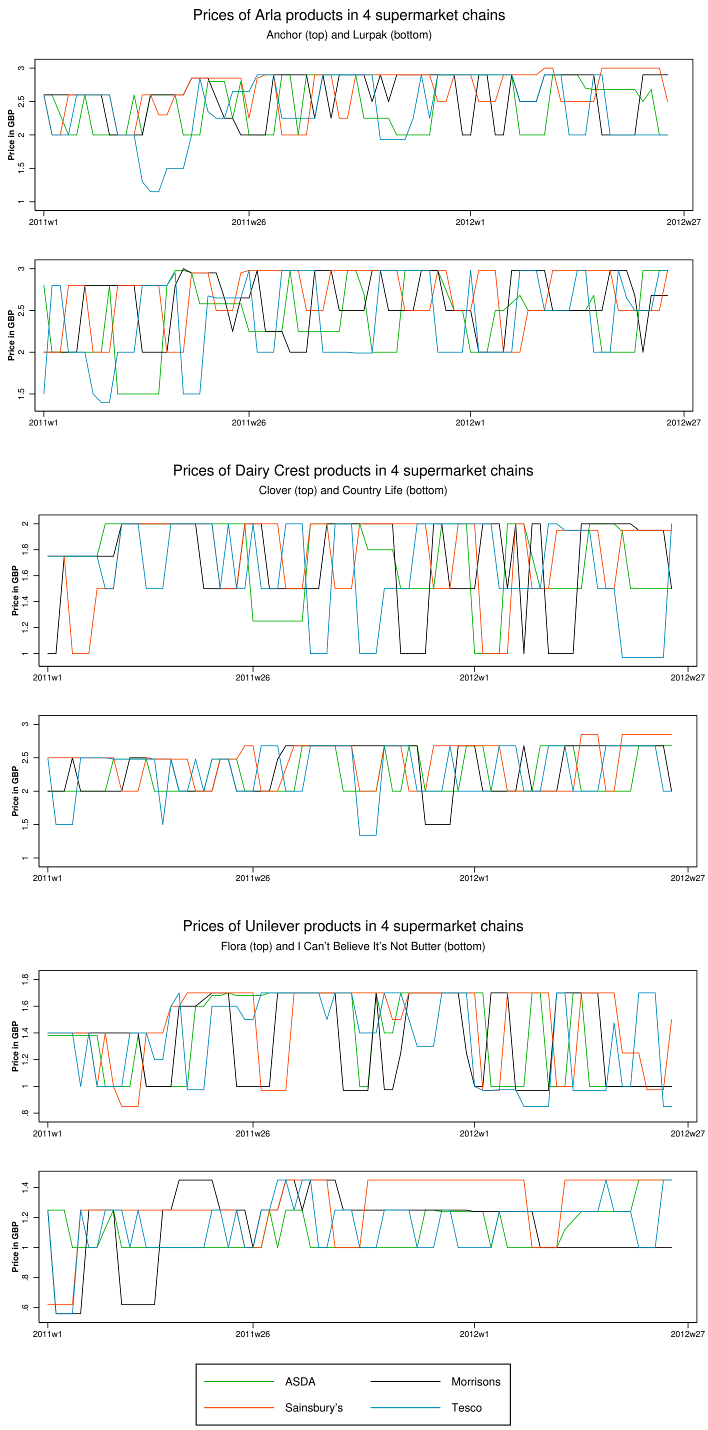
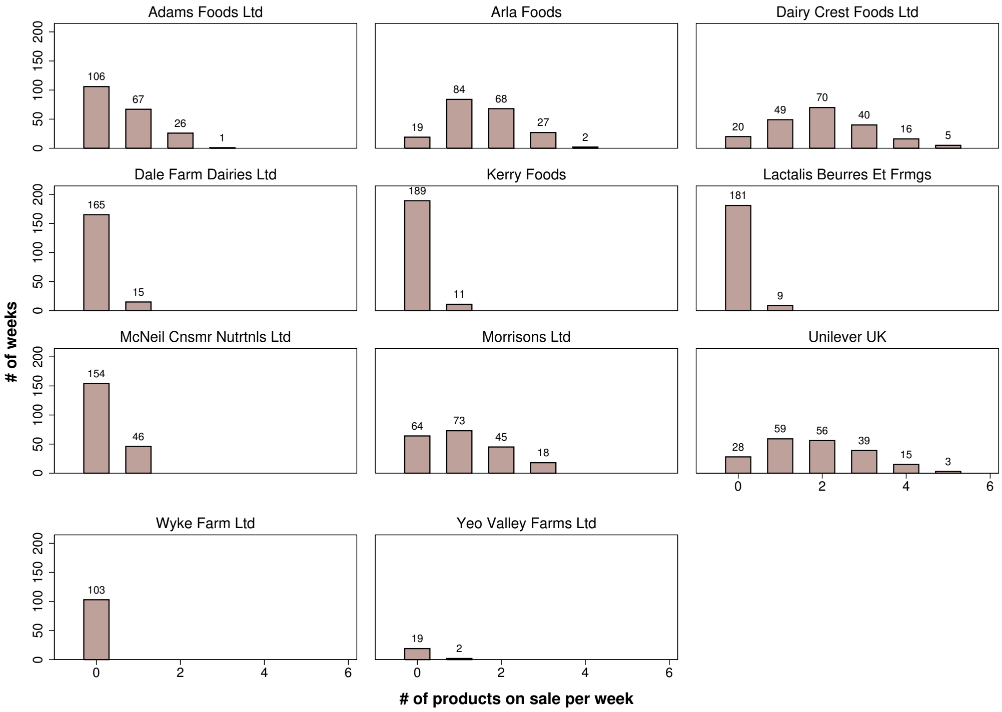


**Figure B.3:** Histograms of the number of products on sale by firm.



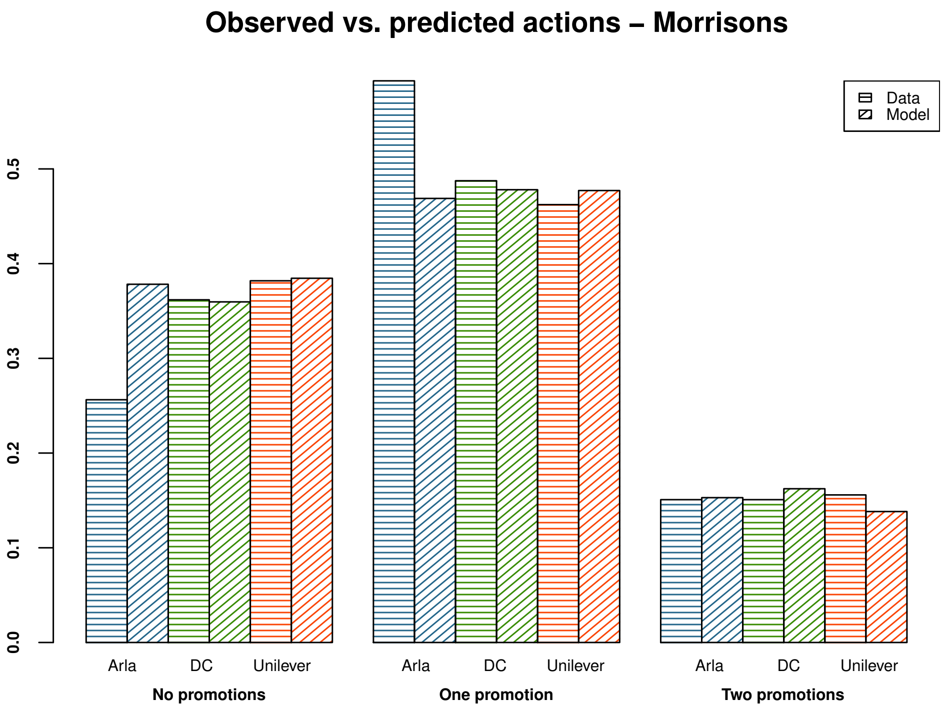

**Note:** Figure constructed using the universe of all 500g spreadable products by recording the promotional flags for each of the products. E.g. for Arla there were 19 weeks with no product on sale, 84 weeks with 1 brand on sale, 68 weeks with 2 brands on sale etc. If the numbers do not sum to 200 for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

**Table B.7:** 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 firms (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 B.4:** Actions played by firms: model vs. data.



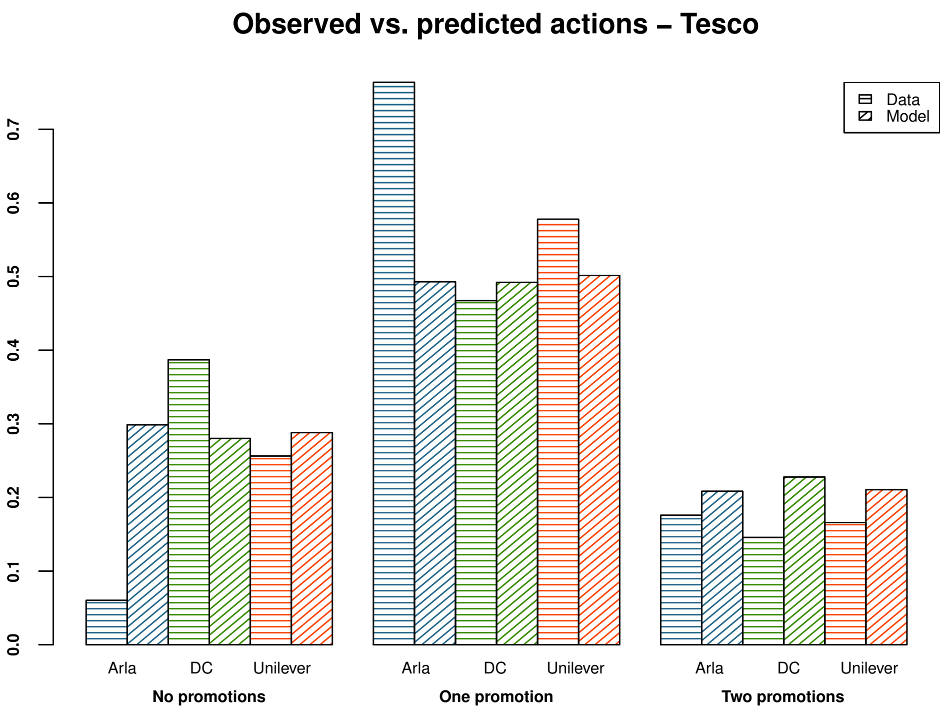
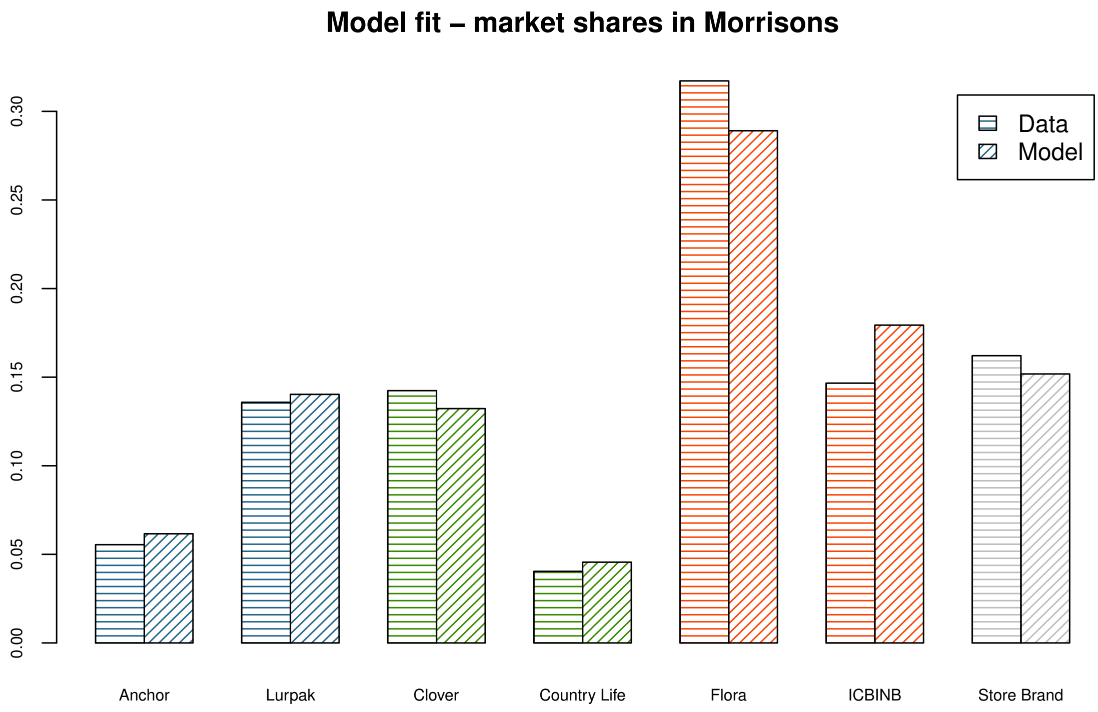
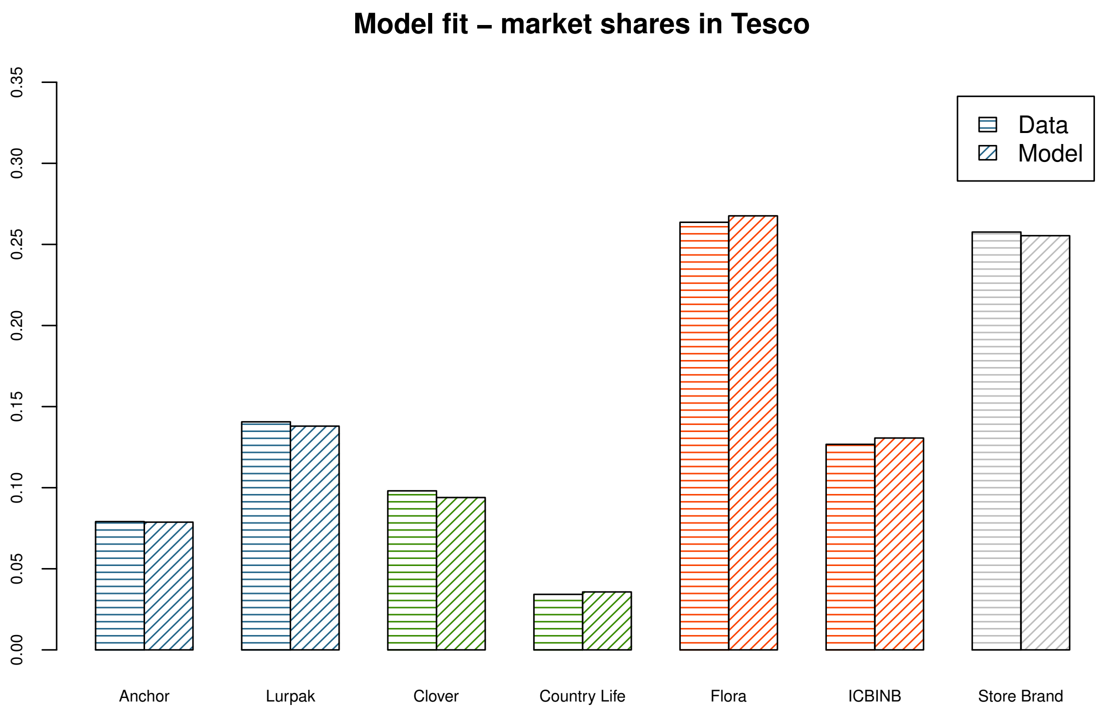



**Figure B.5:** Market shares by brand: model vs. data.



# C Robustness checks

This appendix contains several robustness checks of our baseline model: different calibrations of market size, results using a random coefficients demand model, different specification of price adjustment costs and counterfactuals computed under different assumptions.

**Table C.1:** Estimated discount factors for different calibrations of $H/\zeta$.

| $H/\zeta$ | MORRISONS $\beta$ | TESCO $\beta$ |
|---|---|---|
| 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 C.2:** Magnitude of adjustment costs for different calibrations of $H/\zeta$.

| $H/\zeta$ | MORRISONS | | | TESCO | | |
|---|---|---|---|---|---|---|
| | Arla | DC | Uni | Arla | DC | 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 C.3:** Counterfactual results with $\mathbf{AC} = 0$ for different calibrations of $H/\zeta$.

| $H/\zeta$ | | Morrisons | | | Tesco | | |
|---|---|---|---|---|---|---|---|
| | | Arla | DC | Uni | Arla | DC | Uni |
| 0.5 | $\Delta$s | 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% |
| | $\Delta CS$ | | 0.44% | | | 0.05% | |
| 2.0 | $\Delta$s | 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% |
| | $\Delta CS$ | | 0.70% | | | 0.18% | |
| 4.0 | $\Delta$s | 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% |
| | $\Delta CS$ | | 1.25% | | | 0.37% | |
| 6.0 | $\Delta$s | 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% |
| | $\Delta CS$ | | 2.04% | | | 0.54% | |
| 8.0 | $\Delta$s | 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% |
| | $\Delta CS$ | | 3.27% | | | 0.71% | |

**Note**: Numbers in the table are percentage differences between the counterfactual scenario and the baseline model in: average market share ($\Delta$s), firm profits ($\Delta\Pi$) and consumer surplus ($\Delta CS$). 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 C.4:** Counterfactual results with $\mathbf{AC} = 0$ and different values for the discount factor

| $\beta$ | Morrisons | | | Tesco | | |
|---|---|---|---|---|---|---|
| | $\Delta s$ | $\Delta\Pi$ | $\Delta CS$ | $\Delta s$ | $\Delta\Pi$ | $\Delta CS$ |
| 0.980 | 1.80% | 59.06% | 1.67% | 0.39% | 68.64% | 0.30% |
| 0.981 | 1.76% | 59.00% | 1.63% | 0.38% | 68.56% | 0.29% |
| 0.982 | 1.71% | 58.94% | 1.59% | 0.37% | 68.49% | 0.29% |
| 0.983 | 1.67% | 58.88% | 1.55% | 0.36% | 68.41% | 0.28% |
| 0.984 | 1.64% | 58.82% | 1.52% | 0.36% | 68.33% | 0.28% |
| 0.985 | 1.59% | 58.76% | 1.48% | 0.35% | 68.26% | 0.27% |
| 0.986 | 1.55% | 58.71% | 1.44% | 0.34% | 68.18% | 0.27% |
| 0.987 | 1.51% | 58.65% | 1.40% | 0.33% | 68.11% | 0.26% |
| 0.988 | 1.48% | 58.59% | 1.37% | 0.33% | 68.04% | 0.25% |
| 0.989 | 1.44% | 58.54% | 1.33% | 0.32% | 67.97% | 0.25% |
| 0.990 | 1.40% | 58.48% | 1.30% | 0.31% | 67.90% | 0.24% |
| 0.991 | 1.35% | 58.43% | 1.25% | 0.30% | 67.83% | 0.24% |
| 0.992 | 1.31% | 58.38% | 1.22% | 0.29% | 67.77% | 0.23% |
| 0.993 | 1.27% | 58.33% | 1.17% | 0.29% | 67.70% | 0.22% |
| 0.994 | 1.21% | 58.29% | 1.12% | 0.28% | 67.64% | 0.22% |
| 0.995 | 1.14% | 58.25% | 1.05% | 0.27% | 67.58% | 0.21% |
| 0.996 | 1.07% | 58.21% | 0.98% | 0.26% | 67.53% | 0.20% |

**Table C.5:** Counterfactual results with $AC = 0$ and increase of 20% in low/high price levels

| Firm | Morrisons | | | Tesco | | |
|---|---|---|---|---|---|---|
| | Arla | DC | Uni | Arla | DC | Uni |
| $\Delta s$ | -24.81% | -15.41% | -11.68% | -7.42% | -4.87% | -3.84% |
| $\Delta\Pi$ | 77.83% | 66.93% | 55.30% | 76.76% | 75.34% | 59.71% |
| $\Delta CS$ | | -14.43% | | | -6.01% | |

**Table C.6:** Counterfactual results with $\mathbf{AC} = 0$ and variation in low/high price levels

| | Price Change | Firm | Shares | Cons. Surplus | Total Profits |
|---|---|---|---|---|---|
| MORRISONS | +10% | Arla | 3.78% | 3.03% | 73.40% |
| | | DC | 3.90% | | 63.34% |
| | | Uni | 3.01% | | 49.46% |
| | -10% | Arla | 4.07% | 3.01% | 76.67% |
| | | DC | 3.61% | | 65.41% |
| | | Uni | 2.48% | | 52.04% |
| TESCO | +10% | Arla | 0.69% | 0.32% | 69.66% |
| | | DC | 0.29% | | 71.95% |
| | | Uni | 0.31% | | 53.47% |
| | -10% | Arla | 0.57% | 0.26% | 73.81% |
| | | DC | 0.23% | | 73.86% |
| | | Uni | 0.22% | | 56.16% |

**Table C.7:** Implications of consumer loyalty with and without price adjustment costs and a 10% increase in price levels

| Scaling Factor | $\mathbf{AC} = 0$ | | Estimated $\mathbf{AC}$ | |
|---|---|---|---|---|
| | Price | Difference | Price | Difference |
| MORRISONS | | | | |
| 0.00 | 1.973 | - | 1.924 | - |
| 0.25 | 1.973 | 0.02% | 1.924 | 0.01% |
| 0.75 | 1.974 | 0.06% | 1.924 | 0.03% |
| 0.50 | 1.976 | 0.15% | 1.925 | 0.07% |
| 1.00 | 1.980 | 0.34% | 1.926 | 0.13% |
| 2.00 | 2.084 | 5.62% | 1.993 | 3.57% |
| 3.00 | 2.143 | 8.59% | 2.052 | 6.69% |
| TESCO | | | | |
| 0.00 | 1.930 | - | 1.915 | - |
| 0.25 | 1.930 | -2.16% | 1.915 | -0.47% |
| 0.75 | 1.931 | -2.13% | 1.915 | -0.46% |
| 0.50 | 1.932 | -2.07% | 1.915 | -0.45% |
| 1.00 | 1.934 | -1.96% | 1.916 | -0.41% |
| 2.00 | 2.006 | 1.68% | 1.938 | 0.75% |
| 3.00 | 2.050 | 3.90% | 1.946 | 1.16% |

Table C.8: Demand estimates with heterogeneous brand fixed effects.

| | ASDA | MORRISONS | SAINSBURY'S | TESCO |
|---|---|---|---|---|
| $\delta^h_{Anchor}$ | $-3.301$ | $-3.598$ | $-3.861$ | $-4.424$ |
| | *2.044* | *1.725* | *2.407* | *1.999* |
| $\delta^h_{Lurpak}$ | $-2.778$ | $-2.976$ | $-3.552$ | $-4.215$ |
| | *2.491* | *2.673* | *2.517* | *2.405* |
| $\delta^h_{Clover}$ | $-3.724$ | $-2.784$ | $-3.929$ | $-4.167$ |
| | *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* |
| $\delta^h_{Flora}$ | $-2.473$ | $-2.142$ | $-2.729$ | $-2.961$ |
| | *1.327* | *1.037* | *1.463* | *1.085* |
| $\delta^h_{ICBINB}$ | $-2.646$ | $-2.824$ | $-3.537$ | $-3.650$ |
| | *1.264* | *1.168* | *1.426* | *1.228* |
| $\delta^h_{SB}$ | $-3.291$ | $-3.269$ | $-2.873$ | $-3.235$ |
| | *1.528* | *1.574* | *1.216* | *1.332* |
| $\eta$ | $-0.924$ | $-0.942$ | $-0.677$ | $-0.428$ |
| | $[-0.973; -0.876]$ | $[-0.991; -0.893]$ | $[-0.729; -0.625]$ | $[-0.457; -0.399]$ |
| $\gamma$ | $1.603$ | $1.810$ | $1.352$ | $1.999$ |
| | $[1.568; 1.638]$ | $[1.772; 1.848]$ | $[1.313; 1.390]$ | $[1.977; 2.022]$ |
| $N$ | 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 $\delta^h_j$ 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 (italicised). For $\eta$ and $\gamma$, 95% confidence intervals reported in brackets.

**Table C.9:** Demand estimates (larger choice set)

| | ASDA | | | | MORRISONS | | | | SAINSBURY'S | | | | TESCO | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| $\delta_{Anchor\ 250g}$ | −4.322 | −4.344 | | −4.724 | −4.560 | −4.549 | | −4.636 | −4.564 | −4.568 | | −5.256 | −4.448 | −4.437 | | −4.920 |
| | (0.042) | (0.042) | −4.139 | (0.082) | (0.051) | (0.050) | −4.047 | (0.090) | (0.045) | (0.045) | −4.231 | (0.079) | (0.023) | (0.023) | −3.972 | (0.038) |
| $\delta_{Anchor\ 500g}$ | −3.231 | −3.107 | (0.031) | −3.386 | −3.695 | −3.545 | (0.037) | −3.664 | −3.882 | −3.681 | (0.033) | −4.308 | −4.275 | −4.190 | (0.018) | −4.679 |
| | (0.051) | (0.050) | | (0.080) | (0.061) | (0.060) | | (0.098) | (0.060) | (0.059) | | (0.082) | (0.033) | (0.033) | | (0.045) |
| $\delta_{Lurpak\ 250g}$ | −3.725 | −3.800 | | −3.988 | −3.823 | −3.856 | | −3.808 | −4.066 | −4.062 | | −4.448 | −4.252 | −4.288 | | −4.547 |
| | (0.039) | (0.039) | −3.537 | (0.078) | (0.042) | (0.042) | −3.396 | (0.080) | (0.041) | (0.041) | −3.875 | (0.070) | (0.023) | (0.023) | −3.594 | (0.039) |
| $\delta_{Lurpak\ 500g}$ | −2.573 | −2.436 | (0.030) | −2.651 | −3.068 | −2.925 | (0.033) | −2.905 | −3.528 | −3.403 | (0.032) | −3.824 | −3.793 | −3.681 | (0.018) | −3.986 |
| | (0.050) | (0.050) | | (0.074) | (0.058) | (0.057) | | (0.090) | (0.061) | (0.060) | | (0.079) | (0.032) | (0.031) | | (0.041) |
| $\delta_{Clover\ 500g}$ | −3.484 | −3.322 | −3.727 | −3.512 | −3.338 | −3.155 | −3.158 | −3.267 | −4.032 | −3.872 | −3.987 | −4.428 | −4.152 | −3.982 | −3.674 | −4.438 |
| | (0.039) | (0.039) | (0.032) | (0.068) | (0.038) | (0.037) | (0.030) | (0.068) | (0.043) | (0.042) | (0.033) | (0.070) | (0.024) | (0.023) | (0.019) | (0.037) |
| $\delta_{Country\ Life\ 250g}$ | −3.902 | −3.874 | | −4.338 | −3.994 | −3.934 | | −4.056 | −4.126 | −4.054 | | −4.677 | −4.469 | −4.400 | | −4.864 |
| | (0.034) | (0.033) | −4.080 | (0.068) | (0.039) | (0.039) | −3.908 | (0.076) | (0.037) | (0.037) | −4.287 | (0.066) | (0.023) | (0.023) | −4.263 | (0.039) |
| $\delta_{Country\ Life\ 500g}$ | −3.530 | −3.466 | (0.029) | −3.701 | −3.914 | −3.858 | (0.033) | −4.064 | −4.390 | −4.340 | (0.031) | −4.973 | −4.931 | −4.898 | (0.019) | −5.372 |
| | (0.051) | (0.050) | | (0.079) | (0.060) | (0.059) | | (0.098) | (0.061) | (0.061) | | (0.088) | (0.036) | (0.036) | | (0.049) |
| $\delta_{Flora\ 250g}$ | −4.681 | −4.928 | | −4.914 | −4.632 | −4.980 | | −4.525 | −4.678 | −4.847 | | −5.087 | −5.547 | −5.843 | | −5.928 |
| | (0.068) | (0.068) | −3.492 | (0.127) | (0.060) | (0.060) | −3.201 | (0.116) | (0.053) | (0.053) | −3.722 | (0.090) | (0.041) | (0.041) | −3.468 | (0.067) |
| $\delta_{Flora\ 500g}$ | −2.883 | −2.722 | (0.027) | −2.655 | −2.893 | −2.720 | (0.026) | −2.483 | −3.277 | −3.120 | (0.026) | −3.259 | −3.403 | −3.227 | (0.016) | −3.254 |
| | (0.031) | (0.030) | | (0.046) | (0.031) | (0.030) | | (0.046) | (0.035) | (0.034) | | (0.047) | (0.019) | (0.018) | | (0.024) |
| $\delta_{ICBINB\ 500g}$ | −2.983 | −2.817 | −3.087 | −2.994 | −3.340 | −3.180 | −3.182 | −3.355 | −3.857 | −3.701 | −3.788 | −3.973 | −3.908 | −3.752 | −3.523 | −4.014 |
| | (0.027) | (0.026) | (0.021) | (0.045) | (0.030) | (0.029) | (0.025) | (0.057) | (0.034) | (0.033) | (0.027) | (0.055) | (0.019) | (0.018) | (0.015) | (0.029) |
| $\delta_{SB\ 250g}$ | −3.033 | −3.021 | | −3.106 | −3.666 | −3.728 | | −3.719 | −2.960 | −2.885 | | −2.926 | −3.223 | −3.202 | | −3.121 |
| | (0.026) | (0.026) | −3.464 | (0.042) | (0.036) | (0.036) | −3.532 | (0.071) | (0.028) | (0.028) | −3.246 | (0.034) | (0.016) | (0.016) | −3.154 | (0.019) |
| $\delta_{SB\ 500g}$ | −3.331 | −3.413 | (0.019) | −3.145 | −3.407 | −3.371 | (0.024) | −3.582 | −3.433 | −3.556 | (0.020) | −3.359 | −3.485 | −3.579 | (0.012) | −3.486 |
| | (0.027) | (0.027) | | (0.046) | (0.032) | (0.031) | | (0.065) | (0.031) | (0.031) | | (0.044) | (0.016) | (0.016) | | (0.024) |
| $\eta$ | −0.622 | −0.687 | −0.419 | −0.731 | −0.414 | −0.489 | −0.487 | −0.615 | −0.254 | −0.316 | −0.237 | −0.251 | −0.123 | −0.187 | −0.411 | −0.158 |
| | (0.022) | (0.021) | (0.015) | (0.030) | (0.023) | (0.023) | (0.016) | (0.031) | (0.024) | (0.023) | (0.015) | (0.025) | (0.014) | (0.013) | (0.009) | (0.014) |
| $\gamma$ | 3.466 | 3.115 | 3.129 | 2.379 − 3.947 | 3.447 | 3.110 | 3.114 | 1.737 − 3.980 | 3.334 | 2.912 | 2.915 | 1.848 − 4.433 | 3.532 | 3.138 | 3.132 | 2.614 − 4.412 |
| | (0.013) | (0.013) | (0.013) | † | (0.016) | (0.016) | (0.016) | † | (0.014) | (0.014) | (0.014) | † | (0.008) | (0.008) | (0.008) | † |

**Note**: All coefficients significantly different from 0 at the 1% level. Standard errors in parentheses below. $SB$ denotes store brand. Specifications: (1) - brand-size loyalty and constants, (2) - brand loyalty, brand-size constants, (3) - brand loyalty and constants, (4) nested logit with brand loyalty and brand-size constants. †: the model was estimated without imposing that the loyalty parameter is the same for all brands. We report the range of point estimates of loyalty coefficients. All associated standard errors do not exceed 0.1.

**Table C.10:** Measures of model fit – random coefficients demand.

| $H/\zeta$ | MORRISONS Actions | MORRISONS Shares | TESCO Actions | TESCO 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 C.11:** Magnitude of adjustment costs with random coefficients demand.

| $H/\zeta$ | MORRISONS Arla | MORRISONS DC | MORRISONS Uni | TESCO Arla | TESCO DC | TESCO 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 C.12:** Counterfactual results with $\mathbf{AC} = 0$ – random coefficients.

| | MORRISONS Arla | MORRISONS DC | MORRISONS Uni | TESCO Arla | TESCO DC | TESCO Uni |
|---|---|---|---|---|---|---|
| $\Delta$s | 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% |
| $\Delta CS$ | | 2.50% | | | 0.06% | |

**Note**: Numbers in the table are percentage differences between the counterfactual scenario and the baseline model in: average market share ($\Delta$s), firm profits ($\Delta\Pi$) and consumer surplus ($\Delta CS$). 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 C.13:** 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 $\overline{p}_*$.

**Table C.14:** Fixed promotional costs and discount factors.

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

# Online Appendix (not for publication)

*The Welfare Effects of Supply and Demand Frictions in a Dynamic Pricing Game* by Myśliwski, Sanches, Silva Jr., and Srisuma

# A Unobserved demand heterogeneity

This appendix discusses the effects of time-varying unobserved heterogeneity on our demand estimates. Our analysis is based on three different exercises. First, using aggregate data at brand level we estimated the following regression:

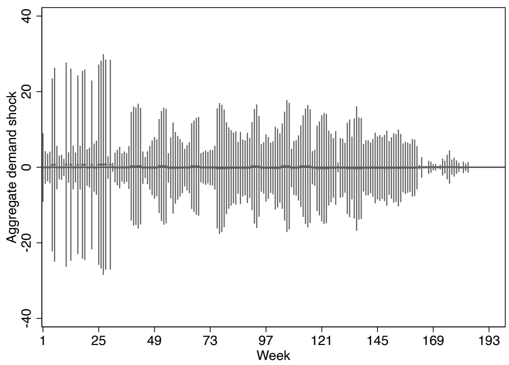
$$s_{jmt} = \alpha + \sum_{j=1}^{J} \beta_j p_{jmt} + \sum_{j=1}^{J} \gamma_j s_{jmt-1} + \delta_j + \delta_t + \varepsilon_{jmt}, \tag{A.1}$$

where, $s_{jmt}$ and $p_{jmt}$ are the share and the price of brand $j$ at supermarket $m$ and week $t$, $\delta_j$ is a brand dummy, $\delta_t$ is a weekly dummy and $\varepsilon_{jmt}$ is an idiosyncratic error term. We see this equation as a reduced form representation of the process governing the evolution of the aggregated market shares as shown by equation (9) in the paper.
We estimated one equation for each supermarket – Morrisons and Tesco – and collected the estimates of the weekly dummies, $\delta_t$. These dummies are interpreted as unobserved demand shocks affecting all butter and margarine brands in each supermarket. Figure OA.1 illustrates the dummies for Morrisons (upper panel) and Tesco (lower panel). The figure on the left hand side shows point estimates of each dummies and 95% confidence intervals. For Morrisons and Tesco virtually all dummy estimates are not significant at 10%. The figures on the right hand side show the same point estimates without the confidence intervals and allows us to better visualize the behavior of these demand shocks over time. In both figures we do not see any clear pattern (cycle, trend, seasonality) of these demand shocks over time.

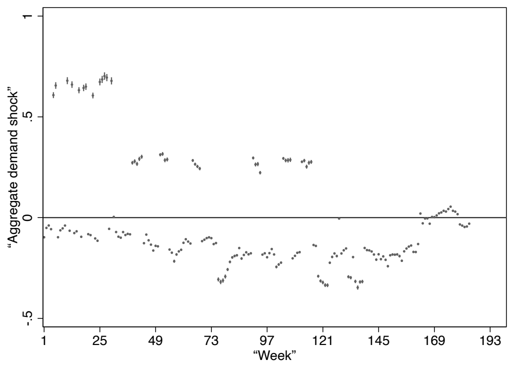
As mentioned, the coefficients in Figure OA.1 capture unobserved demand shocks affecting all brands in each supermarket. To see how these shocks differ across brands we estimate a separate regression for each brand separately pooling both supermarkets (and including supermarket dummies). The time dummies in this regression are now interpreted as brand specific unobserved demand shocks. Figure OA.2 shows these time dummies. For each brand, the figure shows two graphs. The first has point estimates with 95% confidence intervals and the second has the point estimates without confidence intervals. A quick inspection of the figure reveals that all the point estimates are not significant at 10%. They also appear to do not show any clear pattern over time.

For our third exercise, we use the same scanner data that we use to estimate the demand models in our paper. Using a similar idea above, we re-estimate our demand model that now includes weekly dummies in our models. Ideally, we would like to include a time varying brand dummy to mimic BLP's $\xi_{jt}$ – instead of a brand fixed effect as in the previous version of the paper – but estimating a non linear model with more than 1400 dummies showed infeasible. Noting here that we have to perform maximum likelihood estimation to capture the unobserved time effects because we cannot use Berry's inversion. As an alternative, we included 200

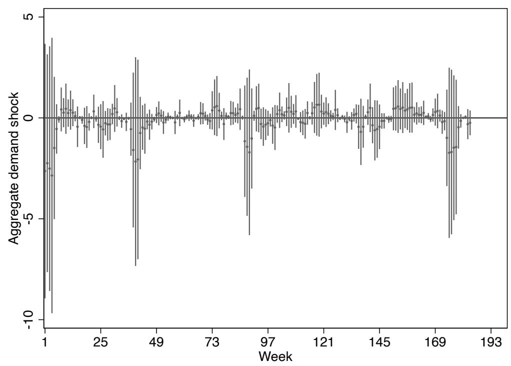
**Figure OA.1:** Weekly Dummies (Demand Shock) for each Supermarket



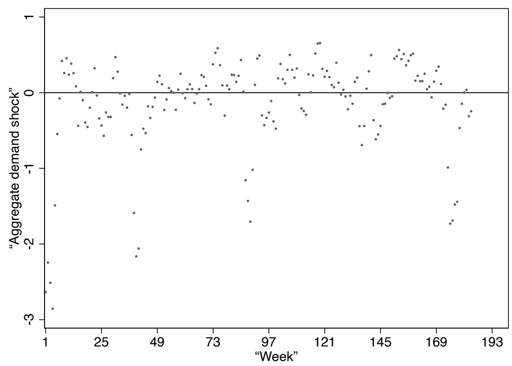

(a) Morrisons




(b) Morrisons




(c) Tesco



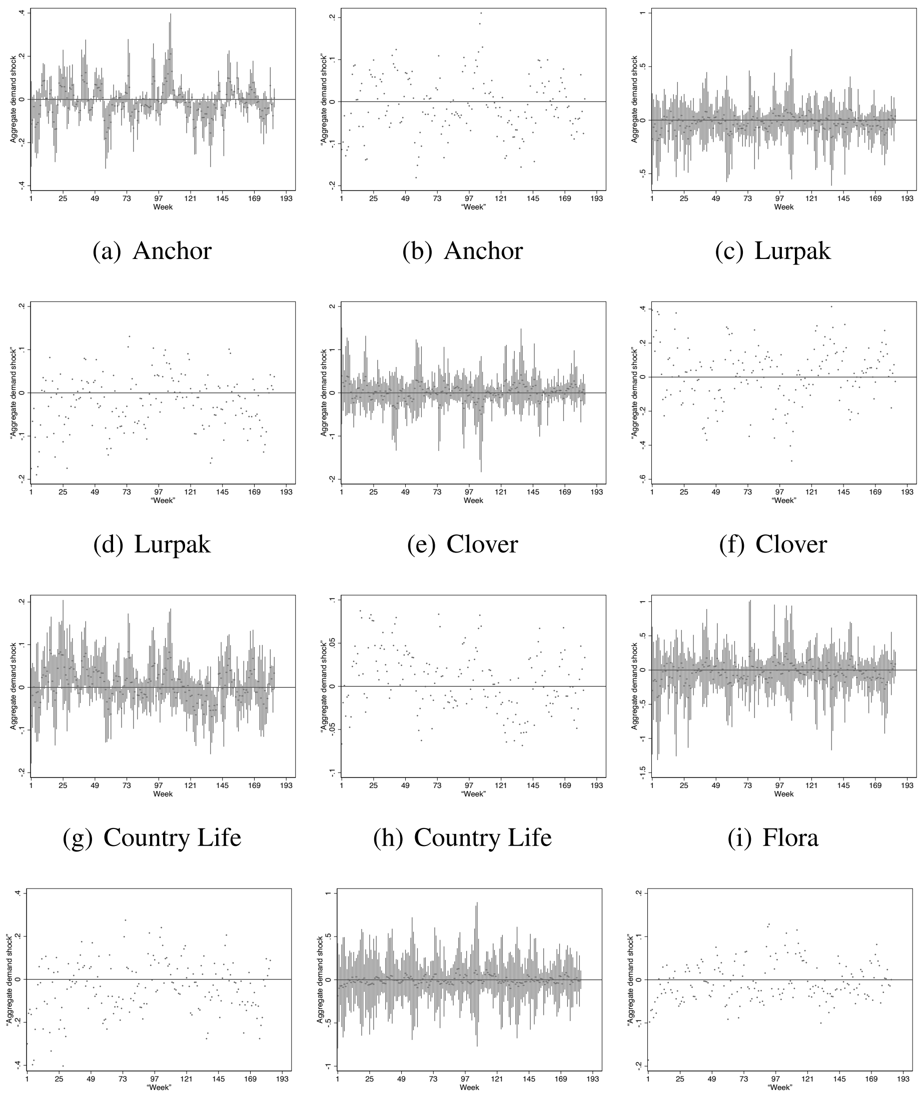

(d) Tesco

weekly dummies shifting the indirect utility from choosing the outside option, so that:

$$u^h_{0t} = \delta_{0t} + \xi^h_{0t} \tag{A.2}$$

The estimated $\hat{\delta}_{0t}$ are interpreted as unobserved demand shocks affecting all brands at the same supermarket and are plotted in Figure 8. Similarly to the aggregate-level exercise, we find no clear patterns or cycles. For Morrisons, the majority of shocks are not significantly different from 0. For Tesco, the confidence intervals are narrower, but the magnitudes are not economically significant either when compared to the estimated brand constants $\delta_j$. The normalisation in the baseline model implies that all those coefficients are 0, whilst here most of the estimates are between 0 and -0.1. We therefore believe that the bias in the baseline model is negligible. Overall, this set of results seems to suggest that time varying unobserved heterogeneity affecting individual demand is not an important issue in this market. A potential explanation for these patterns is that all these brands are well established in the market and the relevant space of characteristics of these products is pretty stable over this period. The same type of arguments were used in Griffith et al. (2017) to model the demand for butter and margarine using the same dataset used in this paper.

**Figure OA.2:** Weekly Dummies (Demand Shock) for each Brand




(a) Anchor (b) Anchor (c) Lurpak

(d) Lurpak (e) Clover (f) Clover

(g) Country Life (h) Country Life (i) Flora

(j) Flora (k) ICBINB (l) ICBINB

# B Identification, estimation and model solution

This appendix summarises some of the technical details behind identification, estimation and solution of the model. Appendix B.1 shows how relative price adjustment costs can be identified independently of payoff parameters using the arguments in Komarova et al. (2018) and argues how additional, economically meaningful restrictions can be imposed to interpret the parameters as product-specific price adjustment costs (instead of relative differences). Appendix B.2 lays out the procedures used to estimate the discount factor, $\beta$. Finally, Appendix B.3 contains details on the algorithms used to solve for Markov Perfect Equilibrium in the counterfactual scenarios.

## B.1 Closed-form identification of price adjustment costs

In this appendix we lay out the identification result for the vector of price adjustment costs in our model. 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 and give the reader an idea of the dimension of the problem, we will be referring to a specific number of firms, actions and cardinality of the set of possible market shares which will be the same as in our empirical application.

### Notation recap

There are three firms, producing two products each (four actions per firm). 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 firm $i$ is:

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

To simplify the notation in the derivations that follow, we will assume that $\zeta = 1$, so that $AC = AC'$, as defined in section 4.1. Otherwise one should divide both sides of (B.1) by $\zeta$ and use the prime notation to denote rescaled primitives.

Without loss of generality, we also slightly abuse the notation and let $\pi_i(\cdot)$ absorb $FC_i$. This can be done because the component $\sum_{\ell \in \mathcal{A}_i} FC_i^{\ell} \cdot \mathbf{1}(a_{it} = \ell)$ does not depend on past actions and will be integrated out in the derivation together with the remainder of the deterministic, static payoff.

**Derivation of $\Delta$AC**

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

$$\bar{v}_i(\ell, \mathbf{z}_t) = \sum_{\mathbf{a}_{-it} \in \times_{j \neq i} \mathcal{A}_j} \sigma_i(\mathbf{a}_{-it}|\mathbf{z}_t) \Big[ \pi_i(\ell, \mathbf{a}_{-it}, \mathbf{s}_{t-1}) + \beta \sum_{\mathbf{z}_{t+1}} G(\mathbf{z}_{t+1}|\mathbf{s}_{t-1}, \ell, \mathbf{a}_{-it}) \underbrace{\cdot \int V_i(\mathbf{z}_{t+1}, \varepsilon_{t+1}) dQ(\varepsilon_{i,t+1})}_{\tilde{V}(\mathbf{z}_{t+1})} \Big] - \sum_{\ell' \neq \ell} AC_i^{\ell' \to \ell} \cdot \mathbf{1}(a_{i,t-1} = \ell') \tag{B.2}$$

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

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

Using the newly introduced notation, we have:

$$\Delta \bar{v}_i(\ell, \mathbf{z}_t) = \sum_{\mathbf{a}_{-it} \in \times_{j \neq i} \mathcal{A}_j} \sigma_i(\mathbf{a}_{-it}|\mathbf{z}_t) \underbrace{\Big\{ \Delta \pi_i^\ell(\mathbf{a}_{-it}, \mathbf{s}_{t-1}) + \beta \sum_{\mathbf{z}_{t+1}} \Delta G^\ell(\mathbf{z}_{t+1}|\mathbf{a}_{-it}, \mathbf{s}_{t-1}) \tilde{V}(\mathbf{z}_{t+1}) \Big\}}_{\lambda_i(\ell, \mathbf{a}_{-it}, \mathbf{s}_{t-1})} - \Delta AC_i^\ell(a_{i,t-1}) \tag{B.3}$$

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

$$\Delta \bar{v}_i(\ell, \mathbf{z}_t) = \boldsymbol{\sigma}_i(\mathbf{z}_t)' \boldsymbol{\lambda}_i(\ell, \mathbf{s}_{t-1}) - \Delta AC_i^\ell(a_{i,t-1}), \tag{B.4}$$

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 $16 \times 1$ column vectors. (B.4) 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:

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

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

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

Vectorising again:

$$\Delta\bar{\mathbf{v}}_i(\ell,\mathbf{s}^1_{t-1}) = \boldsymbol{\sigma}_i(\mathbf{s}^1_{t-1})\boldsymbol{\lambda}_i(\ell,\mathbf{s}^1_{t-1}) - \Delta\mathbf{AC}^\ell_i, \tag{B.5}$$

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

$$\Delta\bar{\mathbf{v}}_i(\ell) = \underbrace{\begin{bmatrix}\boldsymbol{\sigma}_i(\mathbf{s}^1_{t-1}) & & \mathbf{0}\\ & \ddots & \\ \mathbf{0} & & \boldsymbol{\sigma}_i(\mathbf{s}^{2187}_{t-1})\end{bmatrix}}_{(2187\cdot 64)\times(2187\cdot 16)}\underbrace{\begin{bmatrix}\boldsymbol{\lambda}_i(\ell,\mathbf{s}^1_{t-1})\\ \vdots \\ \boldsymbol{\lambda}_i(\ell,\mathbf{s}^{2187}_{t-1})\end{bmatrix}}_{(2187\cdot 16)\times 1} - \Delta\widetilde{\mathbf{AC}}^\ell_i \tag{B.6}$$

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

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

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:

$$\begin{aligned}\Delta\bar{\mathbf{v}}_i &= [I_3\otimes\boldsymbol{\sigma}_i]\begin{bmatrix}\boldsymbol{\lambda}_i(HL)\\ \boldsymbol{\lambda}_i(LH)\\ \boldsymbol{\lambda}_i(LL)\end{bmatrix} - \begin{bmatrix}\Delta\widetilde{\mathbf{AC}}^{HL}_i\\ \Delta\widetilde{\mathbf{AC}}^{LH}_i\\ \Delta\widetilde{\mathbf{AC}}^{LL}_i\end{bmatrix}\\ &= \mathbf{Z}_i\boldsymbol{\lambda}_i - \Delta\widetilde{\mathbf{AC}}_i\end{aligned} \tag{B.7}$$

The dimension of the object on the LHS of (B.7) is $(139968\cdot 3\times 1) = 419904\times 1$. Define the following $419904\times 419904$ projection matrix:

$$\mathbf{M}^{\mathbf{Z}}_i = I_{419904} - \mathbf{Z}_i(\mathbf{Z}_i'\mathbf{Z}_i)^{-1}\mathbf{Z}_i' \tag{B.8}$$

So far we have not discussed $\Delta\widetilde{\mathbf{AC}}_i$ in detail, but it can be written as: $\Delta\widetilde{\mathbf{AC}}_i = \widetilde{\mathbf{D}}_i\Delta\mathbf{AC}_i$ 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. $\kappa_i$ is the number of dynamic parameters to estimate for firm $i$ and $\Delta\mathbf{AC}_i$ is a $\kappa_i\times 1$ vector of parameters to identify. Multiplying both sides of (B.7) by the projection matrix defined in (B.8), we have:

$$\begin{aligned}\mathbf{M}^{\mathbf{Z}}_i\Delta\bar{\mathbf{v}}_i &= -\mathbf{M}^{\mathbf{Z}}_i\widetilde{\mathbf{D}}_i\Delta\mathbf{AC}_i\\ \widetilde{\mathbf{D}}_i'\mathbf{M}^{\mathbf{Z}}_i\Delta\bar{\mathbf{v}}_i &= -\widetilde{\mathbf{D}}_i'\mathbf{M}^{\boldsymbol{\lambda}}_i\widetilde{\mathbf{D}}_i\Delta\mathbf{AC}_i\\ \Delta\mathbf{AC}_i &= -(\widetilde{\mathbf{D}}_i'\mathbf{M}^{\mathbf{Z}}_i\widetilde{\mathbf{D}}_i)^{-1}(\widetilde{\mathbf{D}}_i'\mathbf{M}^{\mathbf{Z}}_i\Delta\bar{\mathbf{v}}_i)\end{aligned} \tag{B.9}$$

(B.9) defines the identifying correspondence for firm $i$. We can proceed in an identical fashion to recover the parameters for the remaining firms. There is also a straightforward way to incorporate equality restrictions across firms an estimate $\{\Delta \mathbf{AC}_i\}_{i=1}^N$ for all firms in one step.

### Further identifying restrictions

So far we showed how the structure of the model identifies $\{\Delta \mathbf{AC}_i\}_{i=1}^N$, that is the vector of differences in adjustment costs relative to a chosen (baseline) action. For example, with $HH$ being the baseline action, we identify

$$\Delta AC_i^{\ell}(a_{i,t-1} = \ell') = AC_i^{\ell' \to \ell} \cdot \mathbf{1}(a_{i,t-1} = \ell') - AC_i^{\ell' \to HH} \cdot \mathbf{1}(a_{i,t-1} = \ell')$$

Differences are not interpretable as price adjustment costs per se. While it should be straightforward to see that just assuming that switching from any price regime to $HH$ (all products with regular/high price) is always costless would be sufficient to recover $AC_i^{\ell' \to \ell} \cdot \mathbf{1}(a_{i,t-1} = \ell')$ for all $\ell, \ell'$, the model remains heavily overparametrised without further restrictions. This is because we are only interested in recovering one parameter per product, which would be interpreted as the cost of putting a particular product on promotion. Following our exposition, there are no reasons to believe that e.g. $AC_i^{HH \to LH}$ should be different from $AC_i^{HL \to LL}$ – where the only difference is that the second product was on promotion in $t-1$ and $t$, while in the former case $i$ was charging regular (high) price for it. Since the adjustment costs should be invariant to many other combinations of past prices and actions, we spell out three identifying restrictions below as assumptions R1-3. While this is not the only possible set of assumptions allowing for point identification of product-specific adjustment costs, we believe that what we propose has a natural, economically meaningful interpretation.

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

This assumption effectively sets $AC_i^{\ell' \to HH} = 0$ for all $\ell'$ as well as $AC_i^{\ell' \to HL} = 0$ and $AC_i^{\ell' \to LH} = 0$ if $\ell' = LL$. As discussed above, the first restriction is sufficient to recover absolute, instead of relative, levels of adjustment costs.

**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 plus the joint cost of putting more than 1 product on promotion at the same time. R3 can then be used to reduce the dimension of the parameter vector to equal to the number of products. 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 firm one can identify $|\mathcal{A}_i| - 1$ parameters in $\mathbf{AC}_i$. Adding assumption R3 reduces the number of parameters to $|\mathcal{J}_i|$.*

We leave the proposition without a proof which amounts to showing that $\widetilde{\mathbf{D}}_i$ has a full column rank when R1-3 are imposed. This can be easily verified numerically. In an earlier version of the paper, we had a simplified duopoly example where we provided an algebraic expression for $\widetilde{\mathbf{D}}_i$ which made it immediately obvious that the matrix had full column rank. For the sake of brevity we suppress this result here, but the derivations can be obtained from the authors upon request.

## B.2 Discount factor and value function

To estimate the discount factor and subsequently 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 effectively continuous it is computationally infeasible to compute the value function for each state, even with a coarse discretization of market shares. 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:

$$V_i\left(\mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right) = \sum_{\mathbf{a_t} \in \mathcal{A}_i} \sigma_i\left(\mathbf{a_t}|\mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right) \left\{\tilde{\Pi}_i\left(\mathbf{a_t}, \mathbf{a_{t-1}}, \mathbf{s_{t-1}}\right) + \beta V_i\left(\mathbf{a_t}, \mathbf{s}\left(\mathbf{a_t}, \mathbf{s_{t-1}}\right)\right)\right\}, \tag{B.10}$$

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 $\varepsilon_{it}$ 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:

$$V_i(\mathbf{z_t}) \simeq \sum_{k=1}^{K} \lambda_{ki} \phi_{ki}\left(\mathbf{z_t}\right) \equiv \Phi_i\left(\mathbf{z_t}\right) \lambda_\mathbf{i}, \tag{B.11}$$

where $\lambda_{ki}$ 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 ($\lambda_{ki}$'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 (B.11) into (B.10) we get:

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

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

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

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

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

where $\Phi_i$ and $\Phi_i^*$ 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:

$$\lambda_\mathbf{i} = \left[(\Phi_i - \beta\Phi_i^*)'(\Phi_i - \beta\Phi_i^*)\right]^{-1}\left[(\Phi_i - \beta\Phi_i^*)'\,\tilde{\Pi}_i^*\right]. \tag{B.12}$$

Inserting (B.12) into (B.11) we obtain the unconditional value functions associated with problem (3); given the logit assumption on $\varepsilon_{it}$ 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)).

## B.3 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 $\lambda(\sigma^s)$ as a function of the vector of beliefs, $\sigma^s$, substituting equation (B.11) 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 $\lambda(\sigma^s)$ 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 $\psi$ 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 $\psi$ used to update $\sigma^s$ to $\sigma^{s+1}$ was 0.5. We have made several attempts using lower values for the tolerance on $\|\sigma^s - \tilde{\sigma}\|$ and for $\psi$. All these attempts generated very similar equilibrium probabilities, but the time to achieve convergence was larger. The initial guess used to start the algorithm, $\sigma^0$, 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 $\sigma^*$ for states that are not in the data. To do this we assumed that the solution of the model, $\sigma^*$, 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 $\sigma_i^*(a_i = k|\mathbf{z})$ be the probability that firm $i$ plays $a_i = k$ when the state vector is $\mathbf{z}$. We assume that:

$$\sigma_i^*(a_i = k|\mathbf{z}) = \frac{\exp(\mathbf{z}'\gamma_k)}{\sum_{k'} \exp(\mathbf{z}'\gamma_{k'})}. \tag{B.13}$$

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

The probability function (B.13) 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.