Approximating demand dynamics in antitrust policy

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Abstract

Empirical analysis for antitrust policy commonly uses accounting margins as inputs into merger screening tools. This paper shows how these margins can be combined with a static demand model to estimate a set of price elasticities for storable goods that are consistent with dynamic demand responses to permanent, rather than transitory price changes. As a result, demand dynamics that create inter-temporal substitution for storable goods are better captured by the resulting set of price elasticities. To illustrate this method, I apply it to the UK laundry detergent industry from 2002 to 2012. I present evidence that product innovations in this industry that lower storage costs affect demand dynamics and hence the degree of bias of price elasticities that come from static demand models. I also show how adjusting price elasticities to reflect demand dynamics can lead to different policy conclusions. I illustrate this by assessing whether there is any evidence that anti-competitive conduct of a laundry detergent cartel in mainland Europe had any effect on the UK laundry detergent market.

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1 Introduction

Storable fast moving consumer goods are frequently the subject of antitrust investigations. For example, recent mergers include Heinz/HP for table sauces, Campina/Friesland for long-life dairy products, Sara Lee/Unilever for personal care products, AB Inbev/SAB Miller in the beer market, and Diageo/Whyte & Mackay in the Scotch whiskey industry.

When assessing antitrust issues in these industries, authorities typically focus on the effect that changes in market structure or firm conduct have on consumer welfare over the course of 1 to 2 years. In practice, as a proxy for changes in consumer welfare, they analyse the likely impact of the merger or alleged firm conduct on prices. Specifically, authorities examine the likelihood that significant non-transitory increases in prices are likely to result from the change in market structure or alleged anti-competitive conduct over the chosen policy horizon.

For storable fast moving consumer goods, authorities often assume that firms compete according to a differentiated Bertrand model. Therefore, the price elasticity matrix that captures substitution patterns implied by consumer responses to permanent price changes over the next 1 to 2 years is a key input into empirical policy analysis.

In antitrust cases, the most commonly used approach is to estimate price elasticities using a static demand model applied to weekly data. However, because static demand models do not incorporate demand dynamics arising from product storability and promotional pricing, they cannot capture inter-temporal substitution.[1] By not acknowledging that short-run volume increases from temporary price cuts draw down on future sales - including those of the promoted product - static demand models provide biased estimates of demand responses to non-transitory price changes.

Specifically, own prices elasticities are overstated - especially if brand loyalty is prominent. Further, by not including diversion from future sales of rival products, cross-price elasticities are understated. These biases are likely to be most pronounced for the closest substitutes of the promoted good. Therefore, using a static demand model can produce misleading inputs for policy analysis.

When these biased elasticities are used in empirical policy analysis, predicted margins understate market power. Further, because the bias in own and cross price elasticities reinforce one another, diversion ratios are also downward biased - especially for close substitutes. As a result price pressure tests will tend to understate anti-competitive concerns and merger simulation will under predict price rises.

The source of bias is the mis-specification of the demand model. If a dynamic demand is estimated, the price elasticity matrix measuring demand responses to permanent price changes can be simulated. However, with current technology estimating a dynamic demand model is challenging within the timeframe of an antitrust investigation.

In this paper I present an alternative approach to calculating price elasticities for

[1] In seminal papers, both Erdem et al. (2003) and Hendel and Nevo (2006) show that consumer responses to short-run temporary price changes demand for storable goods are much more elastic than their responses to permanent price changes. It is the latter set of price elasticities that are of interest to antitrust policy makers.

antitrust policy that can be easily implemented within the timeframe of an antitrust investigation. Combining the output of a static demand model estimated on weekly data with observed prices and firms' product-level accounting margins, I show how to recover parameters that capture the effect of missing demand dynamics on demand derivatives. I use them to construct set-valued estimates of the price elasticity matrix that are suitable for use in policy simulations of consumer responses to permanent changes in firms' pricing behaviour.

This approach makes use of the fact that margins are typically measured over a longer time horizon (i.e. year) than the period of analysis used to estimate the demand model (i.e. weekly market outcomes). As such they contain information on the aggregate impact of demand dynamics on market power over the period in which they are measured. Beneficially, the severe bias associated with elasticities from a static model are reduced with minimal additional implementation costs.

One potential drawback is the reliance on accounting margins to measure economic profits. However, the use of accounting margins in empirical analysis of mergers is common due to their use in a variety of increasingly common merger screening tools (see Jaffe and Weyl (2013)). In addition to their simplicity, one reason why these methods have become increasingly widespread is the perceived improvement in the quality and availability of detailed cost information.[2] Indeed, notwithstanding the well-documented conceptual differences between the economic and accounting margins, antitrust authorities are placing evidentiary weight on empirical analysis based on firms' margin data.[3]

To illustrate how this method can be employed in practice I apply it to the UK laundry detergent industry. I use it to examine two supply side issues. First, I explore how product innovation that lowers storage costs reinforces consumer demand dynamics and affects mis-specification bias of elasticities estimated from static demand models.

Second, I conduct a policy experiment in which I assess whether anti-competitive conduct in mainland Europe's laundry detergent industry had any spillover effects on the UK market. To test this, I use the 'menu approach' (Bresnahan (1987)) to compare the market power estimates implied by alternative models of competitive interactions during and after the cartel.[4]

I find that without using accounting margins to adjust elasticity estimates, policy simulations suggest observed margins are most likely to be produced by anti-competitive conduct. However, in the policy simulations using the set of bias-adjusted demand derivatives the case is much less clear-cut. If anything, there is little evidence to support the view that there were anti-competitive spill-over effects from the European laundry detergent cartel in the UK between 2002 and 2005.

[2]Antitrust authorities can compel businesses to provide detailed information from management accounts used in the day-to-day running of their commercial activities.

[3]See Pittman et al. (2009) for a recent review of the use of accounting cost information as an input into the antitrust policy.

[4]Nevo (2001), Hausman and Leonard (2002), Slade (2004), Rojas (2008) and Miller and Weinberg (2017) have assessed market power or merger effects in differentiated product industries using the menu approach.

The remainder of the paper is structured as follows. In Section 2 I show how to combine accounting margins and a static demand model to recover parameters that adjust price elasticities to reflect consumer responses to permanent price changes when demand dynamics are present. The remainder of the paper focuses on the application. In Section 3 I describe the UK laundry detergent industry. Section 4 describes and estimates a static demand model and applies the methods described in Section 2. I use the results to examine the impact of product innovation on the degree of bias in the elasticities. Finally, in Section 5 I contrast the conclusions of policy simulations using the unadjusted static demand model and the bias-adjusted version. Section 6 concludes.

2 Approximating demand dynamics

2.1 Dynamic pricing

In each period firms set prices to maximise the present value of expected profit flows. When there are no inter-temporal links in demand or costs, the firm's optimisation problem is separable and is solved independently in each time period. However, in many cases - like laundry detergent - consumer demand is inherently dynamic. As a result, firms account for the impact that their current pricing decisions have on future prices and demand.

To illustrate this consider a firm, f, that chooses current prices, p_t, by maximising expected profits over the next H-periods,[5]

$$\pi_t^f = \sum_{h=0}^{H} \sum_{j \in \mathcal{J}_{t+h}^f} \left(p_{j,t+h} - c_{j,t+h}\right) N_{t+h} s_{j,t} \left(p_t, p_{t-1}, \ldots, p_{t-H}\right) \tag{1}$$

where $\mathcal{J}_t^f$ is the set of J_f products and N_t is the size of the market. Hereafter, for the sake of brevity, the market is assumed to be the same size in each period and is normalised to 1.

The market share for product j in period t is $s_{j,t}$ and depends on the history of prices over the previous H periods. The marginal cost of production for product j in time t is $c_{j,t}$ and these are assumed to be constant.

Assuming that firm f sets current prices according to Bertrand-Nash competition, its optimal prices solve a system of J_f price setting equations

$$s_t^f + \sum_{h=0}^{H} \Delta_{[t,t+h]}^f \left(p_{t+h} - c_{t+h}\right) = 0 \tag{2}$$

where $\Delta_{t,\tau}^f$ is the firm's matrix of demand derivatives for period τ with respect to price changes in period t where $\tau \geq t$. If the firm produces detergents j and k, the $[j,k]$-element of $\Delta_{t,\tau}^f$ are inter-temporal demand derivatives

[5]Where H can be finite or infinite. For brevity of notation, discounting is omitted.

$$\Delta_{t,\tau}^{f}[j,k] = \begin{cases} \frac{\partial s_{k,\tau}}{\partial p_{j,t}} & \text{if } j \in \mathcal{J}_t^f, k \in \mathcal{J}_\tau^f \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Further, let s_t^f be the vector of market shares whose j-th element is s_{jt} if $j \in \mathcal{J}_t^f$ and 0 otherwise.

In addition to profits lost on foregone sales in the current period, the presence of demand dynamics leads firms to consider the effect of inter-temporal substitution on future profitability. In the context of promotional pricing, the firm weighs the short-run profit gains from a price cut against current and expected losses due to inter-temporal cannibalisation of sales they might otherwise make.

These dynamic profit incentives are captured by a matrix of inter-temporal profit ratios, Ψ_t. Its $[j,k]$-th entry measures the relative importance of inter-temporal versus contemporaneous substitution effects. Therefore, it captures the profits forgone of sales of product k in response to a temporary price cut for product j in period t.[6]

$$\Psi_t[j,k] = \frac{\mathbb{E}_t \sum_{h=1}^{H} \Delta_{t,t+h}^{f}[j,k]\,(p_{t+h}[k] - c_{t+h}[k])}{\Delta_{t,t}^{f}[j,k]\,(p_t[k] - c_t[k])} \tag{4}$$

Using Ψ_t, the system of price setting equations can be re-expressed in terms of expected inter-temporal profit ratios as,[7]

$$s_t^f + \left(\Delta_{[t,t]}^{f} \circ (1 + \Psi_t)\right)(p_t - c_t) \quad = \quad 0 \tag{5}$$

where $\circ$ denotes the Hadamard product. From this equation, we can see that inter-temporal profit ratios are parameters that capture the biases in static demand derivatives when demand dynamics are omitted.

However, when promotional demand dynamics are present, the inter-temporal profit ratios implicitly depend, inter alia, on firms' beliefs over rivals' future pricing behaviour, their beliefs over consumers' price expectations, as well as their beliefs about the demand response to a price promotion. The need to ensure consistency of beliefs and the state dependent nature of pricing strategies mean that equilibrium outcomes in these markets are difficult to compute.

2.2 Price dynamics and antitrust policy

Acknowledging the complexities of evaluating antitrust policy in a dynamic setting, antitrust practitioners often use a static differentiated Bertrand model of competition to model industry outcomes.

[6] The denominator in the $[j,k]$-th entry of this matrix is the profit lost on sales of product k in the same response to a temporary price cut of product j. The numerator is the expected sum of profits foregone from reduced future sales of product k over the next H-periods in response to the price cut for product j in period t.

[7] See Annex A.1 for a derivation.

The most commonly used approach is to estimate price elasticities using a static demand model applied to weekly data.[8] However, because static demand models do not incorporate demand dynamics arising from product storability and promotional pricing, they do not capture inter-temporal substitution. There is no allowance for the fact that short-run volume increases from temporary price cuts draw down on future sales.

As a result, static demand models provide biased estimates demand responses to non-transitory price changes. Specifically, own prices elasticities are overstated and cross-price elasticities are understated. Therefore, using a static demand model can produce misleading inputs for policy analysis.

When these biased elasticities are used in empirical policy analysis, predicted margins will understate market power associated with the assumed firm conduct. Moreover, own and cross price elasticities biases reinforce one another in calculation of diversion ratios. As a result, diversion ratios are too low - especially for close substitutes.

As a result, price pressure tests will tend to understate anti-competitive concerns, merger simulation will under predict price rises, and conduct investigations are more likely to incorrectly reject a hypothesis of competitive conduct in favour of abuse of dominance or collusive conduct.

2.3 Approximating price elasticities

If a dynamic demand model were available, these dynamic demand derivatives and elasticities used in policy setting can be simulated.[9] However, as noted above, a dynamic demand model is unlikely to be estimable in the policy making timeframe.

I suggest an easily implementable alternative approach that treats the long run average of the inter-temporal profit ratios as estimable parameters that capture the effect of demand dynamics on demand responses to permanent, rather than transitory price changes. Equivalently, they can be interpreted as approximating the bias from using a mis-specified static demand model to estimate price elasticities.

Once estimated, these parameters can then be used to adjust the demand derivatives in a static model for use in policy simulations that help inform antitrust policy. Implicit in this approach is the restriction that the underlying competitive dynamics approximated by these parameters are invariant to the policy change being analysed.[10]

2.3.1 Recovering Ψ_t

To recover the elements of Ψ_t I propose to use the information contained in accounting margins measured over the time horizon of the antitrust investigation (i.e. 1 year).

[8] In the notation above, this is equivalent to restricting Ψ_t to be a conformable identity matrix.

[9] Dynamic demand models can also simulate the impact on substitution patterns of a richer set of changes to dynamic pricing behaviour.

[10] This would be an issue even if we had a dynamic demand model to simulate elasticities. Dynamic demand models do not typically specify how households' beliefs are updated in the event of changes to the underlying price structure. Simulation of dynamic price elasticities either holds fixed the household's perception of the competitive process generating the price dynamics fixed.

Accounting margins are increasingly widely used in antitrust policy as a proxy for market power.[11] When measured over a relatively long time horizon (i.e. a quarter or year) they also capture the average effect of inter-temporal substitution on market power.

Faced with a costly collection and collation process, firms often report margins aggregated over some partition of its product space (i.e. brands or size) and report them on a periodic basis (i.e. annually). As such, the percentage margins collected by antitrust authorities span multiple products and multiple time periods.

To utilise the information on market power contained in margins, the price setting equations (equation (5)) for each product and time period spanned needs to be aggregated up to the reporting units of the percentage margins.

Returning to equation (5), suppose firm f partitions its J_f products into $n = 1, \ldots, N$ groups: $\mathcal{J}_t^f = \left\{\mathcal{J}_{1,t}^f, \ldots, \mathcal{J}_{N,t}^f\right\}$. Aggregating equation (5) over products and summing over time, the percentage margin earned on the products sold in group n over the T-periods is

$$\mu_{n,[1,T]}^f = -\frac{\sum_{t=1}^{T} s_{n,t}^\top \left(\Delta_{[t,t]}^f \circ (1+\Psi_t)\right)^{-1} s_t^f}{\sum_{t=1}^{T} s_{n,t}^\top p_t} \; \forall\, n = 1, \ldots, N \tag{6}$$

where $s_{n,t}$ is vector of market shares whose j-th entry is $s_{j,t}$ if $j \in \mathcal{J}_{n,t}^f$ and 0 otherwise.[12]

Equation (6) shows that product group margins over T-periods can be expressed as a function of the sequence of prices, revenues, purchase probabilities, short-run demand derivatives and inter-temporal profit ratios. Since prices, revenues, product shares, and $\Delta_{t,t}^f$ are either observed or can be estimated from data on industry outcomes over T-periods, product group margins can be used to estimate the elements of Ψ_t.

Next, I discuss restrictions that allow elements of Ψ_t to be identified from a cross-section of accounting margins.

2.3.2 Identification of Ψ_t

With more products than observed margins, a cross-section of N accounting margins cannot identify all of the TJ^2 parameters in $\{\Psi_t\}_{t=1,\ldots,T}$. Additional restrictions on the elements of Ψ_t are required.

First, because there is no time-series variation in observed margins, only a single inter-temporal profit ratio for any pair of products, $[j, k]$, over the T-periods can be identified. As such, I impose $T - 1$ restrictions and constrain the parameters of Ψ_t to be the same for every period

[11] Baltzopoulos et al. (2015) documents the recent use of these techniques in recent cases in Sweden and across Europe.

[12] See Annex A.2 for a derivation.

$$\Psi = \Psi_t = \Psi_{t'} \tag{7}$$

for all $t, t' = 1, \ldots, T$.

Second, with no variation of product margins within the n groups, I constrain the inter-temporal profit ratios for all products in group n to be the same,

$$\Psi[j,j] = \psi_n^{own} \tag{8}$$

for all $j \in \mathcal{J}_n^f$, $n = 1, \ldots, N$.

Finally, because the cross-section of observed margins has no additional information on covariances between margin, the off-diagonal elements are not identified. As such, I assume that the expected inter-temporal profit ratios are the same for any two products, $k \neq j$ and $k' \neq j$. That is,

$$\Psi[j,k] = \Psi[j,k'] = \psi_n^{cross} \tag{9}$$

where $k, k' \in \mathcal{J}^f j \in \mathcal{J}_n^f$ for $n = 1, \ldots, N$.

Even with these additional restrictions, there are $2N$ parameters and only N pricing equations. With the additional restrictions on Ψ_t, the N-margin equations are linear in ψ_n^{own} and ψ_n^{cross} and the set of parameters identified by the system of equations satisfies

$$\psi_n^{own} = a_n + b_n \psi_n^{cross} \tag{10}$$

By adding inequality restrictions linked to the underlying nature of the firm's problem, the set of values that ψ_n^{own} and ψ_n^{cross} can take can be further restricted. For example, since future sales of a good are likely to be a substitute for current sales one can impose that $\psi_n^{own} \leq 0$. Further, if future sales of rival products are likely to be substitutes for the promoted good, $\psi_n^{cross} \geq 0$. In line with findings in existing literature studying dynamic demand models (i.e. Erdem et al. (2003); Hendel and Nevo (2006)), the bias in the cross price derivative can also be restricted to be less than the bias for own price derivative then $\psi_n^{cross} \leq -\psi_n^{own}$.

Further, under the assumption that inter-temporal substitution of product j alone would not result in losses from the price promotion, $\psi_n^{own} \geq -1$.[13] Therefore, in the extreme scenario where there is no inter-temporal substitution between rival products produced by the same firm (i.e. $\psi_n^{cross} = 0$), the above inequalities imply that $0 \leq a_n \leq -1$ for $n = 1, \ldots, N$.

3 The UK laundry detergent industry

This section describes the UK laundry detergent industry. It provides an overview of the type of detergent products and brands sold at a leading UK retailer UK's largest .

[13]This is arguably a conservative bound. In practice, future sales of other close substitute products produced by the firm are likely affected - lowering the upper bound needed for the promotion to be unprofitable.

Subsequently it compares how industry outcomes have been shaped by product innovation and how pricing strategies have evolved. First, however, I describe the data used in this section and the remainder of the paper.

3.1 Data

The analysis of the UK laundry detergent industry is based on individual household purchase data from 1st January 2002 until 31st October 2012.

Households that take part in the survey scan the barcode of the items they purchase. Using the scanned barcode, the survey records the price and number of packs bought together with the characteristics of the product purchased. In addition, the purchase date and store in which the product was bought is also recorded. The purchase data is supplemented by annually updated household demographics. These include data on composition of the household, social class status, and sundry features of the household.

In the remainder of the paper, to avoid complexities related to store choice, the analysis is conditioned on detergent purchased from a single leading UK's largest supermarket. Prices charged by supermarkets over 280 sqft. of the same fascia are restricted by a UK Competition Commission ruling in 2000 that banned charging different prices for the same SKU in different stores in excess of 280sq ft in size. As such, purchases across different stores within a particular supermarket fascia in the UK can be pooled for the purposes of empirical analysis.

3.2 Overview

The UK laundry detergent industry is populated by a diverse array of brands, formats, and pack sizes. They are sold in Stock Keeping Units (SKUs), each containing a single type of detergent. In general, a detergent is defined by its format, brand and the chemical properties of the enzymes it contains (i.e. non-bio/bio, stain removal properties, scent etc). In the remainder of this paper I focus my analysis on the major distinguishing features of a SKU - its brand and format.

The UK laundry detergent industry is dominated by Manufacturer A and Manufacturer B. Table 1 shows that together they account for around 75 to 85 percent of households' annual purchases of laundry detergents. Outside of these two major producers of branded products, the retailer's private label products commands the largest share, although its share has declined from 25 percent in 2002 to 13 percent in 2012. A fringe of small niche brands account for the remainder of SKUs sold.

Laundry detergent is sold in six formats: powder, liquid, tablets, liquid capsules, super concentrated liquid, and gel. Figure 1 shows how each format's share of household spend evolved from 2002 to 2012. Powder and tablets, the most popular formats in 2002, saw a notable decline in their market share from 2006. Initially, the market share ceded by tablets and powder products was largely captured by the new super concentrated liquid laundry detergents. Subsequent declines in market share, especially for tablets, coincide with the launch of gel products in 2008. Following their introduction both super concentrated liquids and gel products quickly gained market share; by 2010 they

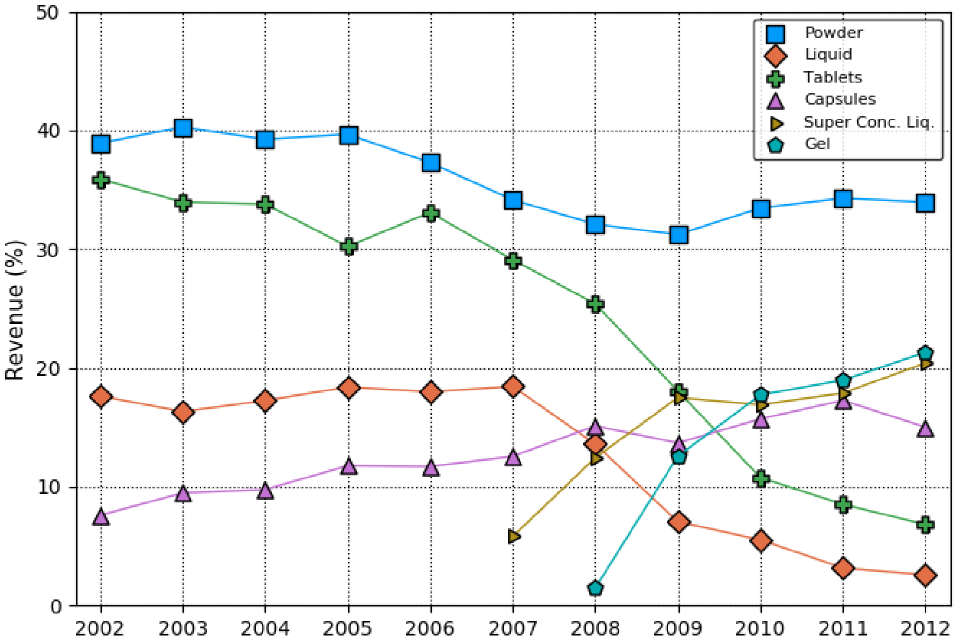
Table 1: Firm shares of expenditure

Firm	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Manufacturer A	43.8	46.0	44.4	51.2	51.6	50.1	48.6	47.4	53.9	52.0	50.5
Manufacturer B	29.7	29.8	31.5	29.1	28.6	30.6	32.8	36.3	31.9	32.3	34.1
Private Label	24.7	22.3	21.5	16.9	17.4	16.8	16.3	14.3	12.9	13.8	12.4
Other	1.8	1.9	2.5	2.8	2.5	2.5	2.3	2.0	1.4	1.9	3.0

Source: TNS

were the second and third most purchased format respectively. Liquid capsules steadily accumulated market share from 8 percent to 15 percent over the sample period.

Figure 1: Share of SKU purchases by format

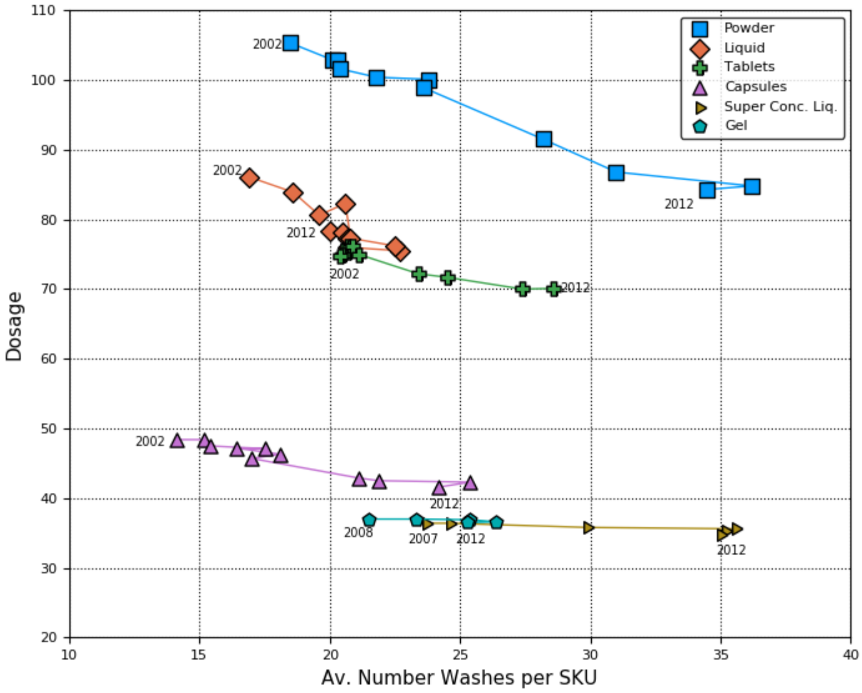


3.3 Product Innovation

In addition to the wide variety of formats, laundry detergents can be purchased in many different pack sizes.[14]

[14]The UK laundry detergent industry differs in this respect from the one studied by Hendel and Nevo (2006). They restrict attention to powder products and examine brand choice conditional on size choice from a small number of discrete sizes: 16oz, 32oz, 64oz, 96oz, and 128oz. Erdem et al. (2003) also focus on only five different weight choices in the US Ketchup market in their dynamic demand estimation.

Figure 2: Compaction and concentration of detergent: Dosage and SKU size



Because formats are defined in different dosage metrics, I use the number of washes in the pack as a common metric across all SKUs. Not only do dosage metrics vary across formats, they also evolve over time within formats. Initially, this was due to a series of industry-wide initiatives that sought to reduce the environmental impact of the production and use of laundry detergents. Later, further product compactions were the result of firm specific innovations.

For most formats, these initiatives served to decrease the dosage per wash over time. A corollary of the reduction in dosage per wash is that more washes can be included in smaller pack sizes. The impact of the evolution in the dosage per wash and the number of washes per pack is shown in Figure 2.

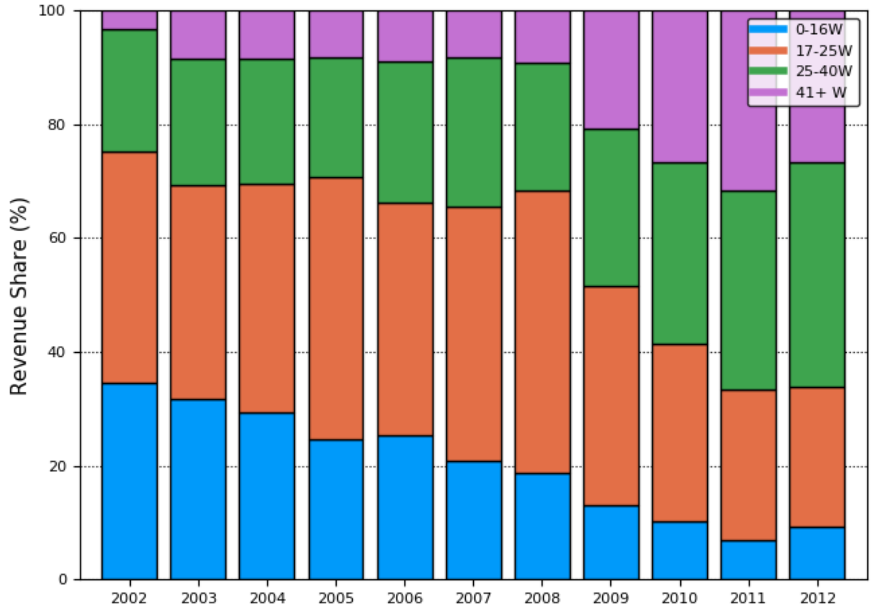
Most notably, for powder products: from 2002 to 2012 the average dosage per wash fell by over 20 percent. Over the same period, the average powder SKU nearly doubled in size - from 18.5 to 34.5 washes. Further, the average super concentrated liquid SKU in 2012 contains 35 washes – which is roughly twice as many washes as the corresponding regular liquid product by 2012 with 17 washes.

The dosage per wash reduction lowers households' cost of storage per wash and exerts downward pressure on firms' transport and packaging costs per wash sold. Figure 3 shows that, as expected, these cost savings have contributed to the increasing popularity of larger packs of laundry detergent.[15] In 2002, around 75% of household spend was on

[15]To maintain a consistent measure of size, SKUs are grouped by the number of washes they contain. Partitioning the sample into groups whose boundaries are defined by 25th, 50th and 75th percentiles of purchased washes from 2002 to 2012 results in groups with 0-17 washes, 17 to 24 washes, 25 to

SKUs with fewer than 24 washes, 10 years later this figure was less than 35 percent.

Figure 3: Number of washes: share of SKUs purchased



As alluded to above, the innovation in terms of compaction was driven by new formats introduced. While the timing of the innovations could be coincidental, it is also the type of competitive response consistent with the ending of a cartel. From January 2002 to March 2005, there was a cartel was in place from January 2002 to March 2005 that covered most of mainland Europe - but not the UK.[16] The cartel included the major suppliers of UK laundry detergent and Manufacturer C - another large laundry detergent manufacturer. Amongst other restrictive practices, it sought to stifle product development, prevent cost-saving pass-through and restrict promotional pricing activity.

Other studies have found that the introduction of new innovative products can achieve a temporary increase in market power.[17] In line with this logic, it possible that the aim of the product innovations that took place only after the cartel was to recover losses in market power.

3.4 Pricing behaviour

Figure 4 uses a series of box plots to display the distribution of prices per wash in each quarter from 2002 to 2012. The top panel shows the price per wash distribution for

40 washes and 41 or more washes respectively.

[16] The cartel included a third firm, Manufacturer C. Manufacturer C informed the competition authorities about the cartel in the countries where it supplied laundry detergent. Manufacturer C does not supply the UK laundry detergent market directly.

[17] In his study of welfare implications of the introduction of mini-vans in the 1980s, Petrin (2002) notes that the motivation behind the firm's innovations was to achieve short-lived gains in market power at the expense of rivals.

Manufacturer A and bottom panel shows this distribution for Manufacturer B.

For both Manufacturer A and Manufacturer B, the whiskers and inter-quartile range of box plots from first quarter in 2002 up to the final quarter in 2006 are relatively constant, if anything they narrow after 2004. Over this period, the whiskers tend to lie between 10p and 30p per wash and the interquartile ranges lie between 15p and 23p per wash. From the first quarter in 2007 onwards, the whiskers and inter-quartile ranges of the box plot fan out for both Manufacturer A and Manufacturer B.

This increased price dispersion coincides with the introduction of new products and the ending of a detergent cartel in mainland Europe. Increased price dispersion has been found in other industries following the removal of pricing restrictions.[18] As such, it is possible that increased price dispersion reflects the restoration of competitive forces following the removal of anti-competitive pricing and advertising restraints imposed by a cartel. As such, these price movements may reflect efforts from Manufacturer A and Manufacturer B to increase the degree of differentiation of the brands from 2006 onwards. However, there may be alternative explanations for the observed change in pricing strategy. For example, pricing strategy might change in response to increased consumer price sensitivity (i.e. perhaps due to a perceived drop in income after the financial crisis) or new format adoption.

The red line in Figure 4 plots the average posted price per wash and the green line plots the average price per wash of purchased products. It shows that the average posted price per wash is steadily increasing for Manufacturer A, but broadly constant for Manufacturer B. However, the average purchased price per wash diverges from the posted price per wash, and this gap increases over time. This is especially pronounced for Manufacturer B, with divergence starting as early as the second quarter in 2005. From 2010 onwards, the average purchased price tracks close to the lower quartile of the posted price distribution.

To further explore this change in the relationship between the posted and purchase prices per wash, the promotional pricing patterns for each Manufacturer B and Manufacturer A are analysed in more detail.

Figure 5 shows the percentage of weeks SKU are on sale and the percentage of household quantity of washes purchased on sale. A non-sale price is defined as the maximum price of the product sold at that fascia during the previous four weeks.

The top panels in the figure show the percentage of weeks that Manufacturer A products were on sale, while the bottom panels show Manufacturer B's discount profiles. The left panels show the percentage of posted product sold on discount and the depth of that discount. The right panels contain the same information conditional on purchase. Common to both firms is that the percentage of washes bought on sale is higher than the percentage of weeks on sale. This suggests that households buy more detergent when it is on sale and choose to stock it ready for future use. Also of note is that sales appear to be deeper and more frequent towards the end of the sample -

[18]Frank and Salkever's (1997) study of post-liberalisation pricing of pharmaceutical products finds that prices of premium branded products typically increase whereas the price of standard branded products tended to fall.

Figure 4: Price Distribution

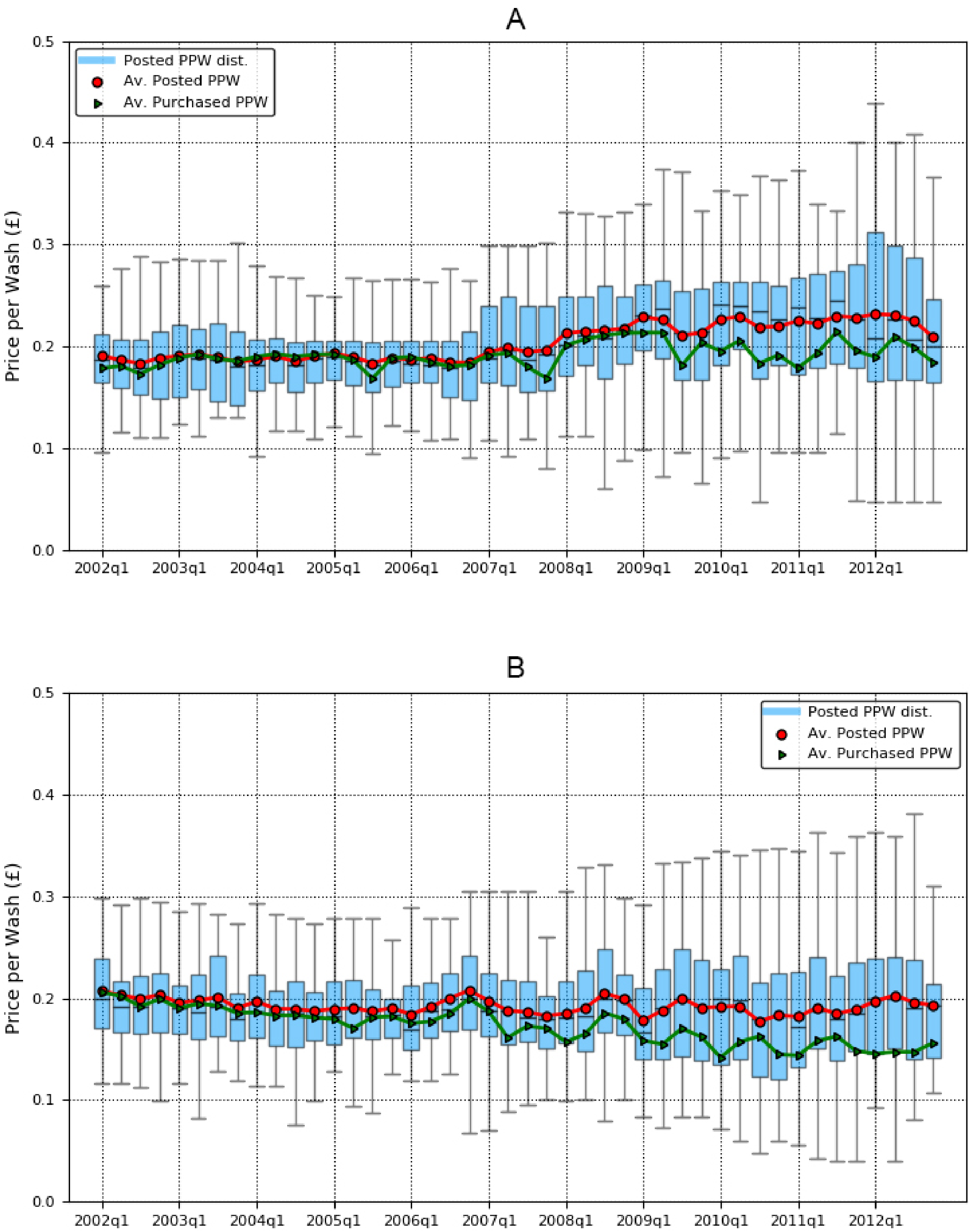
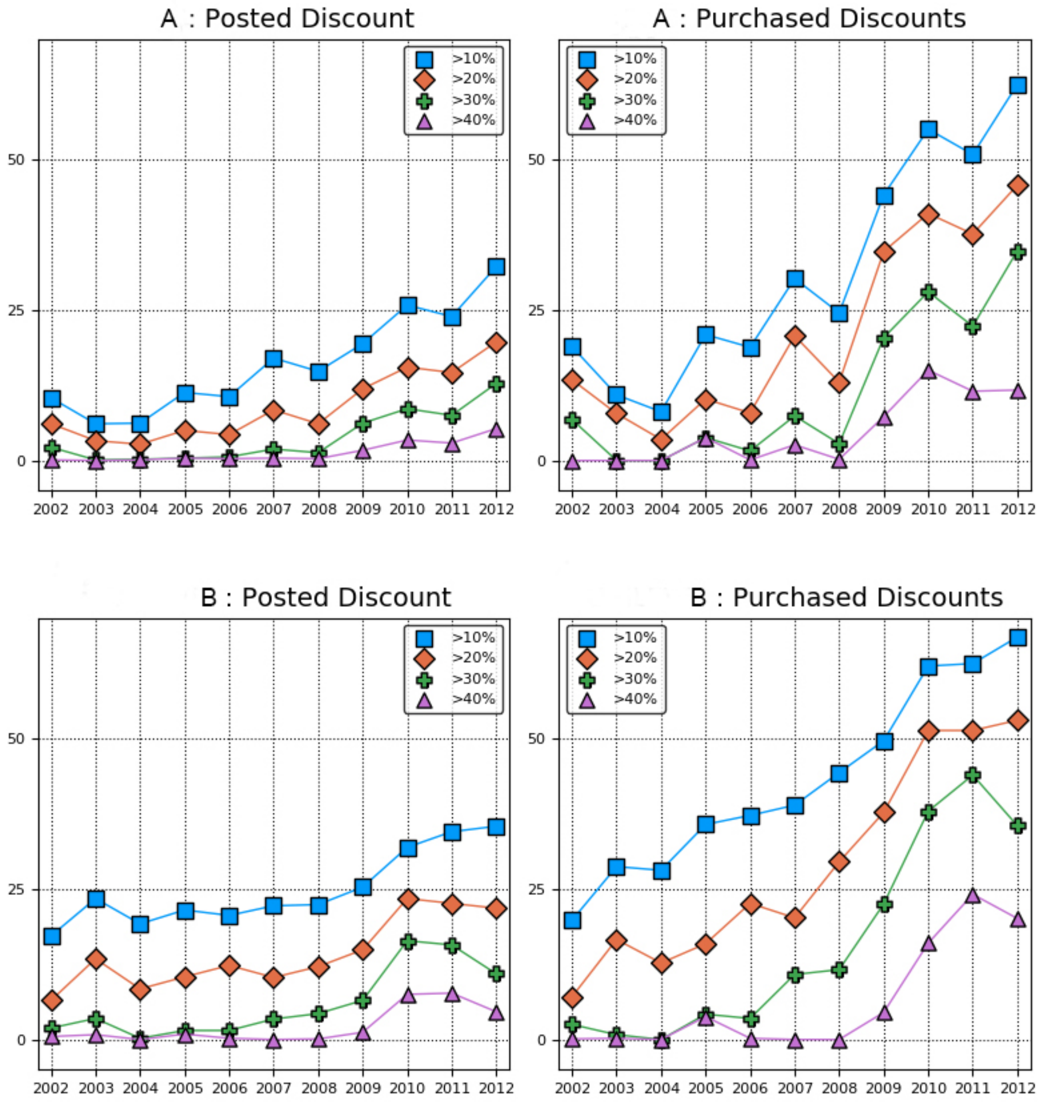


Figure 5: Percentage of SKU Available and Purchased on Sale from 2002 to 2012



especially for Manufacturer A.

This pricing pattern might reflect a change in the pricing behaviour of UK laundry detergent suppliers in the period that followed the ending of the cartel in 2005. Another contributing factor is that product compaction means that a single SKU contains more washes (see Figure 2). A corollary of these innovations is that households can purchase a higher fraction of their detergent demand in a single purchase. In turn, increasing the intensity of competition and contributing to deeper and more frequent discounting. However, as alluded to above, there could be other explanations. These include increased price sensitivity of households due to changes in the macroeconomic climate, or changes in pricing strategy to encourage new product adoption.

4 Approximating elasticities in UK laundry detergent

In this section, I apply the techniques described in Section 2 to the UK laundry detergent sector. First, I specify a static demand model and estimate it using the Kantar data. Then using publicly observed margins for Manufacturer A and Manufacturer B, I recover the sets of inter-temporal profit ratios in each year. Finally, I explore the extent to which product innovation that lowers storage costs affected demand dynamics and therefore mis-specification bias from a static demand model.

4.1 Demand for laundry detergent

In this section I set out a static demand model of the UK laundry detergent and estimate it using the purchase diary data from Kantar data described in Section 3.1. I estimate two demand models that are commonly used in antitrust policy; conditional logit and nested logit.

4.1.1 Demand model

Detergents are sold in one of $j = 1, \ldots, J$ stock keeping units (SKUs). A SKU is defined by the detergent it contains and the number of washes it contains. The SKUs sold in market t, $\mathcal{J}_t$, are manufactured by $f = 1, \ldots, F$ firms. The outside good is denoted by $j = 0$ and represents the decision not to purchase in market t.

Household i elects to purchase good j from a market t to maximise conditional indirect utility, $V_{ijt}\left(x_j, p_{jt}, z_{it}; \theta\right)$

$$j = \arg\max_{k \in \mathcal{J}_t} V_{ikt}\left(x_k, p_{kt}, z_{it}; \theta\right) \tag{11}$$

where p_{jt} is the price of SKU j in market t, x_j is a K-vector of SKU attributes, z_{it} is an L-vector of household characteristics, and θ is the set of parameters entering the conditional indirect utility function.

The conditional indirect utility for household i from purchasing product j in market t is

$$V_{ijt}\left(x_j, p_{jt}, z_{it}; \theta\right) = x_j^\top \beta_{it} - \alpha_{it} p_{jt} + \epsilon_{ijt} \tag{12}$$

The observed product attributes include the number of washes, dosage, and brand-format dummies. Household i's valuation of these attributes is captured by taste parameters,

$$\beta_{it} = \beta + \beta_z z_{it} \tag{13}$$

To capture heterogeneous valuations of these attributes β_i has two components. The first is common to all households and is measured by a K-vector of parameters, β. The second captures the affect of household characteristics and is measured by an L-vector of parameters β_z.

Prices of product j in market t, p_{jt}, enter linearly into the indirect utility function. The marginal utility of income for each household is

$$\alpha_{it} = \alpha + \alpha_z z_{it} \tag{14}$$

The marginal utility of income, α_{it} also depends on household characteristics. In addition to a common component, α, the effect of different household characteristics on the marginal utility of income is measure by an L-vector of parameters, α_z.

To capture the impact of factors observed by the household, but not the econometrician, there is a household specific component of utility, ϵ_{ijt}. This error term is decomposed into two parts,

$$\epsilon_{ijt} = IC_{it} + \varepsilon_{ijt} \tag{15}$$

where IC_{it} are the unobserved inventory costs for household i in market t, and ε_{ijt} is an independently and identically distributed random utility shock that follows a member of the family of Generalised Extreme Value distribution.

Since the random shock is independent of all covariates, any endogeneity concerns arise from correlations between prices and inventory costs. As highlighted by Erdem et al. (2003), this is a prominent source of bias in storable good demand models and arises because inventories are unobserved by the researcher. Specifically, because both current prices and inventories are a function of past prices, the omission of inventories leads to price endogeneity. This problem could be resolved if instruments that are correlated with current prices but uncorrelated with past prices were available. However, since observed prices are serially correlated, finding such instruments is challenging.

Without instruments, the alternative is to estimate a sufficiently rich dynamic demand model that integrates out this source of endogeneity. As noted above, this is likely to be infeasible within the constraints of an antitrust investigation. Without instruments or a dynamic demand model, the source of bias cannot be corrected for fully. Indeed, it is precisely this source of bias I aim to reduce as much as possible by using accounting margins reported by firms.

4.1.2 Estimation and results

The demand model is estimated using maximum likelihood applied to Kantar purchase diary data described in Section 3.1.[19] It uses a sample of 100 purchases in each week

[19] See Train (2009).

from 1st January 2002 until 31st October 2012.[20]

Table 2 shows the results of the estimation of two choice models. The left column contains the parameter estimates of a logit specification and the right column shows the result of a nested logit model.

For the nested logit model, the set of SKUs sold in each week is partitioned into four groups based on the number of washes contained in each SKU: small (S), medium (M), large (L), and extra large (XL). The size boundaries of these groups correspond to the 25th, 50th, and 75th quantile of distribution of washes in each calendar year.

Both models include interactions between price and a measure of household income. Product characteristics include the size of the SKU purchased and the dosage - the amount of material (recommended) for use in a single wash. To control for household size, I also include the amount of washes purchased per equivalent adult in the household.[21] Detergent fixed effects are also included.

Table 2: Demand model parameter estimates

	Logit	**Nested Logit**
Price Params:		
Price	-0.437	-0.512
	(0.004)	(0.005)
Price x Income	0.217	0.337
	(0.009)	(0.012)
Characteristics:		
Washes	0.022	-0.007
	(0.001)	(0.003)
Washes per eq Ad.	-0.019	-0.010
	(0.002)	(0.006)
Dosage of Powder & Tabs	-2.334	-2.235
	(0.083)	(0.086)
Dosage of Liquids, Caps and Gel	-1.615	-1.480
	(0.075)	(0.078)
Other Params:		
Nesting Parameter		0.427
		(0.005)
Detergent Fixed Effects	Yes	Yes
N	56,200	56,200
Likelihood	-246,088	-244,576

As expected, price coefficients in both models are negative and households with higher income have a lower marginal utility of income. Though in the nested logit model, the

[20] The nested logit model is estimated sequentially. As highlighted by Train (2009) standard errors will be under-reported.

[21] To calculate equivalent adults, I use the OECD-modified scale. See http://www.oecd.org/eco/growth/OECD-Note-EquivalenceScales.pdf for details.

price coefficient is more negative, but richer households are less price elastic.

Larger pack sizes are positively valued by households in the conditional logit model, especially in households with fewer people. However, in the nested logit model with size related choice sets, on average households tend to prefer smaller SKUs. However, the disutility from large SKU sizes per equivalent adult accrues more slowly.

The dosage, or amount of material needed to do a single wash is negatively valued, especially for 'solid' detergents. This is consistent with the fact that households value storage space. When the dosage is lower, households can store more washes without necessarily occupying more storage space. Indeed, as noted in Section 3, this is one of the driving factors behind the success of the new super-concentrated and gel detergent products. By itself, this suggest the presence of inter-temporal demand links through inventories - a source of mis-specification for this static demand model.

Finally, the nesting parameter is 0.427 and is significantly different from 1. This indicates that that there are some unobserved correlations in the utility between detergents of similar sizes and rejects the independence of irrelevant alternatives imposed in the conditional logit. In subsequent analysis I use the nested logit specification.

4.2 Estimating inter-temporal profit ratios

In the context of an antitrust investigation brand level margins may be available over several years. However, in my case, I only have access to global, company-wide gross margins published in annual accounts. Therefore, I assume that the published gross margins in Manufacturer A's and Manufacturer B's annual accounts adjusted (if necessary) from 2002 to 2012 are a good approximation to the gross margins earned on sales of their laundry detergent portfolio in the UK.[22]

Recall from Section 2 that the solution to equation (6) is any pair of parameters $(\psi_n^{own}, \psi_n^{cross})$ that satisfies

$$\psi_n^{own} = a_n + b_n \psi_n^{cross} \tag{16}$$

where $n = \{f, y\}$ and $f = \{A, B\}$ and $y = 2002, \ldots, 2012$.

By plugging into equation (6) the observed gross margins, observed prices from the Kantar data, and demand derivatives and purchase probabilities from the demand model, the parameters a_n and b_n can be recovered under the assumption that firms set prices according to differentiated Bertrand competition.[23] Specifically, setting $\psi_n^{cross} = 0$ yields $\psi_n^{own} = a_n$ directly. To calculate b_n, fix $\hat{\psi}_n^{cross} \neq 0$ and let $\hat{\psi}_n^{own}$ be the solution to

[22]The financial year for Manufacturer B starts midway through the year. As such, the annual report margins are adjusted to match calendar years in the data. Figures are omitted for confidentiality reasons.

[23]For the purpose of this section, I assume that the cartel in mainland Europe had no impact on the UK laundry detergent sector, and they priced detergent according to differentiated Bertrand competition between 2002 and 2005. I revisit this issue in Section 5.

equation (6). Then,

$$b_n = \frac{\hat{\psi}_n^{own} - a_n}{\hat{\psi}_n^{cross}} \tag{17}$$

Table 3 shows the value of these parameters for both firms in each of the years in the data.

Table 3: a_n and b_n for Manufacturer A and Manufacturer B from 2002 to 2012

	Manufacturer A		**Manufacturer B**	
Year	a_n	b_n	a_n	b_n
2002	-0.273	0.219	-0.365	0.135
2003	-0.306	0.209	-0.380	0.129
2004	-0.307	0.211	-0.382	0.123
2005	-0.297	0.217	-0.383	0.121
2006	-0.306	0.221	-0.345	0.138
2007	-0.336	0.200	-0.340	0.151
2008	-0.342	0.204	-0.350	0.146
2009	-0.413	0.222	-0.384	0.158
2010	-0.435	0.196	-0.382	0.157
2011	-0.431	0.195	-0.340	0.148
2012	-0.444	0.209	-0.334	0.123

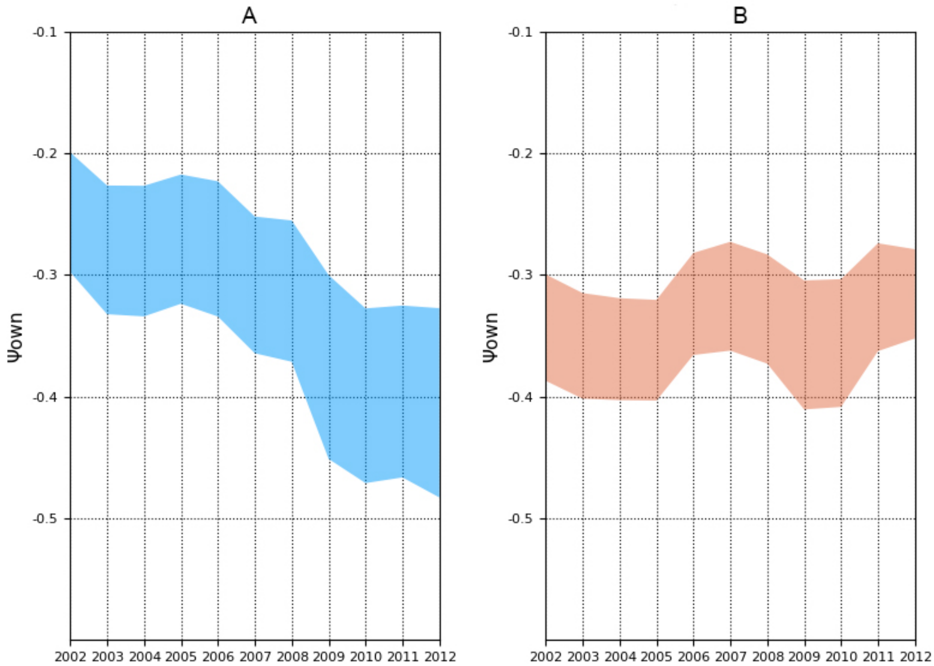
I impose further restrictions that bound the set of values that ψ_n^{cross} can take. First, I assume that the omission of demand dynamics from the demand system estimation leads to understated cross-price elasticities; that is, $\psi_n^{cross} \geq 0$. Second, I assume that the degree to which own-price demand elasticities are overstated by the omission of dynamics exceeds the understatement of cross-price elasticities: $\psi_n^{cross} \leq -\psi_n^{own}$.

The resulting set of values that ψ_n^{own} can take for Manufacturer A and Manufacturer B in each year is shown in Figure 6. The blue band in the left panel of figure shows the range of values that ψ^{own} can take for Manufacturer A in each year from 2002 to 2012. The red band in the right panel shows this same information for Manufacturer B.

For Manufacturer A the figure suggests that the degree to which own-price demand derivatives are overstated by the static demand model increases over time. In 2002, the own-price elasticities are estimated to be overstated by 20% to 30%. In line with the steady rate of product compaction of powder detergent, this range increases gradually over time; by 2008 the estimated range is 25% to 30%. After 2008, when Manufacturer A introduced a new detergent, the degree to which price elasticities are overstated rapidly increases from 32% to 45% by 2010.

These above findings are consistent with the idea that demand dynamics changed as product innovation led to product compaction and storage costs for households fell. Consequently, as shown in Figure 3, households buy larger SKUs. In turn, households needed to buy less frequently and firms had fewer opportunities to cannibalise rivals'

Figure 6: Estimated set for ψ_n^{own} assuming $\psi_n^{cross} \in [0, -\psi_n^{own}]$ for Manufacturer A and Manufacturer B, 2002 to 2012



sales with their promotions. As a result discounts deepened (see Figures 4 and 5) and the intensity of competition increased.

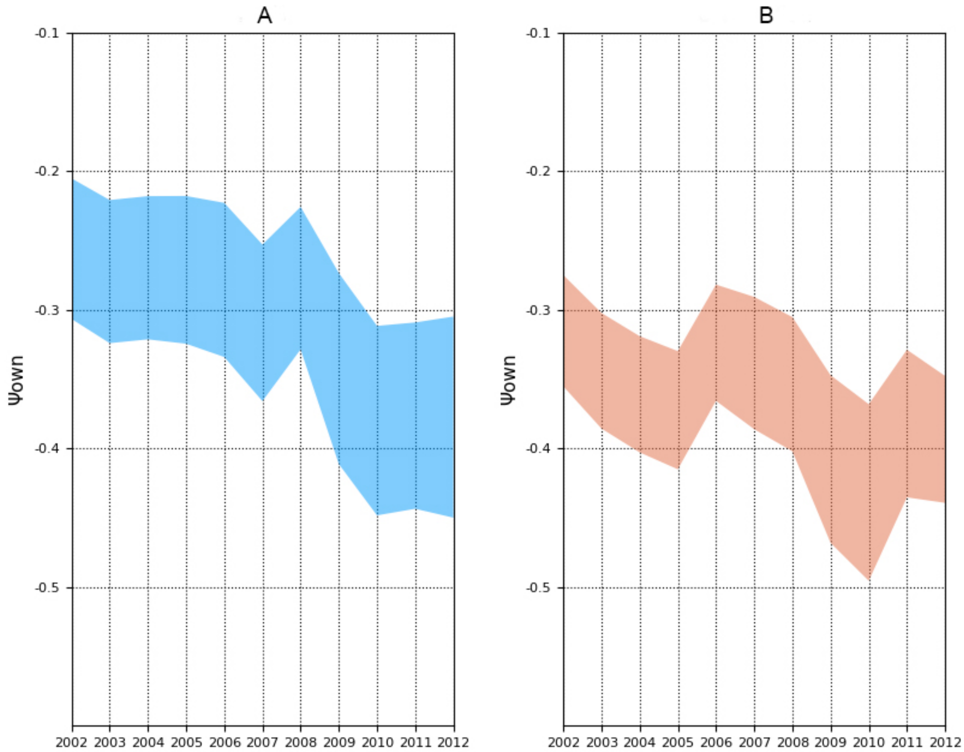
At first glance, the plot in the right panel of Figure 6 for Manufacturer B appears to cast some doubt onto this interpretation. For Manufacturer B, the sets of values taken by ψ^{own} is broadly constant over 2002 to 2012 and suggests that its own-price demand derivatives and elasticities are overstated by 30% and 40% by the static demand model. However, it is important to note that the estimates reflect changes in pricing strategies as well as the impact of product innovations.

Recall from Figure 4 that the pricing strategies of Manufacturer B and Manufacturer A diverge from around 2006. Namely, Manufacturer A increased the average posted price per wash so that the average price per wash paid by households remains broadly constant over time. In contrast, Manufacturer B held posted prices per wash approximately constant. As a result, deeper discounting for Manufacturer B lead to lower purchase prices.

To isolate the impact product innovation has on the degree of bias in the own-price and cross-price demand derivatives, I divide through the range of values for ψ_n^{own} by the price index of purchased prices for each firm in each year. Figure 7 shows the set of values these adjusted estimates take on for Manufacturer A and Manufacturer B.

The figure shows that, because Manufacturer A purchase prices were relatively constant over time, the estimates of the bias are very similar to those in Figure 6. However, the estimate of the bias for Manufacturer B now more closely resembles the plot for Manufacturer A. One difference between the two figures is that the set of

Figure 7: Estimated set for ψ_n^{own} assuming $\psi_n^{cross} \in [0, -\psi_n^{own}]$ adjusted for observed purchased prices for Manufacturer A and Manufacturer B, 2002 to 2012



values for the bias increases from around 29% to 37% in 2006 to 35% to almost 50% in 2010. As discussed in Section 3.3, this coincides with the roll out of new product innovations.

Controlling for the changes in pricing behaviour, there is evidence from both Manufacturer A and Manufacturer B that innovation that lowered stocking costs exacerbates mis-specification of the static demand model. The result is increased bias in key quantities such as demand derivatives and elasticities that are important inputs into empirical antitrust policy.

5 The EU detergent cartel: UK impact?

In April 2011 the European Commission (EC) found that Manufacturer A, Manufacturer B and a Manufacturer C had entered into a cartel agreement that restricted competition in the market for heavy duty laundry detergent powder. The infringement was first brought to the attention of the EC when Manufacturer C 'blew the whistle' on the cartel in exchange for immunity from prosecution and/or reduced fines. Subsequent investigation led to the finding that the cartel was effective over the period 7th January 2002 to 8th March 2005. The EC highlighted four restrictive elements of cartel:

1. indirect price restrictions resulting from the parties agreeing not to pass on any cost savings that resulted from compaction of products
2. explicit reduction of promotional activity
3. direct price increases
4. an exchange of commercially sensitive information

According to the EC, the laundry detergent cartel (LD cartel) had anti-competitive effects in Belgium, France, Germany, Greece, Italy, Portugal, Spain and The Netherlands.[24] One notable absentee from the list of countries affected is the UK - a country in which the 'whistleblower', Manufacturer C, had virtually no market presence. However, the laundry detergent market in the UK is dominated by the other two firms in the cartel; Manufacturer A and Manufacturer B.

In this section I combine the structural demand model estimated in Section 4 together with various supply-side models to estimate market power under different types of firm conduct. By comparing the estimated margins associated with different models of firm behaviour to the observed margins for Manufacturer A and Manufacturer B from 2002 to 2005, I investigate the possibility that the collusive activities in mainland Europe were also evident in the UK.

I conduct two policy experiments. In the first I use the demand derivatives from the static demand model as the input in to an analysis of the market power of Manufacturer A and Manufacturer B during the cartel period. In the second, I repeat the analysis with the set of demand derivatives adjusted by the parameters $(\psi_n^{own}, \psi_n^{cross})$.

In the previous section, the set of estimates for $(\psi_n^{own}, \psi_n^{cross})$ for Manufacturer A and Manufacturer B in 2002 to 2005 assumed that the observed prices were the result of competitive behaviour. In this section, I wish to test whether this was the case. As such, the set of estimates for $(\psi_n^{own}, \psi_n^{cross})$ must be calibrated using another year where we know there was no cartel. Further, we also saw evidence that the product innovation from 2007 onwards had an impact on demand dynamics and, in turn, on the degree of bias of the estimates from the static demand model. Given these criteria, I use the the set of parameters for $(\psi_n^{own}, \psi_n^{cross})$ from 2006 in the second policy experiment.

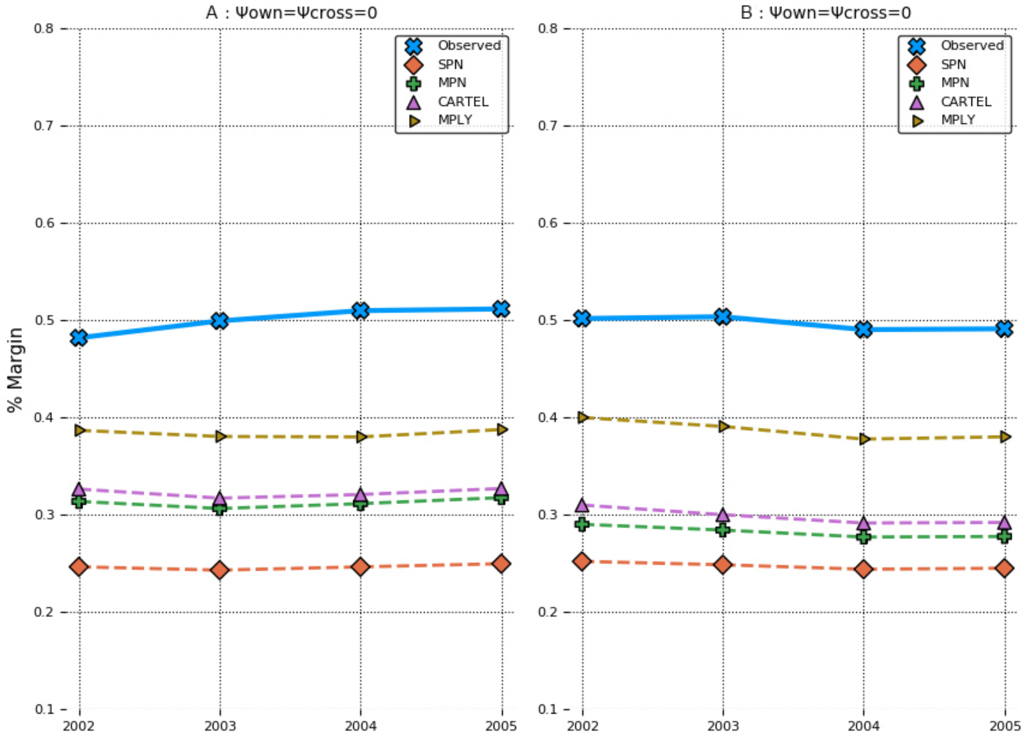
To estimate the market power, assumptions on the nature of supply-side competition and the shape of the cost function are added to each demand model in each experiment. Throughout I assume that marginal cost is (locally) constant.

To examine the impact of the intensity of competition on market power, the ownership matrix is altered to reflect different ownership structures. I consider four different supply side models to analyse market power: (1) firms engage in Bertrand-Nash price competition and each product is manufactured by a single firm, (2) assumes multi-product Bertrand-Nash competition, (3) assume Manufacturer A and Manufacturer B collude over powder products only,[25] and (4) assume that

[24] European Commission Decision, 'COMP/39579 - Consumer Detergents'.

[25] To reflect the cartel scenario, I assume Manufacturer B (Manufacturer A) take into account joint profits of a Manufacturer A (Manufacturer B) powder products, but do not set its price.

Figure 8: Policy experiment 1 ($\psi_n^{own} = \psi_n^{cross} = 0$): gross margins and implied market power during the cartel period: 2002 - 2005



Manufacturer A and Manufacturer B set all prices jointly as a branded product monopolist. Scenarios (1) and (4) are intended as lower and upper bounds on the estimated market power.[26]

The results of the first experiment are shown in Figure 8. The left panel in the figure plots the observed margins in 2002 to 2005 for Manufacturer A alongside the margins implied by the demand model and each of the four firm conduct models. The right panel mirrors this analysis for Manufacturer B.

The figure shows that the observed margins of around 50% are well in excess of the margins implied by multi-product Nash. Moreover, the observed margins are well in excess of the 40% margin implied by monopoly pricing.

The fact that observed margins lie above even the monopoly outcome serve as a warning that the demand model is mis-specified. Especially since the known biases that arise from omitting demand dynamics in storable goods industries would understate market power in this experiment. Based on these results from the mis-specified demand model, a policy analyst might conclude that the collusive conduct of these two dominant firms in Europe spilled over into the UK laundry detergent market.

[26]I do not have information on the identity of producers of private label products. For the purposes of this paper I assume that Manufacturer A and Manufacturer B have no share in private label's profits. This is unlikely to be the case. As such the level of market power in multi-product scenarios (2) and (3) are likely to understate market power compared to the 'true' ownership matrix.

Figure 9: Policy experiment 2: gross margins and implied market power during the cartel period: 2002 - 2005

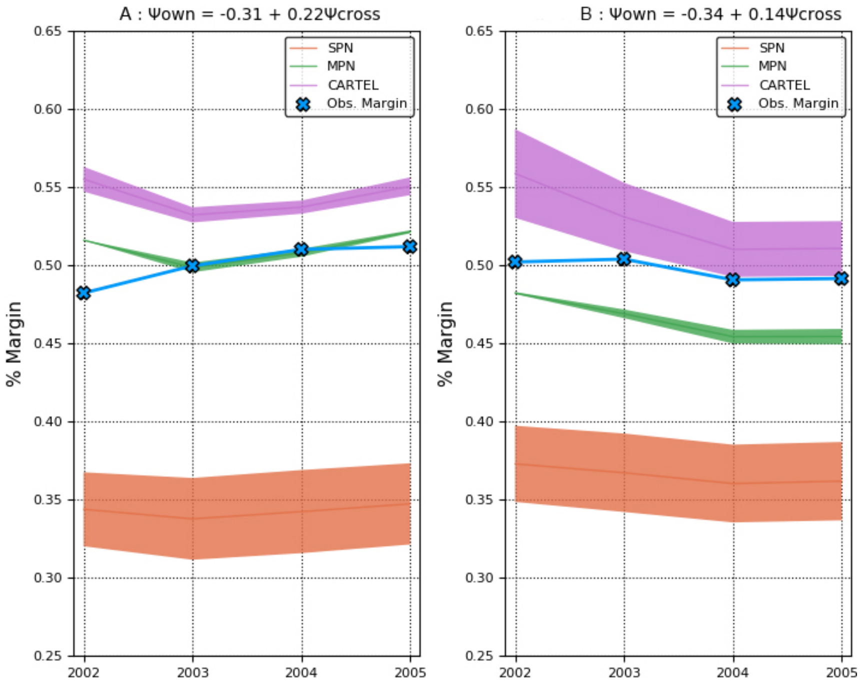


Figure 9 shows the results of the same policy experiment but using the set estimated parameters for ψ_n^{own} and ψ_n^{cross} from 2006 for both firms. The right panel of the figure plots the observed margin for Manufacturer A from 2002 to 2005 with the band of the predicted margins from the different models of conduct. Because the estimates of ψ_n^{own} and ψ_n^{cross} are set valued, the menu approach predicts a range of margins in each year. The left hand panel produces the same information for Manufacturer B. In both panels, the monopoly outcomes are omitted from the plot because they predict margins over 70%.

In contrast to the first policy experiment, the band of margins predicted under competitive conduct largely coincides with the observed margin for Manufacturer A in 2003 to 2005. In 2002, the observed margins lie below those implied by competitive conduct. For Manufacturer B, the predicted band of margins under competitive conduct lies below the observed margins. However, the observed margins also lie just below the lower bound of margins consistent with cartel conduct. While not conclusive, taken together the findings of this policy experiment do not find compelling evidence that the collusive conduct from mainland Europe occurred in the UK.

While it should be borne in mind that this experiment is based on an approximation to observed margins, it shows how important it is to attempt to correct for known biases in empirical policy work.

6 Conclusion

In this paper I present an alternative approach to calculating price elasticities for antitrust policy that can be easily implemented within the timeframe of an antitrust investigation.

Combining the output of a static demand model estimated on weekly data with observed prices and firms' product-level accounting margins, I show how to recover parameters that capture the effect of missing demand dynamics on demand derivatives that are estimated by static models. Assuming firms price using differentiated Bertrand competition, I use these parameters to construct set-valued estimates of the price elasticity matrix that are suitable for use in policy simulations of consumer responses to permanent changes in firms' pricing behaviour.

The proposed approach makes use of the fact that margins are typically measured over a longer time horizon (i.e. year) than the period of analysis used to estimate the demand model (i.e. weekly market outcomes). As such they contain information on the aggregate impact of demand dynamics on market power over the reporting period. Beneficially, the severe bias associated with elasticities from a static model are reduced with minimal additional implementation costs.

This approach is applied to the UK laundry detergent industry. First, I explore the effect of product innovation on consumer demand dynamics, and the associated mis-specification bias of a static demand model. Second, I conduct a policy experiment in which I assess whether anti-competitive conduct in mainland Europe's laundry detergent industry had any spillover effects on the UK market. I find that without using accounting margins to adjust elasticity estimates, policy simulations suggest observed margins are most likely to be produced by anti-competitive conduct. However, when I use the set of bias-adjusted price elasticities the analysis is much less clear-cut. If anything, there is little evidence that there were anti-competitive spill-over effects from the European laundry detergent cartel in the UK.

This exercise highlights that the omission of demand dynamics has the potential to lead to misguided policy conclusions.

References

Baltzopoulos, A., Kim, J., Mandorff, M., et al. (2015). Upp analysis in five recent merger cases. Technical report, Konkurrensverket (Swedish Competition Authority).

Bresnahan, T. (1987). Competition and collusion in the american automobile: The 1955 price war. *The Journal of Industrial Economics*, 35(4):pp457–482.

Erdem, T., Imai, S., and Keane, M. (2003). Brand and quantity choice dynamics under price uncertainty. *Quantitative Marketing and Economics*, 1:5–64.

Frank, R. and Salkever, D. (1997). Generic entry and the pricing of pharmaceuticals. *Journal of Economics and Management Strategy*, Spring:75–90.

Hausman, J. A. and Leonard, G. K. (2002). The competitive effects of a new product introduction: A case study. *The Journal of Industrial Economics*, I(3):237–263.

Hendel, I. and Nevo, A. (2006). Measuring the implications of sales and consumer inventory behaviour. *Econometrica*, 74(6):1637–1673.

Jaffe, S. and Weyl, E. G. (2013). The first-order approach to merger analysis. *American Economic Journal: Microeconomics*, 5(4):188–218.

Miller, N. and Weinberg, M. (2017). Understanding the price effects of the miller/coors joint venture. *Econometrica*.

Nevo, A. (2001). Market power in the ready-to-eat cereal industry. *Econometrica*, 69:307–342.

Petrin, A. (2002). Quantifying the benefits of new products: The case of the minivan. *Journal of Political Economy*, 110(4):705–729.

Pittman, R. et al. (2009). Who are you calling irrational? marginal costs, variable costs, and the pricing practices of firms. Technical report, Department of Justice, Antitrust Division.

Rojas, C. (2008). Price competition in u.s. brewing. *The Journal of Industrial Economics*, 56(1):pp1–31.

Slade, M. (2004). Market power in uk brewing. *The Journal of Industrial Economics*, LII(1):133–163.

Train, K. (2009). *Discrete Choice Methods with Simulation*. Cambridge University Press, second edition.

Annex A: Derivations

A.1 First order conditions

The first order conditions for setting the price of product j is

$$\frac{\partial \pi_t^f}{\partial p_{j,t}} = s_t[j] + \sum_{h=0}^{H} \sum_{k \in \mathcal{J}_t^f} \Delta_{t,t+h}\,[j,k]\,(p_{t+h}[k] - c_{t+h}[k]) = 0 \tag{18}$$

where for ease of exposition the index of the element's position is given in square brackets.

Define a matrix Γ_t whose elements are

$$\Gamma_{t+h}[j,k] \quad := \quad \frac{\Delta_{t,t+h}\left[j,k\right]}{\Delta_{t,t}\left[j,k\right]} \tag{19}$$

Also let $m_t := p_t - c_t$ and define a vector ρ_t whose elements are

$$\rho_{t+h}[k] \quad := \quad \frac{m_t[k]}{m_{t+h}[k]} \tag{20}$$

Re-arranging equation (18) and substituting Γ_{t+h} and ρ_{t+h} yields

$$\begin{aligned}
\frac{\partial \pi_t^f}{\partial p_{j,t}} &= s_t[j] + \sum_{h=0}^{H} \sum_{k \in \mathcal{J}_t^f} \Delta_{t,t+h}\left[j,k\right] \frac{\Delta_{t,t}\left[j,k\right]}{\Delta_{t,t}\left[j,k\right]} m_{t+h}[k] \frac{m_t[k]}{m_t[k]} && (21) \\
&= s_t[j] + \sum_{h=0}^{H} \sum_{k \in \mathcal{J}_t^f} \Delta_{t,t}\left[j,k\right] \frac{\Delta_{t,t+h}\left[j,k\right]}{\Delta_{t,t}\left[j,k\right]} \frac{m_{t+h}[k]}{m_t[k]} m_t[k] && (22) \\
&= s_t[j] + \sum_{h=0}^{H} \sum_{k \in \mathcal{J}_t^f} \Delta_{t,t}\left[j,k\right] \Gamma_{t+h}\left[j,k\right] \rho_{t+h}\left[k\right] m_t[k] && (23) \\
&= s_t[j] + \sum_{h=0}^{H} \sum_{k \in \mathcal{J}_t^f} \Delta_{t,t}\left[j,k\right] \Gamma_{t+h}\left[j,k\right] \rho_{t+h}\left[k\right] m_t[k] && (24) \\
&= s_t[j] + \sum_{k \in \mathcal{J}_t^f} \Delta_{t,t}\left[j,k\right] m_t[k] \underbrace{\sum_{h=0}^{H} \Gamma_{t+h}\left[j,k\right] \rho_{t+h}\left[k\right]}_{:=1+\Psi_t[j,k]} && (25) \\
&= s_t[j] + \sum_{k \in \mathcal{J}_t^f} \Delta_{t,t}\left[j,k\right] m_t[k] \left(1 + \Psi_t[j,k]\right) && (26)
\end{aligned}$$

Define an ownership vector $\omega_{f,t}$ whose j-th element is 1 if $j \in \mathcal{J}_t^f$ and is 0 otherwise. Define the static Jacobian matrix that embeds the ownership structure in period t as, $\Delta_{[t,t]}^f := \omega_{f,t}\omega_{f,t}^\top \circ \Delta_{[t,t]}$. Also let $\mathbf{1}_J$ denote a unit J-vector as $\mathbf{1}_J$. Stacking over all products, equation (24) in matrix form is

$$\begin{aligned}
\frac{\partial \pi_t^f}{\partial p_t^\top} &= s_t^f + \sum_{h=0}^{H} \left(\Delta_{[t,t]}^f \circ \Gamma_{t+h} \circ \rho_{t+h} \mathbf{1}_J^\top\right) m_t && (27) \\
&= s_t^f + \left(\Delta_{[t,t]}^f \circ \sum_{h=0}^{H} \Gamma_{t+h} \circ \rho_{t+h} \mathbf{1}_J^\top\right) m_t && (28) \\
&= s_t^f + \left(\Delta_{[t,t]}^f \circ \left(1 + \Psi_t\right)\right) m_t && (29)
\end{aligned}$$

where $\Psi_t := \sum_{h=1}^{H} \Gamma_{t+h} \circ \rho_{t+h} \mathbf{1}_J^\top$.

A.2 Accounting margins over products and across time

Below I derive the expression for the percentage margin of a group of n products over $t = 1, \ldots, T$ periods.

$$
\begin{aligned}
s_t^f + \left(\Delta_{[t,t]}^f \circ (1+\Psi_t)\right)(p_t - c_t) &= 0 && (30)\\
\implies p_t - c_t &= -\left(\Delta_{[t,t]}^f \circ (1+\Psi_t)\right)^{-1} s_t^f && (31)\\
\implies s_{n,t}^\top (p_t - c_t) &= -s_{n,t}^\top \left(\Delta_{[t,t]}^f \circ (1+\Psi_t)\right)^{-1} s_t^f && (32)\\
\implies \sum_{t=1}^{T} s_{n,t}^\top (p_t - c_t) &= -\sum_{t=1}^{T} s_{n,t}^\top \left(\Delta_{[t,t]}^f \circ (1+\Psi_t)\right)^{-1} s_t^f && (33)\\
\implies \frac{\sum_{t=1}^{T} s_{n,t}^\top (p_t - c_t)}{\sum_{t=1}^{T} s_{n,t}^\top p_t} &= -\frac{\sum_{t=1}^{T} s_{n,t}^\top \left(\Delta_{[t,t]}^f \circ (1+\Psi_t)\right)^{-1} s_t^f}{\sum_{t=1}^{T} s_{n,t}^\top p_t} && (34)\\
\implies \mu_{n,[1,T]}^f &= -\frac{\sum_{t=1}^{T} s_{n,t}^\top \left(\Delta_{[t,t]}^f \circ (1+\Psi_t)\right)^{-1} s_t^f}{\sum_{t=1}^{T} s_{n,t}^\top p_t} && (35)
\end{aligned}
$$