Competition and Oligopoly: A Case of UK *Grocery Retailing*

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In this paper we develop a model of Bertrand price competition with uncertainty as to the number of bidders. The auction models predict retail price dispersion as an observable feature of price discrimination. The implications of the auction models are tested using a logit model on primary data. Some simulations of the logit model further enrich and capture critical states of chain-store rivalry. The findings show that consumer characteristics define type of store choice and that an auction model of price competition with uncertainty is an appropriate way to model retail grocery competition.

Introduction

In this paper, we use the term 'discount stores' to apply to those which offer a wide selection of primary shopping venues and which are characterised by low prices and low service attributes. With particular reference to the North East, the dominant discount formats are represented by Aldi, Lidl, Netto, Kwik Save and Somerfield. The quality supermarket retailers that feature higher quality service levels and higher prices are Asda, Morrisons, Sainsbury's Safeway and Tesco. Competition between these two strategic groups creates price dispersion in urban grocery markets. The aim of the paper is to explain this phenomenon in terms of market segmentation and auction theory. Hypotheses concerning price dispersion derived from the auction model are tested using logit analysis.

In theory, discount stores may enhance price competition in grocery sub-markets because:

1. they represent a significant innovation appealing to price sensitive buyers,
2. they are a means of low cost entry in supermarket sub-markets in metropolitan areas,

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3. discount stores constitute new strategic groups in Porter's (1976) sense, potentially reducing the ability of incumbents to coordinate competition,
4. they stress low prices so their entry is likely to stimulate price rivalry with at least some incumbents.

Apart from the perception of relatively low price levels, there are no universal features that can be applied to describe all discounters, however within the discounter category there are further sub-divisions which are – limited line discounters, discount supermarkets, hypermarket discounters (Kaas 1994).

To date, UK supermarket sub-markets have been dominated by the multiples, Sainsbury's, Tesco, Safeway, Asda and Gateway (Davies 1992). The competition between the dominant players in these markets in the UK has instigated iterative changes in the strategic characteristics of the major supermarket chains. As a consequence, the UK multiples have converged towards adopting a homogeneous format, where all have similar attributes in, for example: national coverage, quality product ranges, quality images, high service levels and superstore/hypermarket locations.

Marion (1998) suggested that each of the food store formats illustrated in Figure 1 constitute new strategic groups. Different formats offer a unique mix of price, non-price and service characteristics. Formats on or above the horizontal axis compete with each other for major shopping trips of consumers: the remaining groups largely compete for secondary shopping activity.

Roberts et al. (1996) argued that price dispersion may result from such factors as costs or other unobserved brand heterogeneity. In this study, we seek to contribute to an understanding of strategic market segmentation between discounters and quality chain-store food retailers. A feature of many studies of supermarket grocery retailing is that the focus of the econometric work is at an aggregative level where time series data exist. The focus of this study is, by contrast, on the demand and supply sides of grocery sub-markets. The contribution of the paper is to estimate the conditional probability that buyers with certain characteristics make repeated trips to similar classes of store. Throughout the rest of the paper the generic discounter groups are referred to as type D store, whereas the quality multiples are dubbed type P stores.

The paper seeks to make a specific contribution in two areas: first developing a Bertrand model with uncertainty as to the number of direct

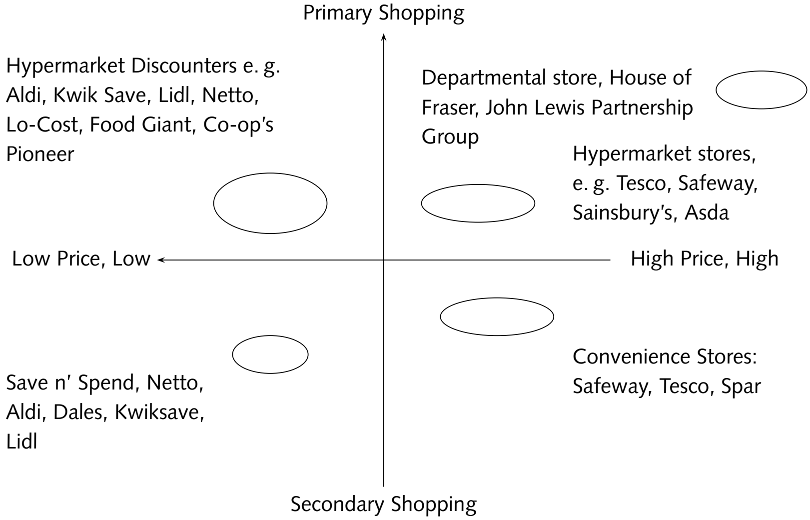

Figure 1: Strategic Groups in Grocery Supermarket Sub-markets in the North East

rivals using an auction format. Second, the paper tests implications of this model regarding consumer choice using logit analysis.

Applying Auction Theory to Retail Grocery Price Competition

The similarities between Bertrand price competition and first price sealed bid auctions is well known (Baye 1997). The model developed here can be viewed as tackling the question as to what is the optimal bid if the number players in a sealed bid auction is not known. However, uncertainties can arise on the demand side too, when consumers know some retail prices today but they do not know all prices today or tomorrow. Moreover, time constrained buyers may regard rival goods as new perfect substitutes, or search costs may be unclear from the grocer's viewpoint or, consumers may simply vary in sophistication regarding search behaviour.

A Simultaneous Symmetric Bertrand Model

Let the variable x represent the probability that a given grocer does not continually compete, so periodically does not bid for particular classes or brands of groceries. This could be because the current supply chain has reached capacity, priced grossly in excess of reservation prices by mistake or, because some consumers have not realised that a particular seller may bid or is bidding. Accordingly we model a first price sealed bid auction for grocery retailing. This captures the essence of Bertrand price competition in grocery sub-markets, where a number of grocers offer repeated bids to consumers without knowing how many rival bidders are actively competing in specific or general branded grocery products.

A PRICE DISCRIMINATION MODEL

Let there be a grocery sub-market: of $N + 1$ risk neutral grocers which submit and announce bids p_i to supply consumers. Each grocer has a marginal cost of c, or, with a probability independent for each grocer, infinity, which is increased only if the grocers capture consumers. Grocers with high marginal costs do not compete or exit general or specific product classes. The consumer buys grocery bundles at the best known prices and pays up to a reservation maximum of $P_{\max}$. If grocer i uses a mixed strategy we depict the distribution of prices as p_i; x represents the probability that a grocer exists but does not compete. The grocers announce bids simultaneously via advertising messages to supply branded products. It is now well known that there are no pure strategy Nash equilibria, unless x is 0 or 1. If x is zero, firms charge c; if $x = 1$, there are no rivals and all grocers exit specific product classes. This could be caused by disruptions to the supply chain.

If $x \in (0, 1)$ no viable unique price equilibrium is possible for $P > c$. If the two lowest prices that exist are not equal or, where all firms have minimum prices, a firm gains by increasing prices (the Edgeworth case). If the two lowest prices were equal, one grocer could cut price and gain market share. However, there is no equilibrium where $p_i = c$; this is the zero profits textbook Bertrand point, because firm raising price could get a surplus of $P_{\max} - c$ with probability of x^N. The equilibrium is now therefore in mixed strategies. Thus, the standard textbook version of the Bertrand Paradox is a false theorem (Klemperer 2000). Each firm picks price $> c$, but less than $P_{\max}$. Since any firm gains positive profits at $P_{\max}$ and wins with a probability of x^N, the range of strategies must be bounded by $(P, P_{\max})$, where $P > c$. A symmetric equilibrium for $N + 1 > 1$ exists where:

$$D(P) \sqrt[N]{1 - \left[\frac{x^N}{1 - x^N}\right] \left[\frac{P_{\max} - P}{P - c}\right]} \tag{1}$$

for the price range

$$[x^N P_{\max} + (1 - x^N) c P_{\max}] \quad \text{(see p. 130).} \tag{2}$$

In this case profits are positive, but expected price and profits fall smoothly as the number of firms increases, as in Cournot. In this model the lowest bid wins consumers with certainty and still earns a profit. Risk averse sellers gain in this model by continually pushing prices down. High prices are a gamble in the hope that rivals are temporarily inactive.

AN ASYMMETRIC BERTRAND MODEL WITH TWO SELLERS: TYPE D AND TYPE P GROCERS

Proposition 1: Two sellers: type D stores are always competing, the type P grocers enter and exit product classes repeatedly.

$$P(c) = (1 - x) \quad \text{where } x \text{ is the probability of exit.} \tag{3}$$

Let both types of seller have different mixing distributions over $[Q, P_{\max}]$. The equilibrium is:

$$\begin{aligned}
&0 \quad \text{for} \quad p \leq (1-x)c + xP_{\max}, \\
&F_1(p) = 1 - \frac{x(P_{\max} - c)}{p - c} \quad \text{for} \quad p \in [(1-x)c + xP_{\max}, P_{\max}], \\
&1 \quad \text{for} \quad p \geq P_{\max}, \\
&0 \quad \text{for} \quad p \leq (1-x)c + xP_{\max}, \\
&F_2(p) = 1 - \frac{x}{1-x}\frac{P_{\max} - p}{p - c} \quad \text{for} \quad p \in [(1-x)c + xP_{\max}, P_{\max}], \\
&1 \quad \text{for} \quad p \geq P_{\max}.
\end{aligned}$$

Continuous price dispersion is the clear outcome for the asymmetric case when $p > c$. Implications of this auction model for sub-market grocer price strategies are as follows:

1. A continuous pure strategy for discounter is not sustainable in repeated plays if consumers search costs change due to, say, increased on-line shopping. Moreover, if due to demographic changes, new consumers enter the sub-market then the equilibrium strategies for both types of supermarket groups need to be mixed.
2. In particular, the discounters will need to use mixed strategies. In such situations, let the probability of not competing for previously segmented bundles of goods be – and indeed is – the probability of competing. The auction model identifies precise boundary conditions for this outcome. Hence repeated plays will induce greater sub-market price dispersion for the two groups as both utilise mixed strategies. The auction model clarifies this important point

as the two groups, being competitive bidders, perceive the game as an ascending and/or descending price auction in branded goods.

Price dispersion will not necessarily narrow even with new entry, as prices vary between $P_i > c$ but less than $P_{\max}$ for both types of store format. Hence third degree price discrimination is a probable strategy for both formats. This could be proved using the revenue equivalence theorem (Klemperer 2000).

Testable Hypotheses Derivable from the Models

The auction model permits the formulation of the testable hypothesis that demand and supply side uncertainties are a primary cause of price dispersion in grocery sub-markets. However, in this model, search costs faced by consumers create the opportunity for sellers to practise price discrimination. The possibility for price discrimination is caused by uncertainty in the market. All sellers adopt mixed strategies targeted at different consumer demand characteristics. Search constraints faced by consumers allow both types of seller to use mixed price strategies to induce periodic price oscillations, thus generating different degrees of price dispersion. An interesting research question implicit in the models concerns the degree to which consumer characteristics of search behaviour may determine store choice in the context of price discrimination. We approach this issue using logit analysis on primary data collected in the UK.

Testing Implications of the Models – Using Logit Analysis

THE DATA

The data were collected between 10 AM to 7 PM in Newcastle upon Tyne, Sunderland and Middlesborough central business districts through direct interview by researchers who approached consumers randomly. Buyers were asked a set of straight-forward questions regarding total weekly grocery expenditure, income, distances travelled for primary shopping, value for money perceptions, type of store preferred, and the most significant reason for choice of store format. Approximately 2000 people were approached, and a total 497 completed questionnaires were obtained. Of the incomplete questionnaires, approximately 603 people refused to give income details and the remainder would not divulge weekly expenditure levels. Nonetheless, the data obtained are rich, geographically diverse and comprehensive. The regressors to be used in the logit analysis were tested for independence. The null hypothesis that there was no association between regressors X_1 to X_7 was rejected in all cases. This is consistent with theoretical propositions relating to differentiation, and in particular the predictions of Hotelling's (1929) oligopoly model. We now turn to consider the econometric model. From a consumer perspective, choice of a store depends upon whether the store is price-orientated or not, as this leads to expectations about relative price levels offered by different stores, as evident in the auction models. However, service levels and other aspects of the store environment are an issue creating product differentiation in consumer services and service quality levels.

THE MODEL AND RESULTS

To analyse the impact of different consumer characteristics in determining store choice, we conducted a logit analysis of the sample data. The objective was to predict the conditional probability of a consumer patronising either type of store given seven characteristics which are illustrated in Table 1. The following equation was estimated:

$$P(Y = 1|X_{1i}, \ldots, X_{7i}) = \frac{1}{1 + exp[-\{\beta_0 + \beta_1 X_{1i} + \cdots + \beta_7 X_{7i}\}]}.$$

The above series of classifications identifies 256 (i. e. 2^8) different types of consumer in the north-east of England. The objective here is to calculate the conditional probability that any one set of consumers choose either a type P or D store. It is important to note that each set of consumers is identified by seven characteristics. All characteristics must therefore be present for different consumer sets to be captured. Hence, the combination of all seven characteristics generates a unique class of consumers. We used the logit model to estimate these conditional probabilities. The model descriptors are given in Table 1. The estimation was carried out using Microfit 4, which has a well established routine for this purpose. The computer output consists of a table containing the estimated coefficients, T-ratios and 'goodness of fit' measures. These values are presented in Table 2. Following these points, it should be pointed out that an insignificant t value reported for a given regressor is not of any particular consequence, since we are not interested in any significant combination of these regressors. We are only interested in the combined influence of all regressors that jointly identify different sets of buyers. Our base run findings are given in Tables 3 and 4. However, by setting the regressors

Table 1: Consumer profiles in the UK north-east: Model Descriptors

Consumer characteristics	Status	Descriptions of variables	Input = 1	Input = 0
Y	Dependent	Choice of store	Discounter	Quality multiple
X_1	Independent	Distance to store	Equal to or less than 3 miles	Over 3 miles
X_2	Independent	Value for money by consumers	Both price and non-price expectations are met	Either price or non-price expectations are met
X_3	Independent	Firms are actively competing in identifiable classes of branded groceries	Price	Non-price factors; e. g. convenience, stock range, service, quality of products
X_4	Independent	Consumer type	Strategic buyers	Time-constrained
X_5	Independent	Level of income	Less than or equal to £16,000 per year	Over £16,000 per year
X_6	Independent	Means of transportation	On foot	Public or private transport
X_7	Independent	Store loyalty	Yes	No

X_1–X_7 at different levels permits an interesting set of simulations which can be compared with the base run. With respect to the base-run the 'goodness of fit' statistic and other diagnostics are sound (Table 2).

Summary of Simulations

Table 5 provides the statistic results from the simulations and the findings are summarised as the following:

1. When all are given equal locational distances, a positive change in signs X_5 (income) and a negative change in X_7 (loyalty) are observed, but both are insignificant.
2. Compared with the base case, when value criteria are all met, the only noticeable but insignificant changes are positive on income (X_5) and negative on store loyalty (X_7).
3. When all grocers compete on price factor, compared to the base run, it changes signs for distance (X_1), value (X_2), and means of trans-

Table 2: Logit Maximum Likelihood Estimation for Discount Stores: Base-Run Case

Dependent variable is Store Choice – 497 observations used

Regressor	Coefficient	Standard Error	T-Ratio [Prob]
X_1	-.70603	.21851	-2.5888[.000]
X_2	-.76905	.19374	-3.9695[.000]
X_3	.58802	.22454	2.6388[.004]
X_4	.54369	.22468	2.4645[.004]
X_5	-.50669	.23297	-1.92967[.005]
X_6	-1.4100	.21249	-6.6357[.000]
X_7	.52646	.25663	2.1390[.005]

Marginal effects = .16112

Goodness of fit = .79678

Pseudo-R^2 = .30589

The estimation method converged after 6 iterations

portation (X_6). This is a significant impact on the sign for consumer types (X_4).

4. When all consumers are strategic buyers, positive changes to incomes coefficient (X_5) are noticed and store loyalty dramatically falls.
5. When all consumers are on low incomes, all coefficients stay very similar but again store loyalty drops significantly compared to base case.
6. When consumers all have zero travelling costs, again income (X_5) and store loyalty (X_7) observably change the signs.
7. When there is repeated store switching, compared to base run, this changes the sign of the income coefficient.

The findings of base-run compared with simulations are summarised in Table 6 for comparative purposes. The consistency of the base findings with the simulated results for high probability cases is extraordinary. The base case characteristics of consumers who patronise discount stores are seen to be those who travel less than 3 miles, search for good value, perceive the store as competing in price, have low incomes and travel on foot to the store. They also exhibit high store loyalty. For the high probability cases there is a good degree of harmony between the base-run and the simulations. Thus, in these simulations, consumers who use discount

Table 3: Base-run of consumers profiles and probabilities of choosing discount stores

Probabilities	Consumers' profiles													
	Distance 3 miles residual		Value for money		Firms are actively competing in identifiable classes of branded goods		Consumer behavioural type		Income level at £16,000 *p. a.*		Means of transportation (costs incurred)		Store loyalty	
	>	<=	Yes	No	Non-price	Price	T. c.[1]	S. b.[2]	>=	<	Cars, etc	On foot	Yes	No
0.77871		*	*			*		*	*			*	*	
0.68676		*	*			*		*		*	*		*	
0.60858		*	*			*	*			*	*		*	
0.58478		*		*		*		*		*	*		*	
0.52049	*		*			*	*		*		*		*	
0.5		*	*		*		*		*		*			*
0.45487		*		*		*	*		*		*		*	
0.38265		*	*			*		*	*		*			*
0.25586		*		*		*		*		*		*		*
0.21889	*			*	*		*		*		*			*
0.1811		*		*	*			*	*			*		*
0.16035		*		*	*			*		*		*		*
0.1376		*		*	*			*	*		*			*
0.11928	*			*	*		*			*		*	*	
0.10165	*			*	*		*			*		*		*
0.095889	*			*		*	*			*	*			*
0.076697	*			*	*			*		*	*			*
0.05563	*			*	*		*			*	*			*

1. Time constrained consumer 2. Strategic buyers

Table 4: Base-run of consumers profiles and probabilities of choosing promotional stores

Probabi-lities	Consumers' profiles													
	Distance 3 miles residual		Value for money		Firms are actively competing in identifiable classes of branded goods		Consumer behavioural type		Income level at £16,000 *p. a.*		Means of transportation (costs incurred)		Store loyalty	
	>	<=	Yes	No	Non-price	Price	T. c.[1]	S. b.[2]	>=	<	Cars, etc	On foot	Yes	No
0.97297	*		*		*		*		*		*			*
0.96827	*		*		*		*		*		*		*	
0.94928	*			*	*		*		*		*		*	
0.932		*	*		*		*			*	*		*	
0.9215	*			*	*		*			*	*		*	
0.9029	*			*	*			*	*		*		*	
0.88968	*		*		*			*		*	*		*	
0.85239	*			*	*			*		*	*		*	
0.8318		*		*	*			*		*	*			*
0.8068		*		*	*			*		*	*		*	
0.77978	*			*		*	*		*			*	*	
0.7624	*			*		*	*			*	*			*
0.70358	*			*		*		*	*			*		*
0.65636	*			*		*		*	*		*		*	
0.58032	*		*		*		*			*		*	*	
0.5	*			*		*		*		*		*	*	
0.45886	*			*		*		*		*		*	*	

1. Time constrained consumer 2. Strategic buyers

Table 5: Results of Simulations on Each Variable; Coefficients and T-ratios

Coefficient	X_1*	X_2*	X_3*	X_4*	X_5*	X_6*	X_7*
X_1	−2.4211	−.25682	**.065416**	−.37271	−.26749	−.20416	−.31525
X_2	−.56811	−2.2108	**.19094**	−.51745	−.51901	−.60455	−.58748
X_3	1.4726	1.3588	1.7518	1.6312	1.4943	1.5010	1.5048
X_4	.94262	.89269	**−1.1405**	−1.7298	.99876	.93296	.92905
X_5	**.50905**	**.45390**	−.50610	**.64867**	−1.8872	.61875	**.51952**
X_6	−.46711	−.54512	**.53017**	−.52046	−.64258	.61875	−.51575
X_7	**−.10519**	**−.11539**	.23538	−.058869	**−.032405**	−.079572	−2.2172
T-Ratio [Prob.]							
X_1	−5.3720 [.000]	−.76773 [.443]	.20150 [.840]	−1.1144 [.266]	−.79297 [.428]	−.61555 [.538]	−.94004 [.348]
X_2	−2.0181 [.044]	−4.2221 [.000]	.72642 [.468]	−1.8713 [.062]	−1.8616 [.063]	−2.1572 [.031]	−2.0896 [.037]
X_3	5.5405 [.000]	5.2908 [.000]	3.4654 [.001]	6.2179 [.000]	.6090 [.000]	5.6422 [.000]	5.6501 [.000]
X_4	3.4752 [.001]	3.3075 [.001]	−4.3561 [.000]	−3.4309 [.001]	3.7153 [.000]	3.4434 [.001]	3.4195 [.001]
X_5	1.8780 [.061]	1.6912 [.091]	−1.9314 [.054]	2.4367 [.015]	−3.7357 [.000]	2.3327 [.020]	1.9138 [.056]
X_6	−1.5885 [.113]	−1.8361 [.067]	1.8551 [.064]	−1.7702 [.077]	−2.2072 [.028]	−6.1829 [.000]	−1.7245 [.085]
X_7	−.33819 [.735]	−.37383 [.709]	.79065 [.430]	−.19160 [.848]	−.10420 [.917]	−.25521 [.799]	−4.5640 [.000]
Marginal effects	.12210	.12310	.134719	.12726	.12337	.12256	.12144
Goodness of fit	.82093	.81690	.81690	.81891	.82294	.83099	.82495

* Targeted variables; changing in sign indicated in bold case.

stores, are consistently revealed to be strategic buyers who perceive price competition as a key factor. This is true in all the simulations (Table 6). However, for the lowest probabilities cases, there is no consistency with the base run. For example, although store loyalty is high in the base run, it is not observed in the low probability cases. Thus, for example, store loyalty is low and most buyers are time-constrained. The use of the logit model for simulations is a powerful way of restating some results from the base run. Moreover, the simulations are a legitimate way to configure consumer characteristics when all the regressors are 'environmental' or not directly under the control of the firm. Use of logit analysis for simulation on variables under the firms' control would be inappropriate. The simulations create different computer generated sub-data sets of the base case. In a sense they are clones of the base run when one regressor is altered each time. In this way, consumer profiles are enriched.

Implications of the Findings

The findings of the logit model and simulations indicate significant features relating to consumers who patronise discount and quality grocers. Quality stores clearly have an advertising communications strategy which links directly to service levels and non-price factors which time-constrained buyers need. Consumers who regularly conduct primary shopping at discount stores are typically strategic buyers. The auction models predict that both stores are strategically positioned for price discrimination targeted on grocery sub-markets. Time-constrained buyers will on the basis of the logit model regard prices at quality stores as representing poor value for money compared to discount stores. A typical consumer profile for a discounter's consumer would be a strategic buyer who was price sensitive with an income level higher or lower than £16,000 p.a. A fundamental feature depicted in Tables 3 and 4 is that there is clear linkage between value for money, price as the most important reason for store choice and strategic buying clearly locating the grocery discounters sub-market base. This is clear from the simulations, too. By contrast, a quality store's customer base is defined by time-constraints rather than 'value-for-money' or price considerations. That said, there is high probability that a consumer using a quality store will perceive prices as being too high and 'value-for-money' low compared with a discounter. Hence the time-constrained consumers using quality stores trade off value for money and relatively high prices against high service levels and other aspects of vertical product differentiation. The findings in Tables 3 and 4 produce clear possibilities for third degree price discrimination in grocery sub-markets and provide an explanation of enduring price dispersion (Walsh and Whellan 1999). Indeed, the grocery sub-market price dispersions are endogenous to the auction model. Moreover, consumers who choose discount stores generally believe that these stores offer better 'value-for-money' than those consumers who normally use quality stores. This is true in the base run and the simulations. Paradoxically, enhanced price dispersion may be an outcome of increased new entry in grocery retailing. Inspection of Tables 3, 4 and 6 shows clear market segmentation built on the characteristics of consumers and the potential for price discrimination. The simulations underline this, too. Critically, if search behaviour changes or time-constraints rise or fall then both types of format need to use mixed strategies or exit product lines periodically. This is clear from the auction model and is supported in the literature (Cotterill 1983, 1986, 1992).

The simulations using the logit model are a powerful tool for estimating differences in characteristics. Thus when all stores are given the same location details, the other coefficients are much of the same in terms of directional changes. When all stores in the sample are given value for money equivalence – when all compete in price – the change in the coefficients is marginal. Again when all consumers are strategic buyers with no time constraints, the main change is that store loyalty goes down.

Conclusions

Most spatial models have a single-dimensional feature on which sellers are placed (straight lines or cycles) about which consumers are distributed uniformly. The assumption in such models is that consumers differ in preferences with respect to a single good characteristic. In reality, grocery consumers may have different tastes and preferences over many sellers and goods characteristics. An exception to this is Palma et al. (1994) and others who have treated two or more characteristics of spatial price dispersion of market space and search costs within it using nested logit specifications. Our focus is on the effects of vertical and horizontal product differentiation on price equilibria and dispersion, in grocery sub-markets. One of our findings is that large sellers emphasising service quality and wide choice charge higher prices for wide ranges of branded groceries. This is at odds with the Palma et al. result (ibid). However, the findings of the logit are robust and point to consistency in findings between the base-run and the simulations (Table 6). The simulations consistently changed store loyalty, means of transportation, perceptions of value for money. The other coefficients are, in many cases, very similar. This is further evidence of the robustness of the logit model/developed.

Proof

$$D(P) = \sqrt[N]{1 - \left[\frac{x^N}{1 - x^N}\right]\left[\frac{P_{\max} - P}{P - c}\right]}. \tag{1}$$

For the price range $[x^N P_{\max} + (1 - x^N) c P_{\max}]$.

Table 6: A Comparison of Consistencies of the Base Run with the Simulations

		Characteristics						
		$X_1 < 3$ miles	X_2 – value	X_3 – firm competing on price	X_4 – strategic buyers	X_5 – income < 16,000	X_6 – means of travel	X_7 – store loyalty
	Highest probabilities							
Base-run	0.77871	✓	✓	✓	✓	✗	✓	✓
Simulation 1	0.62318	✓	✗	✓	✓	✓	✗	✓
Simulation 2	0.55917	✓	✓	✓	✓	✓	✗	✓
Simulation 3	0.72673	✓	✗	✓	✓	✓	✗	✓
Simulation 4	0.54422	✓	✗	✓	✓	✓	✗	✓
Simulation 5	0.5838	✓	✗	✓	✓	✓	✗	✓
Simulation 6	0.58883	✗	✗	✓	✓	✓	✓	✓
Simulation 7	0.60371	✓	✓	✓	✓	✓	✗	✗
	Lowest probabilities							
Original	0.05563	✗	✗	✗	✗	✓	✗	✗
Simulation 1	0.027611	✓	✓	✗	✗	✗	✓	✗
Simulation 2	0.041964	✓	✓	✗	✗	✗	✓	✗
Simulation 3	0.051048	✓	✓	✓	✗	✗	✓	✗
Simulation 4	0.039191	✓	✓	✗	✓	✗	✓	✗
Simulation 5	0.03394	✓	✓	✗	✗	✓	✓	✗
Simulation 6	0.027069	✓	✓	✗	✗	✗	✓	✗
Simulation 7	0.02569	✓	✓	✗	✗	✗	✓	✗

A Proof of the Simultaneous Symmetric Bertrand case

We hypothese that, with equilibrium existing in the range (P, P_{max}), the expected payoff to firm i, is from a pure strategy, $p_i = p$ is then:

$$\pi_i(p) = \sqrt{(x^N + (1 - r^N)(1 - f(p))^N[p - c]}. \quad (2)$$

Over this range *is equal for any price. When $P = P_{max}$

$$\pi_i(P_{\max}) = x^N(P_{\max} - c). \quad (3)$$

Since i, wins if and only if (iff) no other firm bids (except when other prices are $P_{\max}$ which has zero probability).

Equating (2) to (3):

$$\sqrt{(x^N + (1 - r^N)(1 - f(p))^N[p - c]} = x^N(P_{\max} - c), \quad (4)$$

which solved yields:

$$f(P) = \sqrt[N]{1 - \left[\frac{x^N}{1 - x^N}\right]\left[\frac{P_{\max} - P}{P - c}\right]}, \quad (5)$$

by definition P from (5).

$$0 = 1 - \left[\frac{x^N}{1 - x^N}\right]\left[\frac{P_{\max} - P}{P - c}\right], \quad (6)$$

which yields:

$$P = x^N P_{\max} + (1 - x^N)c. \quad (7)$$

The expected price that a firm charges is P' such that:

$$0.5 = f(P') = \sqrt[N]{1 - \left[\frac{x^N}{1 - x^N}\right]\left[\frac{P_{\max} - P'}{P' - c}\right]}, \quad (8)$$

which yields:

$$P' = \frac{c + (P_{\max} - c)x^N}{[1 - 0.5^N(1 + x^N)]}. \quad (9)$$

The expected π for ith firm is:

$$\pi_1 = (1 - x)x^N(P_{\max} - c). \quad (10)$$

Profit decline as N increases for individual firms.

Expected industry profit is therefore:

$$\sum_{i=1}^{N+1} = (N + 1)(1 - x)x^N(P_{\max} - c). \quad (11)$$

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