Estimation of Product Category Sales' Responsiveness to Assortment Size

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Abstract Assortment is one of the most important competitive tools a retailer has at his disposal to gain sustainable differentiation. Offering more variety should help a retailer to attract more consumers into the store and direct them towards the category as well as induce them to make purchases once inside. This paper presents an empirical estimate of assortment size elasticities of 12 FMCG categories across five store formats. Results show that assortment size elasticities are higher for fill-in categories, i.e., those categories bought occasionally by a small percentage of households, and which are dependent on store format.

Keywords Assortment • Assortment size elasticities • Hypermarket • Supermarket

1 Introduction

Product assortment is one of the most important competitive tools a retailer has at his disposal to gain sustainable differentiation (Simonson, 1999; Stassen, Mittelstaedt, & Mittelstaedt, 1999). Retailer practice reveals that assortment, together with factors such as price or promotions, help attract consumers into the store (Kahn, 1999) and retain core customers (Grewal, Levy, Mehrotra, & Sharma, 1999).

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J.C. Gázquez-Abad et al. (eds.), *National Brands and Private Labels in Retailing*, Springer Proceedings in Business and Economics, DOI 10.1007/978-3-319-07194-7_1,

The notion of assortment variety in retailing could plausibly be discussed on a technical level, then at the operational or measurement level. On the former, assortment variety refers to the number of choices available within a product group (e.g., a category). On the operational or measurement level, assortment variety could be further segregated into objective and perceptual assortment variety according to the measure adopted (Peng, 2008). Regarding objective measures of assortment variety, assortment size—measured by the total number of SKUs—(Chiang & Wilcox, 1997) or assortment composition—e.g., category attributes such as brand and flavour—(Boatwright & Nunes, 2001) can be included in this group. On the other hand, the perceptual measure of assortment variety includes aspects such as the ease of shopping (Broniarczyk & Hoyer, 2006), the availability of the consumer's preferred brand (Broniarczyk, Hoyer, & McAlister, 1998) or the congruency between consumers' internal and retailers' external assortment organization (Morales, Kahn, McAlister, & Broniarczyk, 2005). This paper focuses on objective assortment variety measured by the total number of SKUs.

The notion that perceived variety is a function of assortment size is fairly straightforward (Chernev, 2011). For example, Amine and Cadenat (2003) found that, besides the availability of the leading national brands and the presence of favourite brands, individuals primarily use the number of SKUs when forming their assortment evaluation. In this respect, a larger assortment tends to be perceived as having greater variety. Conventional wisdom suggests that greater variety benefits consumers (Chernev, 2006). The assumption that more choice is always better is not only intuitively appealing but is also supported by numerous findings in many disciplines (Chernev, 2003a), such as decision making, social psychology and economics.

Nevertheless, a recently advanced alternative viewpoint has suggested that larger assortments do not always benefit choice (Chernev, 2003a), because they can confuse consumers, increasing the probability of delaying their choice or not choosing at all (Chernev, 2003a, 2003b; Dhar, 1997; Greenleaf & Lehmann, 1995; Schwartz et al., 2002). Indeed, there are some studies showing that retailers can eliminate a substantial number of SKUs without negatively affecting category sales (Zhang & Krishna, 2007). This is interesting, as it is known that although larger assortments might be more attractive, they also tend to diminish returns because the marginal benefits from each additional alternative tend to decrease with the increase in assortment size (Chernev & Hamilton, 2009). Therefore, and given that the increase in benefits happens at a decreasing rate, there is a point at which benefits are offset by the additional costs of evaluating all the available alternatives (Roberts & Lattin, 1991). Nevertheless, such an optimal level seems to depend on the product category under analysis, as van Ketel (2006) showed. In other words, consumers may have different thresholds or "optimal points" for different products (van Ketel, 2006).

Understanding the relationship between assortment size and category sales is particularly important for retailers. A clearer knowledge on how category sales react to a change in the number of SKUs will help retailers to better organize their assortments. In this paper, we propose an empirical estimate of assortment size elasticities of 12 FMCG categories across five store formats. We extend prior research in the relationship between assortment size and category sales by estimating assortment size elasticities, not explicitly done by previous research. We estimate assortment size elasticities from several FMCG categories characterized using the penetration-frequency distinction developed by Dhar, Hoch, and Kumar (2001) and across store formats (hypermarket and supermarket), providing additional insights.

2 Assortment Size–Category Sales Relationship

Wroe Alderson defined the assortment concept in marketing in the early 1950s (Wind, 1977) as "a heterogeneous collection of products designed to serve the needs of some behaviour system" (Alderson, 1957:195). Assortment reflects a retailer's strategic positioning (McGoldrick, 2002) and differentiates the various formats of bricks-and-mortar retailers (Peng, 2008). Thus, a specialty retailer tends to carry a narrower but deeper assortment than e.g., a supermarket or—especially—a discounter. In this respect, few retailers offer both a very wide and very deep assortment as they are essentially limited by their resources, especially by the physical site or shelf space (McGoldrick, 2002). For example, in the context of FMCG, a hypermarket is the type of retailer offering the widest and deepest assortment.

The literature on assortment has traditionally supported the view that greater assortments benefit consumers. Thus, prior research has identified a number of benefits associated with a large assortment (Chernev, 2011). From the point of view of economic research, larger assortments offer an opportunity for a better match between an individual's preferences and the characteristics of the alternatives in the choice set (see Lancaster, 1990 for a review). In this respect, consumers might feel more confident when selecting from those retailers offering large assortments because it is unlikely that a potentially superior alternative is represented in the available choice set (Karni & Schwartz, 1977). An additional economic explanation for the greater preference for large assortments relates to the greater efficiency of time and effort involved in identifying the available alternatives in the case of one-stop shopping associated with retailers offering such larger assortments (Messinger & Narasimhan, 1997). Based on these benefits, several previous studies have found a positive relationship between the number of SKUs contained in a given assortment and sales (e.g., Cadeaux, 1999; Koelemeijer & Oppewal, 1999). Nevertheless, recent research argues that adding new options to a given assortment will have an asymmetric impact on the probability of choosing an option from that assortment (Chernev, 2011:13), depending on the category under study and the store type (Schiffman, Dash, & Dillon, 1977).

Notwithstanding, literature has recently identified a number of negative consequences of larger assortments. One possible explanation is related to the greater cognitive effort that making a choice from larger assortments may require, simply because it involves evaluating a greater number of alternatives, attribute dimensions and attribute levels (Haynes, 2009; Iyengar & Lepper, 2000). Another explanation is related to the confusion that larger assortments may create among those consumers who are uncertain of their preferences (Chernev, 2011). Such confusion is a consequence of the larger number of attributes and/or attribute levels that must be evaluated in order to form a preference and make a choice (Dhar, 1997; Greenleaf & Lehmann, 1995). Such confusion is also increased as a consequence of the greater number of tradeoffs consumers have to make when comparing the benefits and costs of the different options (Chernev, 2003b). Considered together, these findings suggest that, in the presence of preference uncertainty, choices from large assortments can potentially lead to a lower choice probability and weaker preferences for the selected alternative (Chernev, 2006:51). Indeed, there are many papers supporting this idea. For instance, Iyengar and Lepper (2000), in the context of gourmet jams, showed that consumers were more likely to make a purchase when being presented with an assortment comprising six items than with an assortment comprising 24 items (30 % versus 3 %). Similar findings have been reported by many authors in a variety of product categories, such as consumer electronics (Chernev, 2003a), chocolates (Berger, Draganska, & Simonson, 2007; Chernev, 2003b) and mutual funds (Morrin, Broniarczyk, & Inman, 2011).

Given these contradictory conclusions, the direction of causality is one of the primary problems that researchers have to face with regard to sales—assortment size relationship. Although the above mentioned papers have examined the relationship between these two aspects, most of them use experimentation. However, this methodology is often rather inconclusive (Corstjens & Doyle, 1981); additionally, although it can be used to detect a correlation between differences in assortment size and variations of demand, it does not demonstrate the existence of a casual link between both variables.

3 Empirical Estimation of the Sales-Assortment Relationship

A sales-assortment relationship is estimated from a pooled database of 17,496 stores provided by IRI Worldwide. This number can be assumed to represent virtually 100 % of all Spanish grocery retailers. Stores are classified into two categories, namely hypermarkets and supermarkets. Hypermarkets are classified into two categories: big hypermarkets (>5,000 m^2 of surface area) and small hypermarkets (2,501–5,000 m^2 of surface area). Supermarkets are classified into three categories: big supermarkets (1,001–2,500 m^2 of surface area), medium-sized supermarkets (401–1,001 m^2 of surface area) and small supermarkets (100–1,000 m^2 of surface area). Table 1 shows the number of stores for each retailing format and geographical area.

Table 1 Grocery stores database

Spain by geographical area	# stores
(I) Barcelona Metropolitan Area	1,514
(II) North-East	2,494
(III) Central-East	2,284
(IV) South	4,084
(V) Madrid Metropolitan Area	1,467
(VI) Centrum	1,758
(VII) North-West	2,196
(VIII) North	1,735
	17,496
Store format	# stores
Small Supermarket	8,285
Medium-sized Supermarket	5,799
Big Supermarket	2,988
Supermarkets	*17,072*
Small Hypermarket	131
Big Hypermarket	293
Hypermarkets	*424*
	17,496

The database includes information gathered over 5 years (2008–2012) on weekly sales and on assortment size by category. In total, 12 categories have been analyzed (*beer*, *milk*, *yoghurt*, *bakery*, *fresh bread*, *nuts*, *coffee*, *tuna*, *toilet tissue*, *deodorant*, *freshener* and *laundry detergent*). These categories are characterized using the penetration-frequency distinction developed by Dhar et al. (2001). These authors classified categories into "high" and "low" penetration (percentage of households that purchase the category) and frequency (average number of times per year that category is purchased) (Dhar et al., 2001:170). According to both aspects, categories fall into one of four groups: (1) *staples* (high penetration/high frequency); (2) *niches* (low penetration/high frequency; (3) *variety enhancers* (high penetration/low frequency); and (4) *fill-ins* (low penetration/low frequency). The selection of product categories (and placing them in each of the four groups defined by Dhar and colleagues) has been made based on a sample of 53 categories accounting for more than 60 % of Spanish market FMCG sales. Using data on rotation and sales volume, we have ranked all 53 categories according to their levels of penetration and frequency. From such ranking we have classified product categories as follows: beer, milk and yoghurt (*staples*); bakery, fresh bread and nuts (*niches*); coffee, tuna and toilet tissue (*variety enhancers*), and deodorant, freshener and laundry detergent (*fill-ins*). In selecting such categories, we have considered the presence of food categories (the most important in the typical Spanish shopping-basket), but also of personal care and cleaning products.

We estimate regular assortment elasticity for each store and category using a demand model function linking sales to assortment size. Unit sales are used as the dependent variable, and assortment size and the lagged dependent variable as the explanatory variables. Unit sales are most commonly used in sales response models for store-level scanner data (Blattberg & George, 1991). Assortment size is measured as the number of SKUs in the category. The use of the number of SKUs to measure assortment size is consistent with the view of previous literature (e.g., Chiang & Wilcox, 1997). The lagged dependent variable is included to capture the dynamics of sales response and to eliminate residual serial correlation (see Blattberg & George, 1991).

A log model was selected to model the response function because (1) regular assortment elasticity is directly provided by the estimated parameters; (2) it provides better fits in terms of the lowest sum of the squared error for a greater number of stores (Shankar & Krishnamurthi, 1996), and (3) the overstatement of elasticity estimates, if any, is lowest for the log form when compared to the linear form (Bolton, 1989).

Therefore, the following model is used for the sales response function for each store format and product category.

$$LS_{ijt} = \beta_{0ij} + \beta_{1ij} LAS_{ijt} + \beta_{2ij} LS_{ij(t\text{-}1)} + \varepsilon_{ijt}$$

where $i = 1,2,\ldots 12$ denotes the product category, $j = 1, 2, 3, 4, 5$ the store format, t $(1,\ldots 260)$ the week of observation, and

LS_{ijt} = Logarithm of unit sales

LAS_{ijt} = Logarithm of assortment size in number of SKUs

β_{0ij} = Intercept term

β_{1ij} = Assortment size elasticity of the product category i, format j

ε_{ijt} = Stochastic disturbance term assumed to be independent and identically distributed normal with mean 0 and variance $\sigma^2_{\varepsilon ij}$

4 Results

Statistical estimates of assortment size elasticities are satisfactory as shown by the F-tests, all significant at 0.01 %. High values for R^2 are obtained, ranging from 0.024 to 0.859 for product categories and store formats (the average R^2 is 0.5737). The distribution of the assortment size elasticity for the different store formats and product categories is given in Tables 2 and 3, respectively. The average value for the assortment size elasticity is 0.2039.

Assortment size elasticities[1] for each product category and store format vary considerably from −0.138 to 0.694 (Fig. 1). Looking at the lowest values, there are a significant number of product categories with elasticities which do not differ notably from zero at 0.05 % level (4 in *big hypermarkets*, 4 in *small hypermarkets*, 3 in *big supermarkets*, 2 in *medium-sized supermarkets* and 3 in *small*

[1] The complete results on assortment size elasticities can be found in Appendix.

Table 2 Distribution of assortment elasticities across store formats

	Big hypermarket	Small hypermarket	Big supermarket	Medium-sized supermarket	Small supermarket
Mean	0.2535	0.1199	0.1382	0.3032	0.2046
Standard deviation	0.2422	0.1170	0.2015	0.2495	0.2201
Minimum	0	0	−0.1380	0	0
Maximum	0.6940	0.3850	0.6590	0.6740	0.6270

Table 3 Distribution of assortment elasticities across product categories

	Staples			Niche		
	Beer	Milk	Yoghurt	Bakery	Fresh bread	Nuts
Mean	0.0862	0.0310	0.1756	0.2582	−0.0008	0.0944
Standard deviation	0.0882	0.0693	0.0738	0.1070	0.0961	0.1032
Minimum	0	0	0.0790	0.1200	−0.1380	0
Maximum	0.1930	0.1550	0.2610	0.4150	0.1340	0.25
	Variety enhancers			Fill-in		
	Coffee	Tuna	Toilet tissue	Deodorant	Freshener	Laundry detergent
Mean	0.1642	0.1748	0.140	0.3294	0.3994	0.5946
Standard deviation	0.2329	0.0516	0.0955	0.2818	0.2885	0.1225
Minimum	0	0.1070	0	0	0	0.3850
Maximum	0.5620	0.2330	0.2680	0.6110	0.6740	0.6940

supermarkets); a share of assortment size increase does not result in any change in share of sales. These unresponsive categories cover mainly milk, fresh bread, beer, nuts and coffee. Excepting coffee, unresponsive categories are included either in the staples (beer and milk) or niche (fresh bread and nuts) categories. More surprisingly, we found a negative assortment size elasticity (−0.138) for the fresh bread category in big supermarkets. We can, therefore, assume that in big supermarkets, for fresh bread, criteria other than sales optimization are taken into account to increase the number of SKUs. In terms of store format, both hypermarkets and supermarkets show the same number (8) of elasticities which do not differ notably from zero. Nevertheless, while both big and small hypermarkets show the same number (4 each) of elasticities not differing notably from zero, there are differences in supermarket stores. Thus, we find 3 elasticities in the case of big and small supermarkets, and 2 in the case of medium-sized supermarkets.

Regarding hypermarkets, store profiles for big and small stores are very similar, as can be seen in Fig. 1. Nevertheless, the 95 % confidence level for the average comparison test for these two store types does confirm that the average assortment size elasticity for big hypermarkets is more than twice as large (0.2535 vs. 0.1199).

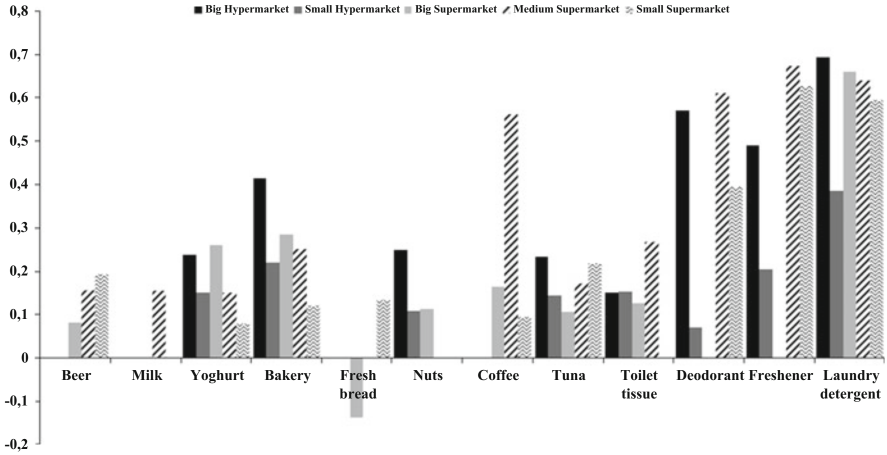

Fig. 1 Assortment size elasticities

In the case of supermarkets, average comparison tests confirm that the average assortment size elasticity for medium-sized supermarkets is the highest (0.3032). Nevertheless, the average comparison test for big and small supermarkets does not confirm the existence of differences between average assortment size elasticities between them. We can, therefore, assume that in the hypermarket format, the greater the selling surface the stronger the relationship between assortment size and category sales. By contrast, in the supermarket format, we find evidence of an inverted-U relationship between assortment size and category sales.

5 Conclusions and Managerial Implications

Our results support the positive relationship between assortment size and sales found in previous studies using experimentation. Thus, assortment size elasticities are significantly non-zero for most product categories and store formats (average assortment size elasticity is 0.2039). The two exceptions are the milk and fresh bread categories (four out of five elasticities and three out of five elasticities, respectively, which do not differ notably from zero). Nevertheless, elasticities vary greatly from one category to another as well as from one store format to another (except for big and small supermarkets), suggesting that various store and category characteristics might explain the sensitivity to assortment size.

Regarding product category, our results show that fill-in categories have the highest assortment size elasticities. The average assortment size elasticity for those product categories classified as fill-in (deodorant, freshener and laundry detergent) is 0.4411. This result indicates that increasing the number of SKUs will be most effective in those categories with a lesser percentage of households that purchase the product and with a lower frequency. By contrast, staple categories (i.e., those categories bought frequently by a high percentage of households), have the lowest assortment size elasticities. The average assortment size elasticity for these categories (i.e., beer, milk and yoghurt) is 0.0976, which is consistent with the results of Dhar and colleagues (2001), who found that the positive effects of increasing both category breadth and depth of an assortment were only found in variety-enhancers such as pickles, niches such as cheese and fill-ins such as pancake mix, but not in staple categories. This could be a consequence of staple categories having reached saturation levels (Drèze, Hoch, & Purk, 1994). The low value we have obtained in this paper seems to confirm the limited role played by assortment as staples' sales enhancer. Niches and variety enhancers show a medium (and very similar) level of assortment size elasticities. Average value is 0.1172 (niches) and 0.1596 (variety enhancers).

All in all, our results suggest—as in the Dhar and colleagues' (2001) conclusions—that a retailer's decision to reduce assortment in staples categories is less risky, as it is expected to have little impact on sales, unlike decisions taken on niches, variety enhancers and specially, on fill-ins, where assortment size elasticities are higher.

Acknowledgments The authors wish to acknowledge the financial support provided by the *Fundación Ramón Areces* (Spain).

Appendix: Assortment Size Elasticities for Each Product Category and Store Format

		Staples			Niche		
		Beer	Milk	Yoghurt	Bakery	Fresh bread	Nuts
Big Hypermarkets	Assortment size	0.032	−0.081	0.238***	0.415***	−0.050	0.250***
	Lagged depen-dent variable	0.702***	0.271***	0.609***	0.563***	0.373***	0.577***
	Adjusted R^2	0.494	0.082	0.614	0.849	0.138	0.507
Small Hypermarkets	Assortment size	0.060	−0.003	0.150**	0.221***	−0.004	0.109*
	Lagged dependent variable	0.858***	0.177**	0.755***	0.724***	0.655***	0.622***
	Adjusted R^2	0.766	0.024	0.747	0.765	0.424	0.418
Big Supermarkets	Assortment size	0.082**	0.068	0.261***	0.284***	−0.138**	0.113***
	Lagged dependent variable	0.876***	0.480***	0.675***	0.627***	0.768***	0.853***
	Adjusted R^2	0.828	0.231	0.810	0.682	0.743	0.810
Medium Supermarkets	Assortment size	0.156***	0.155**	0.150**	0.251***	0.009	0.043
	Lagged dependent variable	0.815***	0.511***	0.690***	0.719***	0.646***	0.775***
	Adjusted R^2	0.843	0.294	0.611	0.855	0.413	0.597
Small Supermarkets	Assortment size	0.193***	−0.078	0.079*	0.120**	0.134**	0.016
	Lagged dependent variable	0.752***	0.631***	0.787***	0.810***	0.575***	0.783***
	Adjusted R^2	0.787	0.435	0.680	0.766	0.365	0.602

		Variety enhancers			Fill-in		
		Coffee	Tuna	Toilet tissue	Deodorant	Freshener	Laundry detergent
Big Hypermarkets	Assortment size	0.027	0.233***	0.151*	0.571***	0.491***	0.694***
	Lagged dependent variable	0.349***	0.511***	0.245***	0.282***	0.414***	0.183***
	Adjusted R^2	0.115	0.369	0.088	0.582	0.509	0.714
Small Hypermarkets	Assortment size	0.013	0.145***	0.154**	0.070*	0.205***	0.385***
	Lagged dependent variable	0.377***	0.765***	0.511***	0.822***	0.554***	0.543***
	Adjusted R^2	0.134	0.705	0.317	0.697	0.405	0.776
Big Supermarkets	Assortment size	0.164***	0.107**	0.127***	0.035	−0.077	0.659***
	Lagged dependent variable	0.748***	0.840***	0.822***	0.899***	0.789***	0.176**
	Adjusted R^2	0.697	0.735	0.806	0.789	0.708	0.630
Medium Supermarkets	Assortment size	0.562***	0.172***	0.268***	0.611***	0.674***	0.640***
	Lagged dependent variable	0.252***	0.744***	0.276***	0.369***	0.316***	0.319***
	Adjusted R^2	0.520	0.676	0.187	0.820	0.820	0.849
Small Supermarkets	Assortment size	0.095*	0.217***	0.021	0.395***	0.627***	0.595***
	Lagged dependent variable	0.713***	0.724***	0.300***	0.586***	0.354***	0.366***
	Adjusted R^2	0.488	0.750	0.082	0.787	0.630	0.859

*Significant at 0.05 level; **significant at 0.01 level; ***significant at 0.000 level

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