Article

Estimating Demand Using Space Elastic Demand Model for Retail Assortment Planning

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Abstract

A retailer assortment is defined as a mix of products stocked in a retail store. The identification of proper assortment has become difficult in the current consumer-centric environment. Assortment planning (AP) in a retail chain largely depends on the estimation of demand of various products under consideration. The knowledge of the true demand rates and substitution rates is important for a retailer for a variety of management decisions, such as the ideal assortment to carry, the quantum of each item to be stocked and how often to replenish the stock (Anupindi, Dada & Gupta, 1998).

Space elastic demand model is one of the models which have been widely used for demand estimation in retail AP literature. However, there is paucity of empirical studies in this field of research. In this article, the demand has been estimated using space elastic demand model for two product categories comprising 11 products within the category. The study illustrates the methodology for estimation of demand using space elastic demand model. The results obtained are consistent with the results obtained in few of the empirical studies done in other contexts.

Keywords

Retail assortment, demand models, space elastic demand model, product category

Introduction

Retailer assortment problem has remained a challenging and significant problem for the researchers in recent times. It is defined as the mix of products carried by a retail store. The identification of proper assortment has become difficult in the current consumer-centric environment. The increasing need of consumers in terms of variety has increased the difficulties for the retailers. The consumers have different preferences of products and retailers must offer the array of products that satisfies the needs of

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various consumers (Ulu, Honhon & Alptekinoğlu, 2012). The purpose of selecting a subset of products from the available products is to maximize the retailers' objective, for example, profit, under consideration of constraints, such as limited space available for display, defined budget for the number of products and their stock keeping units (SKU), inventory to be carried to meet a desired service level and, last but not the least, to fulfil the ever-changing needs of the consumers.

In the current retail merchandising scenario, consumers have a tendency to search for the products offered by the retailers. Sometimes, the search is for the current purchase and sometimes it is done for extending the list for future buying (Morales, Kahn, McAlister & Broniarczyk, 2005). As stated by Quelch and Kenny (1994), the number of products in the market for sale are increasing at a faster rate than the realized sales of the products. It is understood that the assortment selected by any retailer has a greater impact on its gross margin or sales and hence the exercise of assortment planning (AP) plays an important role in retail management.

Assortment planning is a process of selecting types and the number of products to be kept from a given product line and also determining the optimal level of inventory of these products. Though the retail market is growing in India, there are also challenges attached to the business especially in these emerging markets (Basu, 2015). One of the critical issues faced by a retailer in the process of AP is to estimate the demand for each product and by using these demand estimates, developing a profit function and choosing the best array of products to maximize profit under various constraints (Rajaram, 2001). Assortment planning is relatively a new field for both the academicians and the practitioners in terms of specialized models for optimizing assortment. Though AP always remained an issue of concern for the retailers, the development of scientific methods is limited in this field.

The estimation of demand is a complex phenomenon. There exist some models to estimate the demands. In the present study, the space elastic demand model has been studied for the estimation of the demand for two product categories in a hyper store which is one of the 200 stores of a big Indian retail chain. The demand derived through the model has been compared with the actual demand obtained from the store. Most of the earlier works in demand estimation are analytical and there is a lack of literature on empirical studies. The application of the models developed and the estimation of various parameters used in the analytical work are also lacking. In this work, an attempt is being made to explain the method for parameter estimation in real time which is further used for demand estimation. The appropriate variables explaining the demand more accurately are identified and their application in the space elasticity model is explained.

The remaining article is organized as follows. The first section gives an introduction of the topic and describes its relevance and importance for business and different industries. The second section discusses the detailed literature review of the topic. We have focused on the area where AP has been applied considering the specific demand model. The third section describes the methodology in which the demand model has been explained along with the methodology for parameter estimation of the demand model for the study, that is, space elastic demand models. The fourth section describes the data collection process. The fifth section shows the results of the study and includes discussion on the results. The sixth section includes managerial implications. Finally, the seventh, eighth and ninth sections include limitations, conclusion and future scope of the work, respectively.

Literature Review

In a typical supermarket, the customers buy product without the help of any sales personnel, that is, the product displayed has to sell itself (Hansen & Heinsbroek, 1979). The shelf-space utilization and assortment carried by the retailer hence becomes an important factor in a new business scenario. It has become important for the retailers to carry the products that minimize the lost sales due to stock-outs and maximize its profit. Consumer reaction towards assortment carried by a retailer has always remained a complicated issue for the researchers. In few researches, it has been concluded that increasing the varieties in any store increases the probability of purchase. However, in a recent research (Kök, Fisher & Vaidyanathan, 2009), it has been reasoned that the product variety has reached its saturation and that now, a decrease in assortment has led to an increase in profits. Similar results has been concluded by Chernev and Hamilton (2009). The idea is that more number of products in the assortment led to confusion in the minds of consumers, increased searching cost and hence sometimes led to no purchase.

Researchers have developed models in the last three to four decades to address the various objectives associated with retail shelf allocation and AP. It has been observed that the demand estimation in any AP problem mostly considered shelf-space and substitution parameters. In this section, the assortment problem dealt by various researchers with shelf-space allocation models has been reviewed.

Assortment Planning with Space Elastic Demand Model

It has been posited in the literature that sales of a product in a self-service type of atmosphere are influenced by the shelf space provided to the product. As in any superstore, the space is limited; there is always a problem of shelf-space distribution among different brands and products. In a very early work, Lee (1960) investigated the variables affecting the shelf-space allocation decision in agriculture-based products. Many important issues which are interrelated with each other, such as like the merchandising effect, frequency of replenishment, lot size of replenishment and cost associated in terms of labour, were considered in the model. Brown and Tucker (1961) examined the effect of shelf space on the sales of three categories of products. The products were classified as unresponsive products like salt, general use products like breakfast food and occasionally purchased products like canned nuts. The study found mixed results among the categories and there were no definite results concluded between the sales and the space allocated.

Cairns (1963) used a graphical solution to allocate shelf space among two products to maximize profits while taking space elasticity into account. Direct shelf elasticity/cross-space elasticity is defined as the ratio of the relative change in unit sales of the considered product to the relative change in the shelf space of that product/competing products (Chen, Chen & Tung, 2006). The model considered by Cairns does not take into account the limited shelf space as well as integral facing restrictions. Kotzan and Evanson (1969) examined the effect of shelf-space alteration on the sales of the four products in drug category.

In a seminal paper by Corstjens and Doyle (1981), a geometric programming model was developed where both product and cross-space elasticity were considered and the objective was profit maximization. The model highlights sales–space elasticity that gauges the sales response of a given product to the space allocated to another. It is the first space allocation model to incorporate such interdependencies. Costs were modelled as functions of inventory investment and handling expenses. Other constraints included store size, upper and lower bounds on space of each category as well as availability/minimum service level of products. A geometric programming approach was used to solve the problem. It was reported that the optimal space allocation is dependent on product profitability, direct space elasticity of the product and the product's cross-space elasticity. The model developed by Corstjens and Doyle has been the base of many studies incorporating space elastic demand model.

Corstjens and Doyle (1983) extended the static model to a dynamic one that allows for the anticipation of changing customer tastes and changing product growth and life cycles that could motivate retailers to allocate more space to new products and to divest from declining ones. Zufryden (1986) proposed a model that considered space elasticity, cost of sales and demand-related marketing variables, but neglected cross-space elasticity between products while fixing non-space marketing variables. A dynamic programming approach to the model was used to solve the problem.

The work of Bultez and Naert (1988) builds on the work of Corstjens and Doyle and extends modelling cross-elasticity in product category management models. A shelf allocation for retailers' profit (SHARP) model was developed, which is similar to the (Corstjens and Dolye) C-D model and optimized space allocation within a product category, taking into account interdependencies within product groups and across groups. Borin, Farris and Freeland (1994) addressed product assortment and space allocation in a constrained optimization problem. The total demand was distinguished as unmodified, modified, stock-out and acquired demand. Borin and Farris (1995) analyzed the deviation in parameter estimation which yielded almost same assortments and shelf allocations when compared to the actual results. It was concluded that even a 50 per cent error in parameter estimation would lead to actual results.

Desmet and Renaudin (1998) used the C-D model framework in an empirical study of product category sales responsiveness to allocated shelf space where the model was based on a demand function linking the share of sales to the share of space allocated to the product category. Urban (1998) studied the integration of inventory control models, product assortment models and shelf-space allocation models. A suitable algorithm heuristics was used for solving the problem.

Bookbinder and Zarour (2001) integrated direct product profit (DPP) into shelf-space allocation optimization problem. The C-D framework was used with an addition of the DPP method. Yang (2001) developed a model based on the non-linear model of C-D. However, because the latter is difficult to apply in realistic situations, a simplified yet practicable alternative model in the form of a linear multi-knapsack integer programme was proposed. Irion, Al-Khayyal and Lu (2004) extend the C-D model to study the shelf-space allocation problem at the product level. It was posited that the demand for each product is a function of its own and other products' shelf space through own and cross-space elasticity.

It is evident from the literature review that most of the papers on retail AP are either analytical or have used simulated data for their studies. The probable reason for lack of empirical studies is the lack of interest of the store manager and the companies owning the stores. The collection of real-time data sometimes needs intervention in the regular operations of the store.

For more detailed literature review on the application of space elastic demand model in AP, refer Singh and Kapoor (2013).

Methodology

Space Elastic Demand Model

Under the space elastic demand model, the demand of a product is measured in terms of the space allocated to the given product as well as the space allocated to its competitive products. In a supermarket scenario, a category of products are kept at the same place. Hence, it is rational to assume that the space allocated to competing products has an influence on the sales/demand of the products. Lee (1960), in his paper, mentioned the space as an important variable in agriculture-based product selection. Since then, many authors have used space and cross-space elasticity as a measure for demand.

The demand function under this model is written as

$$D = a_i * f(S_i, S_j), \tag{1}$$

where a_i = Latent demand for product i,
S_i = Space allocated to product i and
S_j = Space allocated to product j.

The same expression has been used by many researchers in the context of retail demand estimation. However, many authors have extended this model by incorporating some more variables in the model, which were important in the context studied. The structure of the equation, however, remained unchanged in all these extensions.

Estimation of Parameter of Space Elasticity Demand

The log-linear function is a common function taken for representing demand.

The function will be

$$D = a * f(x_i),$$

where

a is some scale constant and

$f(x_i)$ is a multiplicative function of variables affecting the demand.

For demand which is assumed to be dependent only on space and cross-space elasticity, the function will be

$$D_i = a * (S_i)^{\alpha_i} * \Pi_{J \neq i}^{N} (S_j)^{\beta_{ji}} \tag{2}$$

where a = Latent demand for product i,
S_i = Space allocated to product i,
S_j = Space allocated to product j,
α_i = Direct space elasticity of demand for product i and
β_{ji} = Cross space elasticity of demand of product i with respect to product j.

The expression is similar to the expression used by Corstjens and Doyle (1981).

The given function can be converted in log-linear function by taking log on both sides. The resulting equation will be

$$\ln D_i = \ln a + \alpha_i \ln S_i + \sum_{j \neq i}^{N} \beta_{ji} * \ln S_j \tag{3}$$

For a function like this, the coefficients of the terms are also the coefficients of the elasticity of demand with respect to that variable. By partially differentiating both sides with respect to S_i, we get

$$\frac{1}{D}\frac{\partial D_i}{\partial S_i} = \alpha_{\mathrm{i}} * \frac{1}{S_i}$$

$$\Rightarrow \frac{S_i}{D}\frac{\partial D_i}{\partial S_i} = \alpha_i \tag{4}$$

which is nothing but the direct space elasticity of demand. Similarly, if we differentiate the Equation (3) with respect to S_j, we get

$$\frac{1}{D}\frac{\partial D_i}{\partial S_{ji}} = \beta_{ji} * \frac{1}{S_j}$$

$$\Rightarrow \frac{S_j}{D_i} * \frac{\partial D_i}{\partial S_j} = \beta_{ji} \quad (5)$$

Equation (5) is the expression for the cross-space elasticity of demand of product i with respect to product j. The last expression concludes that if we run a log linear regression, the coefficient of any of the variable is the coefficient of the variable elasticity of demand.

Data Collection

The present work is an exploratory research. The cross-sectional data were collected from a hyper store located in the eastern part of the country. The store is a part of a company dealing in retail business and has almost 200 stores across India including hypermarkets and superstores. The company has almost 2 million customers per month around the country. The store selected for study is spread in almost 20,000 sq ft of area and carries almost 60,000 SKUs.

The data were collected for a period of 3 months from February 2013 to April 2013. Ideally, a variety of products should be tested but we narrowed down to the product categories which satisfy certain criteria/assumptions which are explained below.

The number of products during the study period in the category did not increase or decrease. The price within the category is assumed to be approximately constant (prices not changing significantly) during the study period. The product category selection was from the retailer's categorization of the product as food and non-food item. The frozen food products were discarded on the basis of limited shelf-space availability. Small-sized products were discarded as it was difficult to capture data for them. Based on these criteria/assumptions, the two categories, namely 600 ml pet bottled soft drinks from food and mosquito repellents from non-food category, were chosen. It has been observed that the presence of competing products taking almost equal space and having prices almost similar also make consumers substitute their initial preference. Also, these products are sometimes instantaneous purchases.

For space elastic demand model, the demand was taken from the point of sales (POS) data. For space allocation, the data were recorded on daily basis. No interference was made into the daily working of the staff members. The spaces allocated to the products were recorded every day. The store staff and/or the staff from the company kept an eye on the stocks and the sales. Once the shelves were arranged in the morning, no refilling was done throughout the day. The monitoring of the products in shelves was done in two stages. The number of billings of the store was recorded from the POS data which also included the number of bills generated for a given category and the number of persons buying from the category and the sub-category. Any promotions made by either the company or the store were recorded. Any in-store advertisement done by the store or supported by the company was also recorded. The other factors recorded were the number of billing counters operational each day and the number of personnel at the shelves of each product which is an indicator of the service provided by the store for the customers. The selling price and cost of the product were also observed and any change in them at any point during the period of study was recorded.

Results and Discussion

The space elastic demand model was tested on the two product categories. The multi-collinearity among the variables for all the models was tested beforehand. All the values in the correlation matrix were found in the low and medium range of correlation (Bluman, 1995). The related correlation matrices have been provided in Appendix A, Tables A12 and A13.

The result of the space elastic demand model for product 1 in category 1 is given in Table 1. The analysis of variance (ANOVA) table for the model for product 1 of category 1 is shown in Table 1.

It is observed from Table 1 that the F value for the model is higher than the significant F value. The F value for the product 1 in category is 14.2509 which is much higher than the significant F value. Hence, we can conclude that the space elastic demand model is valid for product 1 of category 1. Similar results for all the products in category 1 are summarized in Table 2.

It is evident from the F values of all the models in Table 2 that all the models are valid for all the products in category 1.

The result of the space elastic demand model for all the products in category 2 is summarized in Table 3.

Table 1. ANOVA Result for Product 1 in Category 1

	df	SS	MS	F	Significance F
Regression	6.0000	21.0783	3.5130	14.2509	0.0000
Residual	82.0000	20.2142	0.2465		
Total	88.0000	41.2924			

Source: Own findings.

Table 2. ANOVA Result for All Products in Category 1

	df	SS	MS	F	Significance F
Product 1	6.0000	21.0783	3.5130	14.2509	0.0000
Product 2	6.0000	20.5510	3.4252	9.8312	0.0000
Product 3	6.0000	9.8855	1.6476	3.6109	0.0032
Product 4	6.0000	18.4905	3.0817	8.5111	0.0000
Product 5	6.0000	24.8372	4.1395	11.0774	0.0000
Product 6	6.0000	20.0182	3.3364	12.9343	0.0000

Source: Own findings.

Table 3. ANOVA Result for All Products in Category 2

	df	SS	MS	F	Significance F
Product 1	5.0000	18.4610	3.6922	11.0026	0.0000
Product 2	5.0000	24.8680	4.9736	17.3246	0.0000
Product 3	5.0000	25.7346	5.1469	17.4409	0.0000
Product 4	5.0000	16.1130	3.2226	8.9230	0.0000
Product 5	5.0000	14.1291	2.8258	13.9795	0.0000

Source: Own findings.

The F values of the models for all the products in category 2 in Table 3 indicate that the space elastic models are valid for all the products.

The other results for the space elastic models for all the products in categories 1 and 2 have been summarized in Appendix A.

Managerial Implication

Assortment planning has been the focus of numerous industry studies. Many researchers as well as practitioners have stressed on the importance of AP in retail sector. It is very important for any retailer to efficiently manage this process of AP. In the present work, empirical testing of space elastic demand model has been carried out. The analysis showed that space elastic demand model is valid in the Indian context for predicting the demand. As there are very limited studies in the Indian context, this work will help the researchers and practitioners to learn the nuances of retail AP in the given context. The demand has been estimated from a retailer's perspective. The demand models incorporate some parameters. The estimation of these parameters using the data collected is a contribution of the work. The readers will be able to learn the method of parameter estimation. The present work can be used to estimate the demand of new products in the market and may help retailers in their selection or deselection.

Limitation of the Study

Although the scope of the work has been achieved, there are many limitations of the study. The literature review and scope of the problem have been defined as per the availability of the literature on the past works on the demand model areas and assortment optimization field. The selection of the store is also a limitation of the work. The selection of the store was dependent on the approval of the store manager for carrying out the research work. In addition, the selection of the product was also affected by the store manager. The number of products selected for the study was also affected by the approval from the store manager. In the current study, 11 products from two categories have been studied. The limited number of product categories for study limits the generalization of the study. In the assortment optimization problem, the values of direct and space elasticity of demand have been used from the current study. These values may improve if the duration of the study is increased. Also, addition of some more variables to explain the phenomena more accurately may increase the suitability of the models. The other limitation of the work is the time frame of study. The study has been carried out for almost 3 months from February 2013 to April 2013. The data of 89 days and the analysis limit the applicability of the models and also affect the results. As there was restriction on the interaction with the consumers, the variables affecting the demand have been explored from the literature only. The interaction with consumers may give some deep insights into the factors affecting the demand.

Conclusion

A retailer assortment is defined as the mix of products stocked in a retail store. The identification of proper assortment has become difficult in the current consumer-centric environment. The increasing needs of consumers in terms of variety have increased the difficulty of the retailers. The purpose of selecting a subset of products from the available products is to maximize the retailers objective, for example, profit, under consideration of constraints, such as limited space available for display, defined budget for the number of products and their SKUs, inventory to be carried to meet a desired service level and, last but not the least, to fulfil the ever-changing needs of the consumers. The assortment optimization problem in the literature varies because of the type of demand models considered by the authors or because of the context of the problem considered. In the present study, the behaviour of the space elastic demand models has been studied in two different categories in a big Indian retail chain.

Most of the earlier works in demand estimation are analytical and there is lack of literature on empirical studies. The application of the model and the estimation of various parameters used in the analytical work are also lacking. In the present work, the method for parameter estimation in real time has been explained which is used for demand estimation. Space elastic model has been explained and the parameters required for this type of demand model have been explained. With the data collected, the parameters were estimated using Microsoft Excel.

The results obtained from the work indicate that the model is valid in the given context. However, in some of the products, the cross-space elasticity is not significant. The probable reason for this could be that the product is one of the offerings from the same company which is offering the other brand or flavour of the product. Under these circumstances, there may not be significant effect of cross-elasticity.

Future Scope

The work is limited to a single format of store and a single store. Future works can include more number of stores from different formats of stores and from different regions of the country. This may provide more insight into the process of demand estimation. Experimental study for the demand estimation can be performed. This will eliminate the problem for the retailers to conduct the study in the store. A comparative study with other demand models, namely, multinomial logit (MNL) model, exogenous demand model and locational choice model, may give more options to the retailers.

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Appendix A. Results of Space Elastic Demand Model

Table A1. Space and Cross-space Elasticities for Product 1 Category 1

Regression Statistics	
Multiple R	0.7145
R^2	0.5105
Adjusted R^2	0.4746
Standard Error	0.4965
Observations	89.0000

(Appendix A1 continued)

(Appendix A1 continued)

ANOVA					
	df	SS	MS	F	Significance F
Regression	6.0000	21.0783	3.5130	14.2509	0.0000
Residual	82.0000	20.2142	0.2465		
Total	88.0000	41.2924			

	Coefficients	Standard Error	t-stat.	p-value
Intercept	–9.7554	1.9727	–4.9451	0.0000
α_1	3.6219	0.4016	9.0179	0.0000
β_{21}	0.1246	0.4826	0.2582	0.7969
β_{31}	0.2143	0.2828	0.7576	0.4509
β_{41}	–0.3694	0.4550	–0.8118	0.4193
β_{51}	0.3066	0.2280	1.3452	0.1823
β_{61}	0.2237	0.2141	1.0450	0.2991

Source: Own finding.

Table A2. Space and Cross-space Elasticities for Product 2 Category 1

Regression Statistics	
Multiple *R*	0.6468
R^2	0.4184
Adjusted R^2	0.3758
Standard Error	0.5903
Observations	89.0000

ANOVA					
	df	SS	MS	F	Significance F
Regression	6.0000	20.5510	3.4252	9.8312	0.0000
Residual	82.0000	28.5685	0.3484		
Total	88.0000	49.1195			

	Coefficients	Standard Error	t-stat.	p-value
Intercept	–11.8250	2.3452	–5.0422	0.0000
β_{12}	0.0062	0.4775	0.0129	0.9897
α_2	3.3590	0.5738	5.8541	0.0000
β_{32}	0.2402	0.3363	0.7145	0.4770
β_{42}	0.4908	0.5410	0.9072	0.3670
β_{52}	0.7294	0.2710	2.6915	0.0086
β_{62}	0.1605	0.2545	0.6305	0.5301

Source: Own finding.

Table A3. Space and Cross-space Elasticities for Product 3 Category 1

Regression Statistics	
Multiple R	0.4572
R^2	0.2090
Adjusted R^2	0.1511
Standard Error	0.6755
Observations	89.0000

ANOVA					
	df	SS	MS	F	Significance F
Regression	6.0000	9.8855	1.6476	3.6109	0.0032
Residual	82.0000	37.4148	0.4563		
Total	88.0000	47.3003			

	Coefficients	Standard Error	t-stat.	p-value
Intercept	–2.5391	2.6839	–0.9461	0.3469
β_{13}	0.3322	0.5464	0.6079	0.5450
β_{23}	0.0281	0.6566	0.0428	0.9660
α_3	1.4091	0.3848	3.6619	0.0004
β_{43}	–0.8097	0.6191	–1.3079	0.1946
β_{53}	0.2944	0.3101	0.9492	0.3453
β_{63}	0.3566	0.2913	1.2245	0.2243

Source: Own finding.

Table A4. Space and Cross-space Elasticities for Product 4 Category 1

Regression Statistics	
Multiple R	0.6195
R^2	0.3838
Adjusted R^2	0.3387
Standard Error	0.6017
Observations	89.0000

ANOVA					
	df	SS	MS	F	Significance F
Regression	6.0000	18.4905	3.0817	8.5111	0.0000
Residual	82.0000	29.6910	0.3621		
Total	88.0000	48.1815			

(Appendix A4 continued)

(Appendix A4 continued)

	Coefficients	Standard Error	t-stat.	p-value
Intercept	–6.3680	2.3909	–2.6635	0.0093
β_{14}	–1.3454	0.4868	–2.7639	0.0071
β_{24}	0.5596	0.5849	0.9566	0.3416
β_{34}	–0.0811	0.3428	–0.2366	0.8135
α_4	2.8766	0.5515	5.2161	0.0000
β_{54}	0.3690	0.2763	1.3355	0.1854
β_{64}	0.5199	0.2595	2.0038	0.0484

Source: Own finding.

Table A5. Space and Cross-space Elasticities for Product 5 Category 1

Regression Statistics	
Multiple R	0.6691
R^2	0.4477
Adjusted R^2	0.4073
Standard Error	0.6113
Observations	89.0000

ANOVA					
	df	SS	MS	F	Significance F
Regression	6.0000	24.8372	4.1395	11.0774	0.0000
Residual	82.0000	30.6428	0.3737		
Total	88.0000	55.4800			

	Coefficients	Standard Error	t-stat.	p-value
Intercept	–4.9604	2.4289	–2.0423	0.0443
β_{15}	–0.1982	0.4945	–0.4008	0.6896
β_{25}	0.9586	0.5942	1.6132	0.1105
β_{35}	–0.7022	0.3482	–2.0165	0.0470
β_{45}	0.5519	0.5603	0.9851	0.3275
α_5	1.9674	0.2807	7.0100	0.0000
β_{65}	–0.0891	0.2636	–0.3380	0.7362

Source: Own finding.

Table A6. Space and Cross-space Elasticities for Product 6 Category 1

Regression Statistics	
Multiple R	0.6973
R^2	0.4862
Adjusted R^2	0.4486
Standard Error	0.5079
Observations	89.0000

(Appendix A6 continued)

(Appendix A6 continued)

ANOVA					
	df	SS	MS	F	Significance F
Regression	6.0000	20.0182	3.3364	12.9343	0.0000
Residual	82.0000	21.1516	0.2579		
Total	88.0000	41.1699			

	Coefficients	Standard Error	t-stat	p-value
Intercept	–4.5025	2.0180	–2.2312	0.0284
β_{16}	0.0720	0.4108	0.1752	0.8613
β_{26}	–0.5431	0.4937	–1.0999	0.2746
β_{36}	0.3069	0.2893	1.0608	0.2919
β_{46}	0.8969	0.4655	1.9268	0.0575
β_{56}	0.1555	0.2332	0.6669	0.5067
α_6	1.5364	0.2190	7.0159	0.0000

Source: Own finding.

Table A7. Space and Cross-space Elasticities for Product 1 Category 2

Regression Statistics	
Multiple I	0.6314
R^2	0.3986
Adjusted R^2	0.3624
Standard Error	0.5793
Observations	89.0000

ANOVA					
	df	SS	MS	F	Significance F
Regression	5.0000	18.4610	3.6922	11.0026	0.0000
Residual	83.0000	27.8527	0.3356		
Total	88.0000	46.3137			

	Coefficients	Standard Error	t-stat.	p-value
Intercept	–1.3120	1.5348	–0.8549	0.3951
α_1	1.8280	0.2545	7.1819	0.0000
β_{21}	–0.0087	0.3566	–0.0245	0.9805
β_{31}	0.1015	0.2202	0.4609	0.6461
β_{41}	–0.2756	0.2831	–0.9735	0.3331
β_{51}	–0.2803	0.2211	–1.2682	0.2083

Source: Own finding.

Table A8. Space and Cross-space Elasticities for Product 2 Category 2

Regression Statistics	
Multiple R	0.7146
R^2	0.5107
Adjusted R^2	0.4812
Standard Error	0.5358
Observations	89.0000

ANOVA					
	df	SS	MS	F	Significance F
Regression	5.0000	24.8680	4.9736	17.3246	0.0000
Residual	83.0000	23.8279	0.2871		
Total	88.0000	48.6960			

	Coefficients	Standard Error	t-stat	p-value
Intercept	–8.4013	1.4195	–5.9183	0.0000
β_{12}	0.8278	0.2354	3.5163	0.0007
α_2	2.8624	0.3298	8.6788	0.0000
β_{32}	–0.0084	0.2037	–0.0410	0.9674
β_{42}	0.3310	0.2618	1.2643	0.2097
β_{52}	0.0403	0.2045	0.1972	0.8441

Source: Own finding.

Table A9. Space and Cross-space Elasticities for Product 3 Category 2

Regression Statistics	
Multiple R	0.7158
R^2	0.5124
Adjusted R^2	0.4830
Standard Error	0.5432
Observations	89.0000

ANOVA					
	df	SS	MS	F	Significance F
Regression	5.0000	25.7346	5.1469	17.4409	0.0000
Residual	83.0000	24.4938	0.2951		
Total	88.0000	50.2284			

(Appendix A9 continued)

(Appendix A9 continued)

	Coefficients	Standard Error	t-stat.	p-value
Intercept	–3.1244	1.4392	–2.1709	0.0328
β_{13}	–0.1202	0.2387	–0.5035	0.6159
β_{23}	0.5438	0.3344	1.6262	0.1077
α_{3}	1.8078	0.2065	8.7546	0.0000
β_{43}	0.0854	0.2655	0.3216	0.7485
β_{53}	–0.4697	0.2073	–2.2657	0.0261

Source: Own finding.

Table A10. Space and Cross-space Elasticities for Product 4 Category 2

Regression Statistics	
Multiple *R*	0.5913
R^2	0.3496
Adjusted R^2	0.3104
Standard Error	0.6010
Observations	89.0000

ANOVA					
	df	SS	MS	F	Significance F
Regression	5.0000	16.1130	3.2226	8.9230	0.0000
Residual	83.0000	29.9759	0.3612		
Total	88.0000	46.0889			

	Coefficients	Standard Error	t-stat	p-value
Intercept	–4.8870	1.5922	–3.0694	0.0029
β_{14}	–0.0003	0.2640	–0.0012	0.9990
β_{24}	0.0585	0.3699	0.1580	0.8748
β_{34}	0.0710	0.2284	0.3106	0.7569
α_{4}	1.8482	0.2937	6.2935	0.0000
β_{54}	0.4416	0.2293	1.9256	0.0576

Source: Own finding.

Table A11. Space and Cross-space Elasticities for Product 5 Category 2

Regression Statistics	
Multiple *R*	0.6761
R^2	0.4572
Adjusted R^2	0.4245
Standard Error	0.4496
Observations	89.0000

(Appendix A11 continued)

(Appendix A11 continued)

ANOVA					
	df	SS	MS	F	Significance F
Regression	5.0000	14.1291	2.8258	13.9795	0.0000
Residual	83.0000	16.7777	0.2021		
Total	88.0000	30.9067			

	Coefficients	Standard Error	t-stat	p-value
Intercept	–1.9161	1.1912	–1.6086	0.1115
β_{15}	–0.1836	0.1975	–0.9293	0.3554
β_{25}	–0.1228	0.2767	–0.4439	0.6583
β_{35}	–0.1319	0.1709	–0.7721	0.4423
β_{45}	0.3672	0.2197	1.6712	0.0985
α_5	1.3736	0.1716	8.0064	0.0000

Source: Own finding.

Table A12. Correlation Matrix of Space Elastic Demand Model Category 1

	S1	S2	S3	S4	S5	S6
S1	1.0000					
S2	0.1165	1.0000				
S3	0.0000	0.2109	1.0000			
S4	0.0857	0.0901	0.1269	1.0000		
S5	–0.1404	0.1508	0.0088	0.0737	1.0000	
S6	–0.0458	0.1052	0.2782	0.2157	0.2461	1.0000

Source: Own finding.
Note: S1, S2, S3, S4, S5 and S6 are the spaces provided to products 1, 2, 3, 4, 5 and 6, respectively.

Table A13. Correlation Matrix of Space Elastic Demand Model Category 2

	S1	S2	S3	S4	S5
S1	1.0000				
S2	–0.0669	1.0000			
S3	–0.0032	0.0441	1.0000		
S4	–0.0628	0.0403	0.2169	1.0000	
S5	0.0764	0.0120	0.3054	–0.1283	1.0000

Source: Own finding.
Note: S1, S2, S3, S4 and S5 are the spaces provided to products 1, 2, 3, 4 and 5, respectively.

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