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Retail sales forecasting of agricultural products marts in a mid-sized city using the Huff model

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Abstract

This study aimed to predict retail sales of agricultural products marts in mid-sized cities of South Korea in conjunction with the Huff model. The Huff model is widely used in retail sales forecasting because of its easiness of use and the accuracy of its predictions. To forecast sales volume using the model, the parameter λ should be estimated. Although several studies have reported the estimation of λ, its value is often assigned arbitrarily. Besides, no previous studies have conducted a prediction of sales volume with agricultural products marts. For this, first studies included the sales forecasting agricultural products marts in a mid-sized city, designated to be Daejeon and explored the idea that the parameter may be different as the size of the city differs. Consumers in a mid-sized city were less sensitive to travel time (or more sensitive to store size) than those in metropolitan areas. Our estimate of λ for the mid-sized city is 0.38, which indicates that store size has a greater effect than travel time, while the existing studies in the metropolitan areas report λ greater than 1, indicating the reverse condition. The implication from the results is to help locations decision makers estimate a potential sales volume in a mid-sized city especially in the Korean context.

Key words: The Huff model, the new probability model, agriculture product, agricultural product marts, the gravity model, top-of-mind brand recognition.

Introduction

One of the most important decisions retailers have to make is the choice of a store's location [1]. For selecting the right location, return on investment is the most important decision criterion [2]. Therefore, retailers need to evaluate what the potential sales of a new store will be. Three approaches to estimate the potential sales for a store at the location are 1) the Huff gravity model, 2) regression analysis, and 3) the analog model [3].

In this study, we focused on the Huff gravity model, which is widely used in retailing practice [4] because of its ease of use [5] and the accuracy of its predictions [6], even though the two-variable specification is too parsimonious for policy purposes [7]. Several empirical studies [8] support the usefulness of the Huff model in predicting the market share of shopping centers [9].

In this model, the probability that customer *i* shops at location *j* depends upon two factors: the size of the store and the time it takes to travel to the store [10] (the larger the store, the greater the probability of shopping, while the greater the travel time or distance, the lower the probability). The mathematical formula is as follows [11]:

$$P_{ij} = (S_j / T_{ij}^{\lambda}) / (\sum S_j / T_{ij}^{\lambda})$$

where Pij denotes the probability that customer *i* shops at location *j*, *Sj* is the size of the store at location *j*, *Tij* is the travel time for customer *i* to get to loation *j*, and λ is a parameter that is to be estimated empirically to reflect the effect of travel time on various kinds of shopping trips. The expected number of consumers at a given place of origin *i* that shop at a particular shopping location *j* is equal to the number of consumers at *i* multiplied by the probability that a consumer at *i* will shop at location *j* [10].

The exponent λ reflects the relative effect of store size versus travel time. When λ is equal to 1, store size and travel time have an equal but opposite effect on the probability of a consumer shopping at a store location, and when λ is greater than 1, travel time has a greater effect. The value of λ is also affected by the nature of the shopping trips consumers take when visiting the stores [3]. Levy and Weitz [10] give an example. Travel time or distance is generally more important for convenience goods than for shopping goods because people are less willing to travel a great distance for a quart of milk than they are for a new pair of shoes. Several studies have reported the estimation of λ [12]. However, in Japan and S. Korea (hereinafter, Korea), they have used the fixed number 2 for the λ in the formula [13]. Yim and Lee [16] estimate a market share of department stores in Korea using the Huff model, and they have also used 2 for the λ. In addition, all the existing studies have been restricted within the realm of textile products in department stores and, in reality, no studies have sought potential sales volume related to agricultural products.

The research using the Huff model in Japan and Korea reported that distance has a greater effect on shopping probability than store size. Yim and Lee [16] report that the average absolute error rate has been 1.6% (minimum error rate 0.1%, maximum 5.4%) when the λ is set as 2.

However, we assume that there may be a difference in shopping behaviors between people who live in a metropolitan area and people who live in a mid-sized city. People who live in a mid-sized city may have easier access to any stores within the city boundary than people in metropolitan areas. Therefore, we hypothesize that people in a mid-sized city are more sensitive to store size because a bigger store size means greater attractiveness [14], and they have easier access to any stores in the city. Kuo *et al.* [15] show that consumers are willing to travel further to competing stores after passing by nearer stores [15].

Our study is designed to estimate the λ in the mid-sized city with marts especially dealing with agricultural products and to examine whether the value of λ may be different between metropolitan areas and the mid-sized cities. With the upcoming results, we may help locations decision makers estimate potential sales in a mid-sized city.

Estimation of λ in the Huff Model for a Mid-sized City

The city of Daejon in Korea is selected. Deajon, compared to Seoul which is the biggest metropolitan city and the capital in Korea, is a mid-sized city with 439,312 households and eight shopping centers in 2000. Trade areas in the city of Daejon are divided into five communities, and information about store sizes, travel time, and distances is obtained from secondary data sources to forecast sales at the shopping marts dealing with agricultural products (Table 1).

Table 1. Store size and travel time.

Shopping Center	Shopping Center Size	Travel Time (m) (Community i to Store j)				
		Communities				
		I	II	III	IV	V
A	28,909	50	25	5	40	50
B	18,658	50	25	5	40	50
C	23,511	25	15	35	3	15
D	26,294	40	2	25	17	27
E	41,471	25	15	35	3	15
F	74,278	25	15	35	3	15
G	49,587	30	10	30	5	15
H	57,954	35	15	24	16	27

Estimation of the Probability of a Consumer at a Given Point of Origin *i* Traveling to a Particular Agricultural Products Marts *j*

***Probability estimation when λ = 2*:** Table 2 shows the probability that customer *i* shops at agricultural products marts *j*, when we fix λ to 2. For example, the probability of community I residents shopping at the agricultural products marts A is 3.2%.

Table 2. Probability of a consumer at a given point of origin i traveling to a particular agricultural products marts j (when λ=2).

	Probability %				
	Communities				
	I	II	III	IV	V
A	3.2	0.6	52.2	0.1	1.2
B	2.1	0.4	33.7	0.1	0.8
C	10.4	1.3	0.9	14.7	10.7
D	4.6	81.9	1.9	0.5	3.7
E	18.4	2.3	1.5	25.9	18.9
F	32.9	4.1	2.7	46.4	33.9
G	15.3	6.2	2.5	11.1	22.6
H	13.1	3.2	4.5	1.3	8.2
	100.0	100.0	100.0	100.0	100.0

Using the probabilities, we calculated how many households would shop at each agricultural products marts. Table 3 shows the number of households that shop at it.

For example, the number of households that reside in community I is 71,968, of which 2,307 households would shop at the shopping center A.

In Table 3, the total number of households shopping at mart A is 47,622, making the market share of the mart 10.8%.

We compared the estimated market share of the mart with the market share from the actual sales data. Table 4 shows the comparison between the estimated market share and the actual market share as well as errors. The error rate is calculated as follows: Error = Expected market share – Actual market share

Estimation of λ: The parameter λ is estimated in the following way. A value of λ is selected from the range 0.1 to 4, then we calculated, for a given λ, the probability that customer *i* shops at shopping center *j* and the expected sales for each mart. Next, we compared the expected market shares with actual market shares and calculated the error rates. Finally, we found the λ that produces the minimum error rate by repeating the previous steps.

Step 1. Calculation of the probability that customer *i* shops at agricultural products mart *j* for a given λ. In the same way as shown in Table 2, we calculated the probability that customer *i* shops at shopping center *j* for a given λ. Table 5 shows the probability for λ = 1. It can be seen that the probabilities are different from when λ = 2.

Step 2. Calculation of the estimated market shares. Using the probabilities for the given λ, we calculated the number of households shopping at each mart and the expected market share in the same way as shown in Table 3.

Table 3. Number of households shopping at each agricultural products marts (when λ = 2).

Shopping center	Number of households in community / Number of households shopping at shopping center j	Communities I	II	III	IV	V
		71,968	86,291	84,380	146,097	50,576
A	47,622 (10.8%)	2,307	498	44,069	148	601
B	30,735 (7.0%)	1,489	321	28,442	96	388
C	36,224 (8.2%)	7,506	1,124	731	21,436	5,426
D	78,212 (17.8%)	3,279	70,710	1,603	747	1,873
E	63,896 (14.5%	13,240	1,983	1,290	37,812	9,572
F	114,443 (26.1%)	23,713	3,551	2,311	67,724	17,144
G	46,148 (10.5%)	10,994	5,334	2,100	16,276	11,445
H	22,031 (5.0%)	9,440	2,771	3,834	1,858	4,128
Total	439,312 (100%)					

* Market share in the parenthesis.

Table 4. Comparison between the estimated market share and the actual market share and error rate (when λ =2).

Shopping center	Expected %	Actual %	Error (Expected-actual)%	Absolute value of error%
A	10.8	5.0	5.9	5.9
B	7.0	3.7	3.3	3.3
C	8.2	9.1	-0.8	0.8
D	17.8	8.3	9.5	9.5
E	14.5	14.4	0.1	0.1
F	26.1	28.2	-2.1	2.1
G	10.5	15.9	-5.4	5.4
H	5.0	15.5	-10.5	10.5
				37.7

Table 5. Probability of a consumer at a given point of origin *i* traveling to a particular agricultural products mart *j* (when λ= 1).

	Probability %				
	Communities				
	I	II	III	IV	V
A	5.5	3.5	31.1	1.2	3.5
B	3.6	2.3	20.0	0.7	2.2
C	9.0	4.7	3.6	12.5	9.4
D	6.3	39.7	5.7	2.5	5.8
E	15.8	8.3	6.4	22.0	16.6
F	28.3	14.9	11.4	39.5	29.7
G	15.8	15.0	8.9	15.8	19.8
H	15.8	11.7	13.0	5.8	12.9
	100.0	100.0	100.0	100.0	100.0

Step 3. Calculation of error. Then, we calculated the error rates in the same way as shown in Table 4.

Step 4. Finding the λ to bring minimum error rate. Table 6 shows the error rates depending on the different values of λ. Average error rate is calcuted as follows. Average error rate = Summation of error rates/number of stores.

Table 6. Error rates depending upon different λ.

Lambda	Average error rate %	Sum of error rates %
0.10	1.8413	14.73
0.20	1.5225	12.18
0.30	1.2900	10.32
0.35	1.1875	9.50
0.36	1.1675	9.34
0.37	1.1488	9.19
0.38	1.1398	9.1187
0.39	1.1399	9.1190
0.40	1.1403	9.1223
0.41	1.1413	9.13
0.43	1.1438	9.15
0.45	1.1475	9.18
0.50	1.1650	9.32
0.70	1.4138	11.31
0.90	1.8563	14.85
1.00	2.1175	16.94
1.50	3.5538	28.43
2.00	4.7113	37.69
2.50	5.3750	43.00
3.00	5.6963	45.57
3.50	5.8463	46.77
4.00	5.9200	47.36

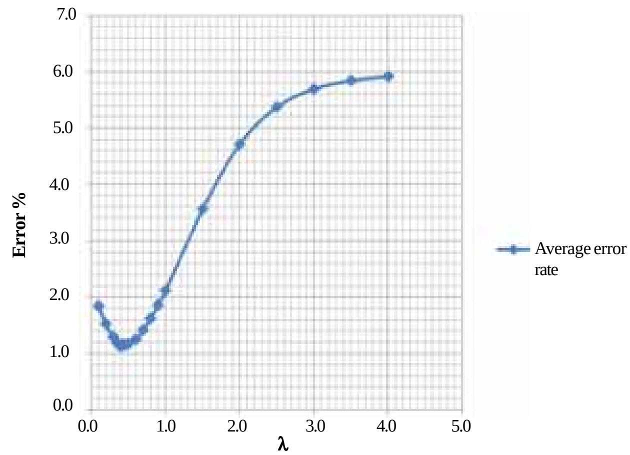

Figure 1. Error rates depending upon different λ.

Fig. 1 shows the distribution of error rates depending upon the value of λ. It shows that the error rate is minimum when λ is 0.38.

Discussion and Conclusions

Using the Huff model, we examined whether the parameter may be different as the size of the city. We found that consumers with intention to purchase agricultural products in a mid-sized city are less sensitive to travel time (or more sensitive to store size) than shoppers in metropolitan areas. Our estimate of λ for the mid-sized city is 0.38, which is less than 1, indicating store size has a greater effect than travel time, while the existing study in a metropolitan area [16] reports that λ is greater than 1, indicating that travel time has a greater effect than store size.

Limitations of the study: While this study attempted to estimate the parameter λ for retail sales forecasting in a mid-sized city using the Huff model, there are several limitations deserving further investigation. First, we estimated the parameter for only one mid-sized city, and thus the results may not necessarily generalize to the total population of mid-sized cities. However, our study may be the starting point from which to consider the size of the city when applying the parameter for retail sales forecasting in a mid-sized city. In future studies, researchers may estimate the parameter for other mid-sized cities and compare their results with ours. With more research, our result (λ = 0.38) can be made generalizable. Second, since we used the data that were collected at a specific time, the research should be augmented by long-term tracking for the estimation of the λ.

Research and managerial implications: Our findings have several implications for researchers. The consideration of city size in retail sales of agricultural products forecasting using the Huff model may serve as a foundation for further research. Our research suggests that the parameter λ in the Huff model for a mid-sized city may be less than 1. Our findings also have implications for managers. When retail managers estimate sales for a new agricultural mart in a mid-sized city, the parameter λ in the Huff model may be assigned as the value that is less than 1.

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