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A modified Lotka-Volterra model for competition forecasting in Taiwan's retail industry



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ABSTRACT

The retail industry is an important component of the supply chain of the goods and services that are consumed daily and competition has been increasing among retailers worldwide. Thus, forecasting the degree of retail competition has become an important issue. However, seasonal patterns and cycles in the level of retail activity dramatically reduce forecasting accuracy. This paper attempts to develop an improved forecasting methodology for retail industry competition subject to seasonal patterns and cycles. Using market share data and the moving average method, a modified Lotka–Volterra model with an additional constraint on the summation of market share is proposed. Furthermore, the mean absolute error is used to measure the forecasting accuracy of the market share. Real Taiwanese retail data from 1999 is used to validate the forecasting accuracy of our modified Lotka–Volterra model. Our methodology successfully mitigates errors from seasonal patterns and cycles and outperforms other benchmark models. These benchmarks include the Bass and Lotka–Volterra models for revenue or market share data, with or without using the moving average method. Our methodology assists the retail industry in the development of management strategies and the determination of investment timing. We also demonstrate how the Lotka–Volterra model can be used to forecast the degree of industry competition.

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1. Introduction

The retail industry is the final element of the supply chain that provides goods and services to consumers. According to Deloitte (2013), aggregate retail sales were \$4.27 trillion US dollars in 2011 for the world's top 250 retailers. Moreover, the 2006–2011 compound annual growth rate of retail sales is 5.4%.

With the new wave of globalization and associated supply chains, the retail industry directly connects manufacturers and consumers, and is thus a source of supply and demand data. In recent years, this key position in the supply chain attracts more retailers to join. With increasing in the number of retailers, the degree of retail competition raises. For example, two Australian retailers were newly included in the top 25 retailers worldwide in 2009 (Deloitte, 2011). As a result, competition forecasts for the retail industry have become an increasingly important issue in supply chain management.

The growth of the retail industry usually reflects the development of a country. A good example is Taiwan. Per capita gross domestic product has grown from \$2700 US dollars in 1982 to over

\$20,000 US dollars in 2011 (Directorate-General of Budget and Statistics (2013)). The retail industry in Taiwan has experienced many transformations during this period. One major transformation is that the retailers gain the power of changing manufacturer and consumer behaviors in Taiwan. New types of retailing were capitalized and harnessed to take advantage of the demand forecasting and price control. As a result, a variety of retail types has emerged and these retailers coexist with a high degree of competition in Taiwan. These new retail types are well developed in Taiwan and have appeared in retail industries in China and Philippines (Goldman, 2001).

There are four major retail types in Taiwan: supermarkets (e.g. Wellcome), hypermarkets (e.g. Costco), convenience stores (e.g. 7-Eleven), and traditional stores. Supermarkets are midsize food providers and are generally located within communities. They sell food and other daily necessities within walking distance of customers. Hypermarkets sell large quantities of goods to customers during one-visit shopping. They are usually located in suburban areas with ample parking. Convenience stores are open for extended hours and are located close to consumers to allow purchases of necessities and services at any time. The services include ticket sales, bill payments, deliveries, etc. Traditional stores are one of the oldest retail styles in Taiwan, existing since the 1940s. They are usually run as a family business in old communities and

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provide warm and friendly service. In Taiwan, the same or similar products are sold in all four retail types. Unavoidable competition among these four retail types has attracted considerable attention.

There are three focuses of retail competition in Taiwan. First, people enjoy searching for low prices. Because of rapid urbanization and fast-paced lifestyle, more people are changing their shopping habits from cost-oriented to convenience-oriented behavior. Of the four retail types, we classify convenience stores and traditional stores as convenience-oriented submarket. This is because convenience stores and traditional stores in Taiwan have the highest density (in an area of 35,980 km² with a population of 23 million, there are more than 10,000 convenience stores and traditional stores (Taiwan Institute of Economic Research, 2012)). In contrast, supermarkets and hypermarkets are classified as cost-oriented submarket. The competition between targeting convenienceoriented and cost-oriented shopping styles highlights the two opposing forces in Taiwan's retail industry.

Second, in the convenience-oriented submarket, people used to shop in traditional stores for everyday necessities. However, as the economy grows, more people prefer to shop in convenience stores for everyday necessities. The competition between convenience stores and traditional stores implies the future trend of the new retail types in Taiwan.

Third, in the cost-oriented submarket, people used to shop in their neighborhood supermarkets for family necessities subject to the cost of private transportation in Taiwan. Recently, people have started to shop in hypermarkets following the American style of shopping in which all requirements are purchased in one visit. The competition between supermarkets and hypermarkets are indicative of the trends in family retail shopping in Taiwan.

Competition forecasts for the retail industry show long-term consumer trends. Accurate forecasts can help managers identify the growth and recession potential of different business models and their speed of adopting new strategies. For retail managers, accurate forecasts can help develop strategies to maintain market share in the years ahead. For investors, it can identify future trends and investment targets. Thus, an accurate forecast of retail competition is necessary for retailers and investors.

Traditionally, the Bass and Lotka-Volterra models have been used to forecast innovation diffusion and competition levels. The Bass model was designed to describe the process of market diffusion. The Lotka-Volterra model was widely used to investigate the competitive relationships among firms by a set of differential equations. Some studies have compared the forecasting capability of the Bass and Lotka-Volterra models for new products or technologies. Also, shipment amounts or revenue data are often used in Bass and Lotka-Volterra models in previous studies.

When investigating the retail competition in Taiwan, we input the revenue data to both Bass and Lotka-Volterra models (see Section 4). Unsatisfactory forecasting errors cause us to consider the characteristics of retail industry. That is, the revenue data is usually mixed with confounding factors such as economic growth, inflation, and cyclical and seasonal patterns. To mitigate these impacts, we think that some premodification on the dataset before selecting a forecasting model is necessary. Furthermore, different datasets may require different models and methods of evaluation. Unfortunately, previous studies have not addressed these issues.

In this paper, we are interested in competition forecasts for the retail industry. Our goal is to develop a methodology for more precise forecasting. For the above issues, we premodify the revenue data into the relative market share before selecting a forecasting model. In addition, we develop a new model based on relative market share that merges the existing Bass and Lotka-Volterra models. Regarding evaluation of the forecasts of the market share data, we use the mean absolute error (MAE) to measure forecasting accuracy. Real data from the retail industry from 1999 to 2012 is used to examine the performance of our methodology. Major improvements in forecasting accuracy were obtained to provide a better picture of the competition in Taiwan's retail industry.

This paper is organized as follows. In Section 2, we review the Bass model and the Lotka–Volterra model, and then compare them. In Section 3, a modified Lotka-Volterra model is proposed for more accurate forecasting of retail competition. In Section 4, real data from Taiwan's retail industry is used to examine retail competition and validate the performance of our methodology. Finally, we summarize our results and discuss several directions for future research in Section 5.

2. Literature review

In this section, we review the Bass and Lotka-Volterra models and variations on them.

2.1. Bass model

The Bass model was first proposed by Bass (1969) and models the diffusion process of a new product among adopters and potential buyers in a market. The diffusion rate of a new product in a market can be described by the following differential equation:

$$\frac{dN(t)}{dt} = (p + qN(t))(M - N(t)), \tag{1}$$

where N(t) is the cumulative number of adopters at time t, and M is the potential market size. The parameter p is the coefficient of innovation, which shows the possibility of new demand by mass media. The parameter q is the coefficient of imitation, which shows the possibility of new demand by oral propagation.

The Bass model has been widely applied in the field of new product/technology development. For example, Sneddon, Soutar, and Mazzarol (2011) investigated the diffusion of wool-testing technologies in Australia using the Bass model. Seol, Park, Lee, and Yoon (2012) adopted the Bass model to forecast the diffusion of new digital broadcasting services in South Korea. Tsai, Li, and Lee (2010) considered the effect of price factors on the coefficient of imitation and modified the Bass model to study the diffusion and evolution of the new liquid crystal display TVs. Heinz, Graeber, and Praktiknjo (2013) studied the diffusion process of fuel cells and hydrogen producers with the Bass model. They verified that the two-sided market effect can accelerate the diffusion of hydrogen economy significantly. Dalla Valle and Furlan (2014) consider the diffusion of nuclear energy in developing countries and adopted the generalized Bass model to estimates the depletion time of uranium.

2.2. Lotka-Volterra model

In the field of ecology, Lotka (1925) investigated the competition and mutualism of two species and was the first to model predator-prey interactions using a set of logistic equations. Volterra (1926) then adopted Lotka's model with real data to study fish catches in the Adriatic Sea. In their models, the following two differential equations are used to describe how two species' population growth rates interact over time:

$$\frac{dx(t)}{dt} = (a_1 + b_1 x(t) + c_1 y(t)) x(t), \tag{2}$$

$$\frac{dx(t)}{dt} = (a_1 + b_1 x(t) + c_1 y(t)) x(t),$$

$$\frac{dy(t)}{dt} = (a_2 + b_2 y(t) + c_2 x(t)) y(t),$$
(2)

where x(t) and y(t) represent the populations of two competing species at time t. The two terms, dx(t)/dt and dy(t)/dt, represent the growth of the two populations over time. Moreover, x^2 and y^2 represent internal self-interaction in the same species and xy

represents the mutual influences of the two species. The model includes three basic parameters that affect the growth rates of both species. Parameter a_i is the logistic parameter of growth for species i. Parameter b_i is the limitation parameter of growth for species i. Parameter c_i is the interaction parameter with the other species for species i.

The Lotka-Volterra model has long been applied in the field of ecology. For example, Geijzendorffer, Van der Werf, Bianchi, and Schulte (2011) used the Lotka-Volterra model to predict long-term coexistence patterns of grassland species. In the field of biodiversity, Roques and Chekroun (2011) explored the competition of multiple species using the Lotka-Volterra model and examined the degree of chaos and the risk of extinction.

Beyond the field of ecology, the Lotka-Volterra model has also been adopted widely for the analysis of competitive behaviors in a market. For example, Lee, Lee, and Oh (2005) investigated the trade values of two Korean stock exchanges. Korean Stock Exchange and Korean Securities Dealers Automated Quotation. They used Lotka-Volterra models to study competitive behaviors and forecast the future trends for the two stock exchanges. Kim, Lee, and Ahn (2006) estimated the dynamic competition of mobile phone subscription in Korea with the Lotka-Volterra model and showed the commensalism relationship. Kreng and Wang (2011) used the Lotka-Volterra model to examine the competitive relationships between liquid-crystal display and plasma display panel televisions in Taiwan and showed equilibrium. Lin (2013) adopted the Grey system theory to predict the diffusion of mobile cellular broadband and fixed broadband in Taiwan. The author then used the Lotka-Volterra model to analyze the competitive relationship and show the commensalism. Duan, Zhu, and Fan (2013) revised the Lotka-Volterra model to study the evolution of wind and photovoltaic solar technologies worldwide. With estimation and simulation, mutualism relationship was found in most of countries and the possible reasons were analyzed.

2.3. From the Bass model to the Lotka-Volterra model

In recent decades, many researchers have constructed models of new-product development based on the Bass model. However, the Bass model does not consider the interaction between the new product and other competing products. In contrast, the Lotka–Volterra model incorporates interactions between competitors and has been used to examine models of competition for products, technologies, and industries.

Some researchers have focused on competitive behaviors and compared the Bass and Lotka–Volterra models in terms of their forecasting capabilities with respect to new-product/technology diffusion. For example, Chiang (2012) explored the predator–prey

relationship between 200 mm and 300 mm silicon wafer technologies in Taiwan. Chiang and Wong (2011) examined the shipment data of notebook and desktop computers and investigated the competitive diffusion relationship. Tsai and Li (2009) split Taiwan's integrated circuit (IC) industry into IC design, manufacturing, and packaging/testing industries, and studied the interindustrial competition and cooperative effects on clustering formation. Chang, Li, and Kim (2014) investigated the saturated mobile phone market with churn effects in Korea and studied the performance of different diffusion models.

The above studies adopted both the Bass and Lotka–Volterra models to examine competition and diffusion and compared both models with data on shipment quantities or foreign direct investment. All of these authors thought that the Lotka–Volterra model embedded the competitive relationships of different products/ technologies and mainly observed smaller forecast errors. As a result, they suggested that the Lotka–Volterra model might be more suitable for forecasting than the Bass model.

3. Methodology

We now propose a methodology to forecast competition among the different retail types. Our methodology involves four parts: (1) data selection, (2) data processing, (3) model selection, and (4) forecasting evaluation.

3.1. Data selection and processing

These previous studies usually used raw revenue or shipment data. However, these data may be influenced by economic growth, inflation, and industry long-term trends that have no relationship with competition forecasting. For illustration, Fig. 1 shows monthly revenues of convenience stores and traditional stores in Taiwan from 1999 to 2012 (Department of Statistics, 2013). We observe the upward trends that may create major problems for traditional forecasting models.

To eliminate these confounding factors and describe the competition between these two retail types, we first transform the raw monthly revenue data into relative market shares. Take the convenience-oriented submarket in April 2012 as an example. There are two retail types in the convenience-oriented submarket, convenience stores and traditional stores, with monthly revenue of NT\$21.25 billion and NT\$13.19 billion, respectively. The total monthly revenue of the convenience-oriented submarket is NT\$34.44 billion. In this submarket, the convenience stores take the relative market share of 61.7% and the traditional stores take the relative market share of 38.3%. The market shares of both retail types are summed up to be 100%. Fig. 2 shows the monthly market

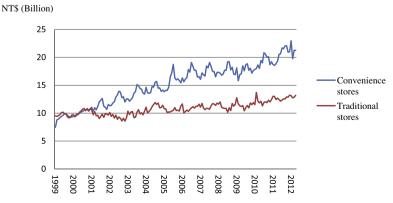


Fig. 1. Monthly revenue of convenience stores vs. traditional stores.

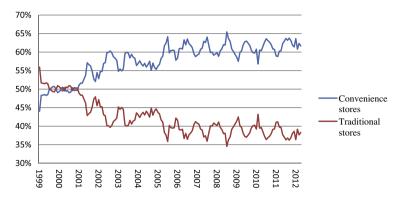


Fig. 2. Monthly market share of convenience stores vs. traditional stores in the convenience-oriented submarket of Taiwan.

shares of convenience stores and traditional stores in the convenience-oriented submarket of Taiwan.

In Fig. 2, some of the trends that may create problems for fore-casting models have been eliminated. However, Fig. 2 still shows fluctuations and volatility in the market share data. This is because the retail industry is easily affected by business cycle, seasonal, and weather factors such as festival celebrations, seasonal promotions, and typhoons, respectively. These factors induce fluctuations in the data and lead to inaccurate forecasting. For better data processing, the moving average method is recommended. Fig. 3 presents a 12-month moving average of market share for convenience stores and traditional stores in Taiwan.

3.2. Model selection

When using the market share data, one notable constraint is that the total market share is fixed at 100%. For the Bass model based on market share data, define M = 1 as the total market share and $\bar{y}(t)$ as the cumulative market share of a retail type at time t. The Bass model given by Eq. (1) can be rewritten as follows:

$$\frac{d\bar{y}(t)}{dt} = (p + q\bar{y}(t))(1 - \bar{y}(t)) = C_1 + B_1\bar{y} + A_1\bar{y}^2, \tag{4}$$

where $C_1 = p$, $B_1 = q - p$ and $A_1 = -q$.

For the Lotka–Volterra model based on market share data, we focus on a pair of retail types as the submarket and let $\bar{x}(t)$ and $\bar{y}(t)$ be their market shares at time t. As a result, the total market share for the pair of retail types is 100%. We can rewrite Eqs. (2) and (3) with the constraint $\bar{x}(t) + \bar{y}(t) = 1$ s follows:

$$\frac{d\bar{x}(t)}{dt} = (a_1 + b_1 \bar{x}(t) + c_1 \bar{y}(t)) \bar{x}(t)
= ((a_1 + c_1) + (b_1 - c_1) \bar{x}) \bar{x}
= B_2 \bar{x} + A_2 \bar{x}^2.$$
(5)

where $B_2 = a_1 + c_1$ and $A_2 = b_1 - c_1$.

From the derivation of the above formulas, we find that with the constraint of 100% total market share, the Bass and Lotka–Volterra models degenerate to the same model. This new model is named the 'modified Lotka–Volterra model'. The modified Lotka–Volterra model is formulated as follows:

$$\begin{cases} \frac{d\bar{\mathbf{x}}(t)}{dt} = B\bar{\mathbf{x}}(t) + A(\bar{\mathbf{x}}(t))^2, \\ \bar{\mathbf{y}}(t) = 1 - \bar{\mathbf{x}}(t). \end{cases}$$
 (6)

Note that the modified Lotka–Volterra model can only be used to study a pair of participants with the total market shares of 1. Without the total market share constraint, applying the Lotka–Volterra model directly on market share data may result in impractical forecasting results.

3.3. Forecasting evaluation

To assess forecasting ability, the mean absolute percentage error (MAPE) has been widely used to estimate forecast errors. The formula for the MAPE is:

MAPE =
$$\frac{1}{n} \sum_{t=1}^{n} \left| \frac{y(t) - \hat{y}(t)}{y(t)} \right|,$$
 (7)

where y(t) is the actual value, $\hat{y}(t)$ is the forecast value, and n is the number of forecast periods. The MAPE is used to measure the errors between the actual and forecast values and is expressed in percentage terms. Unfortunately, small y(t) values may result in misleadingly large MAPE values and actual values close to zero can generate infinitely large MAPEs.

To solve this problem, we propose the MAE for evaluation of forecasting models using market share data. The formula for the MAE is:

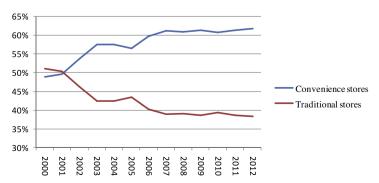


Fig. 3. The 12-month moving average of market share for convenience stores vs. traditional stores in the convenience-oriented submarket of Taiwan.

Table 1The six scenarios of different forward forecast periods.

Scenario	Without 12-month moving ave	rage (160 months)	With 12-month moving average	e (149 months)
	Number of testing periods	Number of estimation periods	Number of testing periods	Number of estimation periods
1	10 months	150 months	10 months	139 months
2	20 months	140 months	20 months	129 months
3	40 months	120 months	40 months	109 months
4	60 months	100 months	60 months	89 months
5	80 months	80 months	80 months	69 months
6	100 months	60 months	100 months	49 months

$$MAE = \frac{1}{n} \sum_{t=1}^{n} |(y(t) - \hat{y}(t))|$$
 (8)

where y(t) is the actual value, $\hat{y}(t)$ is the forecast value, and n is the number of forecast periods.

The MAE estimates the absolute difference between the actual and forecast values. Furthermore, it can handle small actual values. When applied to market share data, the MAE generates the average absolute error in percentage terms. Thus, to ensure the comparability of our forecasting evaluations, we compare the MAEs of our market share forecasts with the MAPEs of our revenue forecasts.

4. Numerical study

As mentioned in Section 1, we are interested in the three focuses of retail competition in Taiwan, the competition between convenience stores and traditional stores (in the convenience-oriented submarket), the competition between supermarkets and hypermarkets (in the cost-oriented submarket), and the competition between convenience-oriented and cost-oriented submarkets. In this section, we collect retail industry data in Taiwan to implement our methodology and other existing forecasting models, which include the Bass and Lotka–Volterra models for revenue or market share data, with or without using the moving average method. Our goals are to examine the three focuses of retail competition in Taiwan, to illustrate our methodology, and to compare our methodology with benchmark models.

4.1. Methodology implementation

We first consider the competition between convenience stores and traditional stores in the convenience-oriented submarket and implement our methodology for purposes of illustration. The monthly revenue data for convenience stores and traditional stores are collected from the Department of Statistics, Ministry of Economic Affairs in Taiwan. From January 1999 to April 2012, we

obtained 160 monthly observations (Fig. 1). Then, the market share data was generated from the 160 monthly observations individually.

Also, we adopted a 12-month moving average method. This is because the retail industry is mainly affected by weather, seasonal patterns, and festival celebrations. These factors are usually cyclical within a yearly period. After the 12-month moving average was calculated, 149 monthly observations remained.

To verify the forecasting capabilities of our model over various time periods, we considered six scenarios of different forecast forward periods. For each scenario, data in the forecast forward period were used as testing data to evaluate forecasting accuracy. The remaining data were used as estimation data for the model parameters. For example, in Scenario 1, the last 10 months of data were used as testing data to verify the forecasting accuracy. The remaining 150 months of data were used to estimate the model parameters. After calculation of the 12-month moving average, 149 monthly observations remained. For the 12-month moving average data, the last 10 months of data were used to verify the forecasting accuracy. The remaining 139 months of data were used to estimate the model parameters. The details of the six scenarios are listed in Table 1.

The modified Lotka–Volterra model was adopted in implementing our methodology. The market share data of convenience stores and traditional stores were applied to estimate the parameters and the forecast errors were calculated using the MAE.

For comparison, the traditional Bass model was implemented. The Bass model estimates the diffusion of a single product, so we examined the diffusion of convenience stores and traditional stores using two separate Bass models. The parameters of the two Bass models were fitted separately and the forecast errors evaluated individually. For the revenue data, the errors were calculated as MAPE. For the market share data, the errors were calculated as MAPE.

The Lotka–Volterra model was implemented for comparison. The revenue data of convenience stores and traditional stores were

Table 2Forecast errors of convenience stores vs. traditional stores without the 12-month moving average.

Scenario	Number of testing periods	Number of estimation periods	Retail types	Forecast errors (without 12-month moving average)				
				Revenue (MA	PE)	Market share	(MAE)	
				Bass model	LV model	Bass model	Modified LV model	
1	10	150	Convenience Traditional	5.66% 9.33%	4.03% 5.32%	0.67% 0.67%	0.64% 0.64%	
2	20	140	Convenience Traditional	9.96% 12.15%	9.32% 8.75%	1.79% 1.79%	1.79% 1.79%	
3	40	120	Convenience Traditional	13.39% 11.88%	15.25% 10.23%	2.58% 2.58%	2.82% 2.82%	
4	60	100	Convenience Traditional	13.71% 12.25%	13.95% 9.61%	2.99% 2.99%	2.57% 2.57%	
5	80	80	Convenience Traditional	18.58% 12.09%	19.49% 9.68%	3.86% 3.78%	3.80% 3.80%	
6	100	60	Convenience Traditional	25.03% 13.07%	25.44% 14.54%	5.60% 4.68%	4.50% 4.50%	

Table 3Forecast errors of convenience stores vs. traditional stores with the 12-month moving average.

Scenario	Number of testing periods	Number of estimation periods	Retail types	Forecast errors (with 12-month moving average)					
				Revenue (MA	PE)	Market share	(MAE)		
				Bass model	LV model	Bass model	Modified LV model		
1	10	139	Convenience Traditional	2.53% 0.27%	2.40% 0.51%	0.50% 1.30%	0.37% 0.37%		
2	20	129	Convenience Traditional	4.75% 1.43%	4.29% 1.85%	0.54% 1.38%	0.31% 0.31%		
3	40	109	Convenience Traditional	4.39% 5.82%	3.67% 3.89%	1.03% 1.40%	0.72% 0.72%		
4	60	89	Convenience Traditional	7.29% 4.94%	7.48% 1.74%	0.33% 1.39%	1.52% 1.52%		
5	80	69	Convenience Traditional	3.92% 4.32%	2.66% 5.08%	2.48% 2.98%	0.56% 0.56%		
6	100	49	Convenience Traditional	6.10% 9.87%	4.42% 11.81%	3.53% 2.50%	2.56% 2.56%		

 Table 4

 Forecast errors of supermarkets vs. hypermarkets without the 12-month moving average.

Scenario	Number of testing periods	Number of estimation periods	Retail types	Forecast error	s (without 12-	month moving a	iverage)	
				Revenue (MA	PE)	Market share (MAE)		
				Bass model	LV model	Bass model	Modified LV model	
1	10	139	Supermarket Hypermarket	12.68% 14.07%	8.85% 8.65%	2.72% 2.57%	2.61% 2.61%	
2	20	129	Supermarket Hypermarket	15.72% 14.28%	13.93% 11.09%	3.30% 3.24%	3.29% 3.29%	
3	40	109	Supermarket Hypermarket	20.09% 14.50%	22.00% 15.38%	3.97% 3.69%	3.85% 3.85%	
4	60	89	Supermarket Hypermarket	23.24% 13.96%	25.44% 15.00%	4.23% 3.94%	3.65% 3.65%	
5	80	69	Supermarket Hypermarket	21.69% 12.59%	22.56% 13.21%	3.37% 3.37%	3.53% 3.53%	
6	100	49	Supermarket Hypermarket	22.34% 11.92%	22.75% 12.34%	3.58% 4.01%	3.72% 3.72%	

Table 5Forecast errors of supermarkets vs. hypermarkets with the 12-month moving average.

Scenario	Number of testing periods	Number of estimation periods	Retail types	Forecast errors (with 12-month moving average)				
				Revenue (MA	PE)	Market share	re (MAE)	
				Bass model	LV model	Bass model	Modified LV model	
1	10	139	Supermarket Hypermarket	0.15% 1.46%	0.92% 1.41%	0.08% 0.08%	0.08% 0.08%	
2	20	129	Supermarket Hypermarket	2.95% 6.08%	0.56% 4.62%	0.20% 0.21%	0.21% 0.21%	
3	40	109	Supermarket Hypermarket	13.64% 6.44%	14.08% 1.81%	1.35% 1.52%	1.37% 1.37%	
4	60	89	Supermarket Hypermarket	15.14% 11.63%	8.87% 12.64%	3.68% 3.09%	2.43% 2.43%	
5	80	69	Supermarket Hypermarket	5.14% 8.89%	19.52% 7.89%	2.60% 3.21%	2.60% 2.60%	
6	100	49	Supermarket Hypermarket	5.70% 6.92%	10.53% 6.04%	4.14% 4.06%	4.05% 4.05%	

used to fit the model parameters and the errors were calculated as MAPE.

We adopt the nonlinear regression method with ordinary least square approach to fit these models. The software used is Statistical Analysis System (SAS, version 9.1) and the hardware is a personal computer with AMD Athlon II X2 250 CPU at 3 GHz

frequency and 4 GB memory. For each scenario, it takes less than one second to finish the fitting and forecasting.

To validate the contribution of the moving average method, all our estimations were conducted without and with the 12-month moving average. The results without and with the 12-month moving average are reported in Tables 2 and 3, respectively.

 Table 6

 Forecast errors of convenience-oriented vs. cost-oriented submarkets without 12-month moving average.

Scenario	Number of testing periods	Number of estimation periods	Retail types	Forecast erro	Forecast errors (without 12-month moving average)			
				Revenue (MA	APE)	Market share	(MAE)	
				Bass model	LV model	Bass model	Modified LV model	
1	10	150	Convenience-oriented Cost-oriented	6.22% 14.75%	4.69% 7.42%	2.14% 1.94%	1.94% 1.94%	
2	20	140	Convenience-oriented Cost-oriented	10.30% 16.20%	9.80% 12.03%	2.07% 1.81%	1.80% 1.80%	
3	40	120	Convenience-oriented Cost-oriented	12.03% 17.60%	15.22% 17.01%	2.26% 2.26%	2.18% 2.18%	
4	60	100	Convenience-oriented Cost-oriented	13.12% 18.42%	13.71% 16.35%	2.28% 2.08%	1.85% 1.85%	
5	80	80	Convenience-oriented Cost-oriented	16.43% 16.23%	19.66% 16.26%	2.95% 2.95%	2.72% 2.72%	
6	100	60	Convenience-oriented Cost-oriented	22.76% 15.77%	22.98% 15.71%	3.40% 3.40%	3.16% 3.16%	

Table 7Forecast errors of convenience-oriented vs. cost-oriented submarkets with 12-month moving average.

Scenario	Number of testing periods	Number of estimation periods	Retail types Forecast errors (with Revenue (MAPE)	Forecast errors (with 12-month moving average)				
				APE)	Market share (MAE)			
				Bass model	LV model	Bass model	Modified LV model	
1	10	150	Convenience-oriented Cost-oriented	1.64% 0.16%	1.64% 0.34%	0.20% 0.15%	0.20% 0.20%	
2	20	140	Convenience-oriented Cost-oriented	3.69% 3.37%	3.38% 3.82%	0.30% 0.43%	0.30% 0.30%	
3	40	120	Convenience-oriented Cost-oriented	4.59% 2.59%	8.60% 4.43%	0.54% 0.54%	0.21% 0.21%	
4	60	100	Convenience-oriented Cost-oriented	4.38% 13.87%	7.71% 9.82%	2.38% 2.38%	2.38% 2.38%	
5	80	80	Convenience-oriented Cost-oriented	2.10% 10.46%	6.39% 6.21%	1.10% 1.10%	1.10% 1.10%	
6	100	60	Convenience-oriented Cost-oriented	5.87% 11.41%	18.58% 9.22%	3.33% 6.90%	1.10% 1.10%	

Table 8 Average forecast errors.

Competition	Retail types	With 12-month moving average	Average forecast errors				
		Revenue	Revenue (MA	Revenue (MAPE)		e (MAE)	
			Bass model	LV model	Bass model	Modified LV mode	
Convenience stores vs. traditional stores	Convenience stores	No	14.39%	14.58%	2.92%	2.69%	
		Yes	4.83%	4.15%	1.40%	1.01%	
	Traditional stores	No	11.80%	9.69%	2.75%	2.69%	
		Yes	4.44%	4.15%	1.83%	1.01%	
Supermarket vs. hypermarket	Supermarket	No	19.29%	19.26%	3.53%	3.44%	
	•	Yes	7.12%	9.08%	2.01%	1.79%	
	Hypermarket	No	13.55%	12.61%	3.47%	3.44%	
	••	Yes	6.90%	5.74%	2.03%	1.79%	
Convenience-oriented vs. cost-oriented	Convenience-oriented	No	13.48%	14.34%	2.52%	2.28%	
		Yes	3.71%	7.72%	1.31%	0.88%	
	Cost-oriented	No	16.50%	14.13%	2.41%	2.28%	
		Yes	6.98%	5.64%	1.92%	0.88%	

4.2. Additional implementations

We now consider the competition between supermarkets and hypermarkets in the cost-oriented submarket. Similar to

Section 4.1, the results without and with the 12-month moving average are reported in Tables 4 and 5, respectively.

We then consider the competition between convenienceoriented and cost-oriented submarkets. Similar to Section 4.1, the

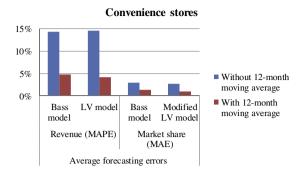


Fig. 4. Average forecasting errors for convenience stores.

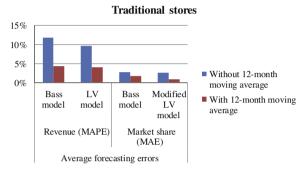


Fig. 5. Average forecasting errors for traditional stores.

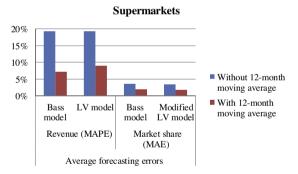


Fig. 6. Average forecasting errors for supermarkets.

results without and with the 12-month moving average are reported in Tables 6 and 7, respectively.

Finally, we summarize Tables 2–7. For each retail type in Tables 2–7, we calculate the average forecast errors among the six scenarios. The results are listed in Table 8 and visualized in Figs. 4–9.

4.3. Analysis and comparison of proposed methodology

4.3.1. Analysis of data selection

The results reported in Sections 4.1 and 4.2 indicate that the forecasts using the market share data were significantly better than the forecasts using the revenue data for both the Bass and Lot-ka–Volterra models. Consider the competition between convenience stores and traditional stores as an example (see Table 2). When using the revenue data in the Bass model, the forecast errors ranged from 5.66% to 25.03% for the six scenarios. When using the market share data in the Bass model, the forecast errors were much smaller: between 0.67% and 5.6% for the six scenarios. Similarly, for the Lotka–Volterra model, using revenue data generates forecast errors of between 4.03% and 25.44%, whereas using market share

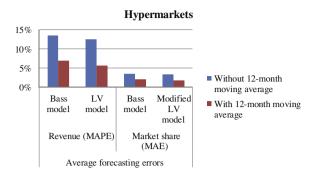


Fig. 7. Average forecasting errors for hypermarkets.

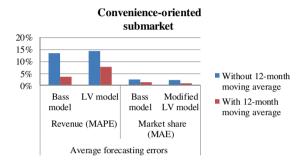


Fig. 8. Average forecasting errors for convenience-oriented submarket.

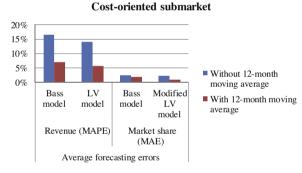


Fig. 9. Average forecasting errors for cost-oriented submarket.

data (the modified Lotka–Volterra model) gave forecast errors of between 0.64% and 4.5% for the six scenarios. The results using the 12-month moving average were also similar (see Table 3). When forecasting the competition between supermarkets and hypermarkets and between convenience-oriented and cost-oriented submarkets, the forecasts of the market share data outperformed the forecasts of the revenue data for both the Bass and Lotka–Volterra models (see Tables 4–7). This result can also be verified for the average forecast errors (see Table 8 and Figs. 4–9).

Inflation and economic growth may raise the prices of necessities and goods, which increases the revenue of retail industry. As a result, the revenue data may not accurately measure the actual growth of each specific retail type. When market share data are used, the market shares of different retail types must sum to 100%. This removes the market fluctuations and helps us to observe the relationships between different retail types clearly. Thus, market share data are more suitable than revenue data for forecasting retail competition.

4.3.2. Analysis of data processing

From the results reported in Sections 4.1 and 4.2, we find that the moving average method improves forecast accuracy. Consider

the competition between convenience stores and traditional stores as an example. When market share data in the Bass model is used, the forecast errors ranged from 0.67% to 5.6% for the six scenarios (see Table 2). When the moving average method is used, the forecast errors fell to between 0.33% and 3.53% for the six scenarios (see Table 3). Similarly, when the market share data in the modified Lotka–Volterra model is used, the forecast errors ranged from 0.64% to 4.5% for the six scenarios (see Table 2). The forecast errors using the moving average method decreased to between 0.31% and 2.56% for the six scenarios (see Table 3). The value of the moving average method can also be found in the analysis of the competition between supermarkets and hypermarkets and between convenience-oriented and cost-oriented submarkets (see Tables 4–7). This result was also observed in the average forecast errors (see Table 8 and Figs. 4–9).

Over the course of a year, the consumption behavior of customers changes with the seasons and traditional festivals. In addition, promotions and sales are used to increase short-term profits. The use of the moving average method removes short-term fluctuation in retail sales associated with the seasons, festivals, promotions, and other factors. As these factors occur over an annual cycle for the retail industry, the 12-month moving average is recommended to mitigate the impact of those events to increase forecast accuracy.

4.3.3. Model selection

From the results reported in Sections 4.1 and 4.2, we confirm that our modified Lotka-Volterra model outperforms other benchmark models for both the revenue and market share data, even with or without the moving average method, including the Bass and standard Lotka-Volterra models. Take the competition between convenience stores and traditional stores as an example (see Table 3). With the 12-month moving average, the forecast errors of the modified Lotka-Volterra model range from 0.31% to 2.56% for the six scenarios, which are smaller than those of the Bass model with revenue data (errors ranged between 0.27% and 9.87%) and with market share data (errors ranged between 0.33% and 3.53%). Moreover, the forecast errors are smaller than in the Lotka-Volterra model with revenue data (errors ranged between 0.51% and 11.81%). Similar results were found without the 12month moving average (Table 2). In examining the competition between supermarkets and hypermarkets and between convenience-oriented and cost-oriented submarkets (see Tables 4-7), the advantages of the modified Lotka-Volterra model were also confirmed. This result was also observed for the average forecast errors (Table 8 and Figs. 4-9).

The Bass model was originally designed for the diffusion of a single product. Although it can mimic the diffusion of a single industry, it may not be suitable for describing the competition between different retail types. However, the Lotka–Volterra model describes the interactions among the populations of different species. When applying it to the retail industry, the revenue data are generally treated as the populations of the different retail types. However, the revenue data may be affected by market fluctuations, thus reducing forecast accuracy. In our modified Lotka–Volterra model, we adopted the market share data instead of revenue data, which led to significant improvements in the accuracy of forecasting.

In addition, our modified Lotka–Volterra model produces forecast errors that are symmetric and increase as the estimation period decreases. The forecast errors are symmetric because the forecast values for the competing retail types sum to 100%. As a result, the forecast values must have the same MAEs. On the contrary, the Bass and Lotka–Volterra models generate unstable results. Consequently, our modified Lotka–Volterra model is recommended for competition forecasting in Taiwan's retail industry.

4.4. Synergy of the three enhancements

In Section 4.3, three extensions were implemented to improve the accuracy of forecasting for the retail industry. First, market share data are more suitable than revenue data when analyzing the competition between retail types. Second, using a 12-month moving average helps to eliminate the short-term noise over the course of a year. Third, the modified Lotka-Volterra model can not only mimic the interaction between different retail types but also eliminate the effects of general market fluctuations.

These three extensions work together to create synergy and dramatically improve the accuracy of short- and long-term fore-casting. That is, the use of any of these two extensions provides better results than using the two methods independently. Take the example of the competition between convenience stores and traditional stores (see Tables 2 and 3). The use of both the market share data and the moving average method provides better results than using each independently. When using only market share data, the forecast errors of the Bass model ranged between 0.67% and 5.6%, and when using only the moving average method, the forecast errors of the Bass model ranged between 0.27% and 9.87% for the six scenarios. When using the market share data and the moving average together, the forecast errors of the Bass model ranged between 0.33% and 3.53% for the six scenarios.

Finally, the use of all three extensions provides even better results than using any two. Consider the following (see Tables 2 and 3). When using the market share data and the moving average in the modified Lotka–Volterra model, the forecast errors ranged between 0.31% and 2.56% for the six scenarios. Similarly, the synergy of using all three extensions can be observed clearly in the competition between supermarkets and hypermarkets and between convenience-oriented and cost-oriented submarkets (see Tables 4–7). This result is also observed in the average forecast errors (see Table 8 and Figs. 4–9).

5. Conclusions and future research

This research focused on the competition between the different retail types and a proposed methodology to improve forecasting of the level of competition, which has four aspects. First, regarding data selection, market share data are recommended for competition forecasting in retail industry. As the characteristics of retail industry, revenue data is usually mixed with confounding factors such as inflation and economic growth. Market share data, which can mitigate some volatility associated with inflation and economic growth, is able to perform better in forecasting.

Second, regarding data transformation, the moving average method can effectively lower forecast errors. This is because the moving average method can smooth seasonal patterns and cycles. Third, regarding model selection, our modified Lotka–Volterra model, which contains the total market share constraint, is able to attain the best forecasting results. Fourth, regarding forecasting evaluation, MAE is recommended to evaluate our modified Lotka–Volterra model with market share data. It is because market share data might contain actual values very close to zero. Some minor forecast errors on these small actual values can result in misleadingly large MAPE values. MAE not only can handle small actual values but also generates the average absolute error in percentage terms

Revenue data from Taiwan's retail industry for a 160-month period are used to verify the performance and accuracy of our proposed methodology. Our numerical results indicate significant improvement in forecasting capabilities.

For future research, we are interested in the following two directions. First, given rising fuel prices and ongoing economic growth, the role of online retailing becomes more important for the modern retail industry. As a result, the competition between online and brick-and-mortar retailing has attracted more attention. We would like to apply our methodology to study the impact of this new retail type.

Second, rather than simply removing seasonal patterns and cycles, we are interested to capturing these features of the data in our model. Some methods, such as the X11 and X12-ARIMA programs, use seasonal adjustments and iterative approaches to estimate seasonality and trends in the data. Other methods, such as the Hodrick–Prescott filter, can separate trends and cycles by adding smoothing parameters. We are interested in these possible extensions to the model and would like to develop a better procedure to capture seasonal patterns and cycles.

References

- Bass, F. M. (1969). A new product growth model for consumer durables. *Management Science*, 15(5), 215–227.
- Chang, B. Y., Li, X., & Kim, Y. B. (2014). Performance comparison of two diffusion models in a saturated mobile phone market. *Technological Forecasting & Social Change*, 86, 41–48.
- Chiang, S. Y., & Wong, G. G. (2011). Competitive diffusion of personal computer shipments in Taiwan. *Technological Forecasting & Social Change*, 78, 526–535.
- Chiang, S.-Y. (2012). An application of Lotka-Volterra model to Taiwan's transition from 200 mm to 300 mm silicon wafers. Technological Forecasting & Social Change, 79, 383–392.
- Dalla Valle, A., & Furlan, C. (2014). Diffusion of nuclear energy in some developing countries. *Technological Forecasting & Social Change*, 81, 143–153.
- Deloitte, (2011). Leaving home. Global powers of retailing. Available at: http://www.deloitte.com/assets/Dcom-Albania/Local%20Content/Articles/E&R%202011/Consumer%20Behavior%202011/al_globPowDeloitte_14%20Jan.pdf.
- Deloitte, (2013). Global powers of retailing. Retail beyond. Available at: http://www.deloitte.com/assets/Dcom-Global/Local%20Assets/Documents/Consumer%20Business/dttl cb GlobalPowersofRetailing2013.pdf>.
- Department of Statistics, Ministry of Economic Affairs, (2013). Industrial and commercial business operation introduction: trade and eating-drinking places activity surveys. Available at: http://www.moea.gov.tw/Mns/english/content/ContentLink2.aspx?menu_id=213.

- Directorate-General of Budget, Accounting and Statistics (2013). Statistical Abstract of National Income. Available at: http://eng.stat.gov.tw/public/data/dgbas03/bs4/nis93_e/NIE.PDF.
- Duan, H. B., Zhu, L., & Fan, Y. (2013). A cross-country study on the relationship between diffusion of wind and photovoltaic solar technology. *Technological Forecasting & Social Change*. http://dx.doi.org/10.1016/j.techfore.2013.07.005. In press.
- Geijzendorffer, I. R., Van der Werf, W., Bianchi, F. J. J. A., & Schulte, R. P. O. (2011). Sustained dynamic transience in a Lotka–Volterra competition model system for grassland species. *Ecological Modelling*, 222, 2817–2824.
- Goldman, A. (2001). The transfer of retail formats into developing economies: The example of China. *Journal of Retailing*, 77, 221–242.
- Heinz, B., Graeber, M., & Praktiknjo, A. J. (2013). The diffusion process of stationary fuel cells in a two-sided market economy. *Energy Policy*, *61*, 1556–1567.
- Kim, J., Lee, D. J., & Ahn, J. (2006). A dynamic competition analysis on the Korean mobile phone market using competitive diffusion model. *Computers & Industrial Engineering*, 51, 174–182.
- Kreng, V. B., & Wang, H. T. (2011). The competition and equilibrium analysis of LCD TV and PDP TV. *Technological Forecasting & Social Change*, 78, 448–457.
- Lee, S. J., Lee, D. J., & Oh, H. S. (2005). Technological forecasting at the Korean stock market: A dynamic competition analysis using Lotka-Volterra model. Technological Forecasting & Social Change, 72, 1044-1057.
- Lin, C. (2013). Forecasting and analyzing the competitive diffusion of mobile cellular broadband and fixed broadband in Taiwan with limited historical data. *Economic Modelling*, 35, 207–213.
- Lotka, A. J. (1925). Elements of physical biology. Baltimore: Williams and Wilkins. Roques, L., & Chekroun, M. (2011). Probing chaos and biodiversity in a simple competition model. Ecological Complexity, 8, 98–104.
- Sneddon, J., Soutar, G., & Mazzarol, T. (2011). Modelling the faddish, fashionable and efficient diffusion of agricultural technologies: A case study of the diffusion of wool testing technology in Australia. *Technological Forecasting & Social Change*, 78. 468–480.
- Seol, H., Park, G., Lee, H., & Yoon, B. (2012). Demand forecasting for new media services with consideration of competitive relationships using the competitive Bass model and the theory of the niche. *Technological Forecasting & Social Change*, 79, 1217–1228.
- Taiwan İnstitute of Economic Research, (2012). Taiwan Chain Store Almanac. Available at: http://library.tier.org.tw/webpac/bookDetail.do?id=13607.
- Tsai, B. H., & Li, Y. (2009). Cluster evolution of IC industry from Taiwan to China. Technological Forecasting & Social Change, 76, 1092–1104.
- Tsai, B., Li, Y., & Lee, G. (2010). Forecasting global adoption of crystal display televisions with modified product diffusion model. *Computers & Industrial Engineering*, 58, 553–562.
- Volterra, V. (1926). Fluctuations in the abundance of a species considered mathematically. *Nature*, 118, 558–560.