Forecasting the sales of an innovative agro-industrial product with limited information: A case of feta cheese from buffalo milk in Thailand

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ABSTRACT

This paper discusses the techniques of sales forecasting with limited information. It raises some critical comments on functional forms, estimation methods and comparison of forecasting accuracy to the work of Kanjanatarakul and Suriya (2012) and Kanjanatarakul and Suriya (2013). The data are from an innovative agro-industrial product, feta cheese made from buffalo milk by the Royal Project Foundation in Thailand. The study also suggests some developments done by Kanjanatarakul (2003) and identifies some issues for further improvements on forecasting techniques with limited information.

Keywords: Innovative product, sales forecasts, limited information, Bass model, Logistic function.

JEL classification: C53, O31, M31

1. Introduction

Kanjanatarakul and Suriya (2012) and Kanjanatarakul and Suriya (2013) have tried several techniques to forecast the sales of innovation. They applied their techniques to an innovative agro-industrial product, the feta cheese produced from buffalo milk by the Royal Project Foundation in Thailand. Their works were challenging with the usage of limited information. This was the issue that Meade and Islam (2006) have encouraged modelers in the new generation to deal with.

However, the techniques proposed in both works rely on many assumptions. Some estimation process needs to be improved. Several possible techniques may yield more accurate forecasts. Therefore, this paper will discuss these topics and suggest further improvement of the forecasting technique with limited information.

2. Functional forms

Works of Kanjanatarakul and Suriya (2012) and Kanjanatarakul and Suriya (2013) use two functional forms to forecast the sales. First, they use the classical Bass model. Second, they compare the performance with Logistic function.

2.1 Bass model

Bass (1969) and Srinivasan and Mason (1986) suggested a functional form to forecast sales of new products as follows:

$$V_T = \frac{M(1-\exp(-(p+q)\,T))}{1+\exp(-\left(\frac{q}{p}\right)(p+q)T)}$$

where V_T = Sales of innovative agro-industrial product

M = Maximum sales of innovative agro-industrial product

p = Coefficient of innovation

q = Coefficient of imitation

T = Time

2.2 Logistic function

Stoneman (2010) suggested the Logistic function for the forecasting of sales of new products especially soft innovation as follows:

$$V_T = \frac{M}{1 + \mathrm{A} * \exp\left(-\beta T\right)}$$

where V_T = Sales of innovative agro-industrial product

M = Maximum sales of innovative agro-industrial product

β = Parameter

T = Time

It is clear that both Bass model and Logistic function present the S-curve. This S-curve is expected to predict the sales forecast following the product life cycle theory. However, there are a lot of functional forms that can construct the S-curve too. Therefore, it is still challenging that researchers of the next generation can try other functional forms apart of just Bass model and Logistic function.

By the way, it is interesting why only Bass model and Logistic function are famous among others. Bass model has its long history in the forecasting front. Rogers (2003) describes this successful history of the model elaborately in his book. The model compiles with good theory of communication and marketing. It deals with the demand to use innovative product and the demand to imitate other people in the society. These explanations are sensible and can be modeled mathematically. That is why Bass model is famous among marketers until today.

For the Logistic function, we thanks to Stoneman (2010) that introduces this functional form to the world in his book of soft innovation. Logistic function is not new to the world in the mathematical sense but new to marketers and somehow new to economists too. It is clear that Logistic function is not only a candidate in the S-curve family but it seems to be the most simple but powerful functional form in the family. Imagine how hard when a researcher has to estimate the S-curve using the functional form of the normal distribution, say Probit function. Therefore, Logistic function seems to be the most practical functional form for practitioners.

3. Estimation methods

Kanjanatarakul and Suriya (2012) and Kanjanatarakul and Suriya (2013) raise four estimation methods as follows:

Method 1: Least squares using quadratic interpolation algorithm

The parameter estimation includes these following steps.

Step 1: Initiate three initial values of parameter M. Transform the data using logistic transformation into linear function.

$$ln\left(\frac{V_T/M}{1-V_T/M}\right)-\ln\left(\frac{1}{\mathrm{A}}\right)=\beta\mathrm{T}$$

Then, estimate parameter β using Ordinary Least Squares (OLS)

Step 2: Take parameter M and β to forecast sales by this formula.

$$\widehat{V_T}=\frac{M}{1+\mathrm{A}*\exp\left(-\beta T\right)}$$

The value of A will be calculated by this formula to fix the y-intercept at the first data of the series (Vo).

$$A=\frac{M}{V_0}-1$$

Step 3: Calculate the Sum Squared Error (SSE).

$$\sum e^2=\sum_{T=0}^{T}\left(V_T-\widehat{V_T}\right)$$

Step 4: Calculate the SSE at the three points using the three initial M values.

Step 5: Search for a new M value by using Quadratic Interpolation

Step 6: Include the new M with other two previous M values which are located nearest to the new M. Then, estimate parameter β and calculate the SSE again.

Step 7: Repeat step 5 and 6 for 10,000 iterations.

Step 8: Summarize the values of parameter M and β.

Method 2: Least squares using Quasi-Newton algorithm

The parameter estimation includes these following steps.

Step 1: Repeat step 1 to 4 of method 1 (Least squares using quadratic interpolation algorithm). This will yield the values of M, β and SSE. Each parameter will contain three values.

Step 2: Calculate the slope between the values of M, β and SSE. Two slopes will be available for each parameter.

Step 3: Initiate the initial value of H (Ho). It should be the identity matrix at the size of 2 ×2.

Step 4: Calculate a new H using this formula.

$$H = H_o + \frac{vv'}{v'u} - \frac{H_o u u' H_o}{u' H_o u}$$

where v = Difference of the parameter

u = Difference of the slope of the parameter

Step 5: Calculate the increment of the parameter by this formula.

$$d = -Hg$$

where d = The increment of the parameter

g = Initial slope of the parameter

Step 6: Calculate a new parameter by adding the increment to the previous parameter.

Step 7: Create two nearby values for parameter M. Repeat the process for parameter β.

Step 8: Calculate the SSE from the new parameter M and β.

Step 9: Repeat step 4 to 8 for 10,000 iterations.

Step 10: Summarize the values of parameter M and β.

Method 3: Maximum likelihood using quadratic interpolation algorithm

This method is like the least squares using quadratic interpolation algorithm. It changes the objective function to be the likelihood function as follows:

$$L = \prod_{T=0}^{T} Pr(V_T|T)$$

and

$$Pr(V_T|T) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{\left(-\frac{1}{2}\right)\frac{(V_T - F_T)^2}{\sigma^2}\right\}$$

where $Pr(V_T|T)$ = Probability of the occurrence of a sales value at a time

σ = Variance

V_T = Sales value

F_T = Forecasted sales value

Method 4: Maximum likelihood using Quasi-Newton algorithm

This method is quite similar to method 3 (Maximum likelihood using quadratic interpolation algorithm). It changes the objective function to be the likelihood function as follows:

$$L = \prod_{T=0}^{T} Pr(V_T|T)$$

and

$$Pr(V_T|T) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{\left(-\frac{1}{2}\right)\frac{(V_T - F_T)^2}{\sigma^2}\right\}$$

The details of the equations are described in method 3.

There are several points that these estimation techniques may be criticized. First, the parameters in the models are time-invariant. It means that the shape of S-curve is fixed over time no matter what happen to the economy. One thing that the authors tried to overcome this problem is to convert all the data into deseasonalized values. Another thing that Kanjanatarakul (2013) tried to do is to apply the method of rolling windows. The estimation using rolling windows may capture the current situation of the economy. Kanjanatarakul (2013) also suggests the best width of the window.

Second, the estimation using OLS in step 1 of method 1 (Least squares using quadratic interpolation algorithm) may be argued that it faces the Heteroscedasticity problem. Due to the suggestion of Judge et al (1996), the Estimated Generalized Least Squares (EGLS) should be applied to solve this problem. To respond this, Kanjanatarakul (2013) has used both OLS and EGLS to estimate the logistic transformed function. She found that the model with OLS yields better forecasting performance than EGLS. This finding might still be unable to stop critics over the competition between OLS and EGLS when theorists may still prefer EGLS to OLS but practitioners may found that OLS suits their forecasting objectives with empirical data more than EGLS.

Third, the usage of normal distribution in the estimation of likelihood function may be questionable. Even though there are several possible distributions that may suit the distribution of the sales, practitioners have only limited data to see what kind of the distribution is. After the innovative product was launched to the market, data from only some months will be available for the forecasting and decision making of the innovator. They have no enough data to test whether the sales at a moment of time distributes normally or not. Therefore, researchers and practitioners cannot make the forecast without making an assumption. The assumption of normal distribution is the safest one because of its symmetric distribution. It is also helpful for the usage of the t-test later for any comparison of means.

Fourth, when these studies use Quasi-Newton in the estimation process, many algorithms may be good competitors to it. To respond to this issue, Kanjanatarakul (2013) has compared the forecasting the performance among Quasi-Newton, Gauss-Newton and Newton-Raphson. In her study, she finds something that may be interesting for further discussion, i.e. the model with larger Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) from the in-sample test may yield better Mean Absolute Percentage Error (MAPE) in the out-of-sample test. This argument has to be proven with more empirical data and further discussed theoretically.

4. Comparisons of the forecasting accuracy

Kanjanatarakul and Suriya (2012) compare the performance between Bass model and logistic function. The study calculates the Mean Absolute Percentage Error (MAPE) in the out-of-sample test. Then match the models which are estimated by the same method and compare their AIC, BIC and MAPE. Moreover, it compares the AIC, BIC and MAPE of the best Bass model to the best logistic function. Statistics that is be used to test the hypothesis is t-statistics.

In this section, there are at least two points of discussion. First, the reasons why the study uses MAPE is because it is easy to interpret the results. MAPE will clarify how much percentage that the forecasts deviate from the true value. While Sum-Squared Error (SSE) may be too huge for the perception of practitioners to understand the accuracy of the forecast, MAPE presents itself more direct in the term of percentage of the error.

Second, the usage of t-test to compare the means of the AIC, BIC and MAPE can be criticized of its underlying assumption of normal distribution. This assumption is set in the estimation method using maximum likelihood where researchers have no enough data to test the type of distribution of the sales. Therefore, they have to assume a kind of distribution and one of the safest ways is the normal distribution. With this assumption of normal distribution, t-test can be used for the comparisons of the means.

Third, the study uses both AIC and BIC for the measurement of goodness of fit in the in-sample test. Although it can be criticized that the study may use only one indicator to present the goodness of fit, the usage of both indicators can make the readers see the consistency of them. When they move in the same direction, the researcher can be sure that the results are good.

5. Conclusions

This paper reviews and discusses the work of Kanjanatarakul and Suriya (2012) and Kanjanatarakul and Suriya (2013) on the sales forecast using limited data of an innovative agro-industrial product. It makes critical comments on the functional forms, the estimation methods and the comparisons of the forecasting accuracy. Some points are solved in the work of Kanjanatarakul (2013). Many points are still open for further studies both empirically and theoretically.

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