MATEC Web of Conferences **62**, 02011 (2016) DOI: 10.1051/matecconf/20166202011
ICCFE 2016

The Organic Food Purchase Behaviour: Using ECT to Explore Customers' Satisfaction

Hui Hsin Huang[1,a]

[1]*Aletheia University, New Taipei City, Taiwan*

Abstract. This paper bases on expectation confirmation theory (ECT) to propose a stochastic model of predicting organic food purchase behaviour. In the model, the expectation of pre-purchase and outcome performance of post-purchase are considered as relative variables. We consider these two variables as two different normal distribution and their probability density function (pdf) and cumulative distribution function(cdf) will be demonstrated to display their correlation. Then the joint density can be computed to show the results of positive or negative disconfirmation. This study also conducts an empirical data for parameter estimation and model application. We use the 0.5 as threshold level of probability to test the fitness of real overall satisfaction and the calculation results of probability. The results of chi-square testing show good fitness. Finally, the conclusion is made.

1 Introduction

The growing trend in the demand for organic food or product has received increased attention by researchers [1-5]. There are many studies [2, 4-10] to investigate the characteristics of organic food producer [7, 9] and consumption [5-12] on both supply and demand [5, 11] side. This research focus on the consumption topic to explore the customer purchase behaviour of organic food product. In this topic, the customers' satisfaction is one of the curial factors to predict the customer purchase tendency [13, 14].

The customer's satisfaction results from a comparison between expectation and outcome performance [14-16]. The comparison of prior expectations with observed performance cases disconfirmation. The disconfirmation is positive, when the outcome performance of product is higher than the expectation. In the contrary, the disconfirmation is negative, if the outcome performance of product is lower than the expectation. The positive disconfirmation reflects satisfaction and negative disconfirmation demonstrates dissatisfaction [15, 17-20]. Oliver [21-22] proposed expectation confirmation theory (ECT) to describe these series process.

Bases on ETC, expectation and outcome performance are two important variables which can influence the judgment of satisfaction measure. Thus, this research proposes two stochastic models of expectation and outcome performance. And through combining these two models into a full distribution, the satisfaction can be predicted.

The remainder of this paper is organized as follows: Firstly, the literature review of ETC is demonstrated in the next section. Secondly, we introduce the expectation and outcome performance models. The probability density function (pdf) and cumulative distribution function (cdf) will be demonstrated in this section. Thirdly, the results of the parameter estimation and empirical test are report. Finally, the conclusion is made.

2 The Research of ECT

ECT is constructed by Oliver [21-22] and is used popularly to discuss the customer satisfaction process. In the process of satisfaction judgments, first buyers may experience from expectations of the specific product or service prior to purchase. Second, consumption reveals a perceive performance level of product which is influence by expectations if difference between actual performance and expectations is perceived as being small. Hence, perceived performance may increase or decrease directly with expectations as indicated by the arrow drawn from expectations to perceived performance. Third, perceived performance may either confirm or disconfirm prepurchase expectation [16-17, 19, 23-24].

Thus, in this theory, satisfaction is a function which includes the difference between observed outcome performance of post-purchase and prior expectations about the outcome's performance of pre-purchase [17,25-7]. The expectations provide a baseline or anchor level of satisfaction. Some research find that the perceived performance which falls short of expectations has greater impact on satisfaction and repurchase intentions than performance which exceeds expectations [27-28]. Thus, the expectation of pre-purchase and outcome performance of post-purchase are relative variables. We consider this characteristic of correlation ship into model development.

[a] Corresponding author: hoyasophia@gmail.com

3 The Model

In the customer satisfaction of organic food purchase behaviour, we base on ECT to construct the stochastic expectation model.

3.1 The expectation

We denote w is the volume of one's expectation of organic food purchase which is a random variable with its probability density function (p.d.f.) as

$$f_W(w)=\frac{1}{w\sigma_a\sqrt{2\pi}}exp\left[-\frac{(log\,w-\mu_a)^2}{2\sigma_a^{\ 2}}\right] \quad , \quad w>0 \qquad (1)$$

$$F_W(w)=\Phi\left[\frac{(log\,w-\mu_a)}{\sigma_a}\right] \quad , \quad W>0 \qquad (2)$$

3.2 The outcome performance

The outcome performance of organic food is considered as an random variable k with its probability density function(p.d.f.)as

$$f_K(k)=\frac{1}{k\sigma_b\sqrt{2\pi}}exp\left[-\frac{(log\,k-\mu_b)^2}{2\sigma_b^{\ 2}}\right] \quad , \quad k>0 \qquad (3)$$

$$F_K(k)=\Phi\left[\frac{(log\,k-\mu_b)}{\sigma_b}\right] \quad , \quad K>0 \qquad (4)$$

3.3 The full model

The models of expectation and outcome performance of organic food can be combined into a joint distribution as

$$\begin{aligned}&f_{WK}(w,k)\\&=\frac{1}{2\pi wk\sigma_a\sigma_b\sqrt{1-\gamma^2}}\times exp\left[-\frac{1}{2(1-\gamma^2)}\right]\times\\&\left[\left(\frac{log\,w-\mu_w}{2\sigma_a}\right)^2-2\rho\left(\frac{log\,w-\mu_w}{2\sigma_a}\right)\left(\frac{log\,k-\mu_k}{2\sigma_b}\right)+\left(\frac{log\,k-\mu_k}{2\sigma_b}\right)^2\right]\end{aligned} \qquad (5)$$

$$\gamma=\frac{\mathrm{cov}(w,k)}{\sigma_a\sigma_b} \qquad (6)$$

$$f_{k|w}(k|w)=\frac{1}{k\sigma_{b|a}\sqrt{2\pi}}exp\left[-\frac{(log\,k-\mu_{b|a})^2}{2\sigma_{b|a}^{\ 2}}\right] \qquad (7)$$

where $\mu_{b|a}=\mu_b-\left[\gamma\frac{\sigma_b}{\sigma_a}(log\,w-\mu_a)\right]$

and $\sigma_{b|a}=\sigma_b\sqrt{(1-\gamma)^2}$.

3.4 The model of ECT

In ETC, if the outcome performance of product is higher than the expectation, then the disconfirmation is positive. On the other hand, if the outcome performance is lower than the expectation, then negative disconfirmation happens. The probability of these two scenarios will be demonstrated as bellow.

3.4.1 Positive disconfirmation

The customer feels satisfaction if the disconfirmation is positive. According equation (1)-(4), the positive disconfirmation can be demonstrated as

$$\begin{aligned}&P(K>w_0|W=w_0)\\&=1-\int_o^{w_0}f_K(k|w_0)\,dk\\&=1-\int_0^{w_0}\frac{1}{k\sigma_{b|a}\sqrt{2\pi}}exp\left[-\frac{(log\,k-\mu_{b|a})^2}{2\sigma_{b|a}^{\ 2}}\right]dk\end{aligned} \qquad (8)$$

3.4.2 Negative disconfirmation

The customer feels dissatisfaction if the disconfirmation is negative. According equation (1)-(4), the negative disconfirmation can be demonstrated as

$$\begin{aligned}&P(K<w_0|W=w_0)\\&=\int_o^{w_0}f_K(k|w_0)\,dk\\&=\int_0^{w_0}\frac{1}{k\sigma_{b|a}\sqrt{2\pi}}exp\left[-\frac{(log\,k-\mu_{b|a})^2}{2\sigma_{b|a}^{\ 2}}\right]dk\end{aligned} \qquad (9)$$

4 The Empirical Data Analysis

We use a real database of an organic food chain store. There are 2566 customers in this database.

4.1 The analysis process

The analysis process is following(see figure1):

Step1:

First, we separate these samples into two parts. One is for parameters estimation. Another is for model application. There are 1280 samples for parameters estimation and 1286 samples for model validation.

Step2:

In step2, we use MLE (maximum likelihood estimate) to estimate the parameters of full model. Then we put the results of parameters estimation into the proposed model.

Step3:

In this step, we use the full model without parameters to calculate the probability of customer satisfaction and compare these results with the real data of satisfaction.

Finally, we use chi-square test to fitness between the proposed model and the real data of customer satisfaction.

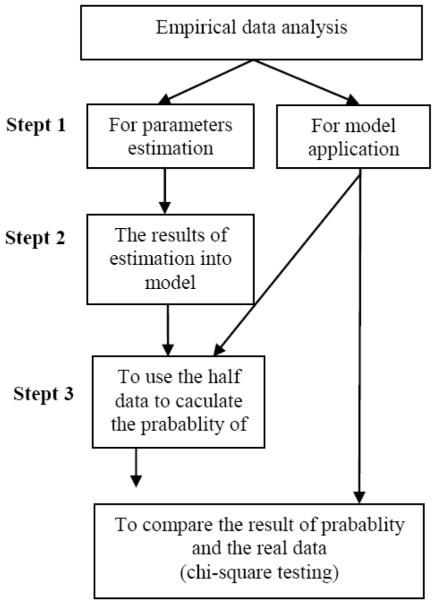

Figure 1. The Analysis Process.

The results of each step will be demonstrated in section 4.2 and 4.3. Section 4.2 shows the result in step2 and section 4.3 shows the result in step3.

4.2 The parameters estimation

The MLE (maximum likelihood estimate) is used to estimate the parameters in our model. Let L denote the total likelihood and n is the sample size.

$$
\begin{aligned}
&L(\mu_a,\mu_b,\sigma_a^{2},\sigma_b^{2},\rho)\\
&=\prod_{i=1}^{n} f_{WK}(\mu_a,\mu_b,\sigma_a^{2},\sigma_b^{2},\rho)\\
&=\left(\frac{1}{2\pi wk\sigma_a\sigma_b\sqrt{1-\rho^2}}\right)^{n}\times\\
&\left\{exp\, n\left[-\frac{1}{2(1-\rho^2)}\right]\right\}\times\\
&\left[\left(\frac{log\,w-\mu_a}{2\sigma_a}\right)^{2}-n\rho\left(\frac{log\,w-\mu_a}{\sigma_a}\right)\left(\frac{log\,k-\mu_b}{\sigma_b}\right)+\left(\frac{log\,k-\mu_b}{2\sigma_b}\right)^{2}\right]
\end{aligned}
\tag{10}
$$

We differentiate $L(\mu_a,\mu_b,\sigma_a^{2},\sigma_b^{2},\rho)$ respectively regarding μ_w, σ_w^{2}, μ_k, $\sigma_k^{2}$and ρ set them equal to zero. That is,

$$
\begin{cases}
\frac{\partial\mu_a}{\partial}L(\mu_a,\mu_b,\sigma_a^{2},\sigma_b^{2},\rho)=0\\
\frac{\partial\mu_b}{\partial}L(\mu_a,\mu_b,\sigma_a^{2},\sigma_b^{2},\rho)=0\\
\frac{\partial\sigma_a^{2}}{\partial}L(\mu_a,\mu_b,\sigma_a^{2},\sigma_b^{2},\rho)=0\\
\frac{\partial\sigma_b^{2}}{\partial}L(\mu_a,\mu_b,\sigma_a^{2},\sigma_b^{2},\rho)=0\\
\frac{\partial\rho}{\partial}L(\mu_a,\mu_b,\sigma_a^{2},\sigma_b^{2},\rho)=0
\end{cases}
\tag{11}
$$

We take the solutions of (11) as MLE forμ_w, σ_w^{2}, μ_k, $\sigma_k^{2}$and ρ. The details of left-hand side of (11) are given in the Appendix.

Finally, we use our empirical data which has been described in previous section to estimate these five parameters.The results are in Table 1.

Table 1. The Parameters Estimate.

μ_w	σ_a^{2}	μ_k	σ_b^{2}	ρ
4.001	0.857	4.897	2.345	0.521

Then, we use the result of parameters estimation to the full model. It shows in equation(12).

$$
\begin{aligned}
&f_{WK}(w,k)\\
&=wke^{-0.686}\times\\
&\begin{bmatrix}0.0271(log\,w-\mu_w)^2\\ -0.017(log\,w-\mu_w)(log\,k-\mu_k)+0.872(log\,k-\mu_k)^2\end{bmatrix}
\end{aligned}
\tag{12}
$$

4.3 The model application

We use the 0.5 as threshold level of probability to test the fitness of real overall satisfaction and the calculation results of probability. The results of chi-square testing are shown in table 2.

Table 2. The results of chi-square testing.

	satisfaction	**dissatisfaction**
Fitness rate	93.67%	92.26%
X^2=18589 (p<.05)	---	---

The rate of fitness is higher than 90% in all scenarios and the chi-square testing are significant. Then prediction analysis shows good fitness between the model and the real data.

5 Conclusion

This research is to propose a stochastic model based on ECT to predict customer satisfaction of organic food. According to the empirical data application, the results of chi-square testing show good fitness of this model. Thus, this model can be used to explore the purchase behaviour of organic food and its impact variables such as expectation evaluation to control the level of making balance or disconfirmation of satisfaction. The company manager or researchers of organic food can decompose the ECT model into prepurchase expectation and postpurchase evaluation to discuss each part of positive or negative disconfirmation according our mathematic model to maximum the profit. For example, managers can manipulate the expectation to be lower than postpurchase performance to achieve the positive disconformation(satisfaction) or to enhance the postpurchase performance higher than expectation to make result of positive disconformation.

The proposed model provides the view of point on mathematical concept to discuss the organic food research. In the future, other impact factors can be involved to explain the purchase behaviour. The researchers can also consider other form of distribution such as log normal or exponential to test mutli-model fitness. For the further research, the relationship of repurchase expectation and postpurchase performance can be consider no relative or nonlinear relative to find different effect of ECT model.

Acknowledgements

The author would like to thank the National Science Council of the Republic of China, Taiwan (NSC 99-2410-H-156-013) and Aletheia University(AU-AR-104-014) for financially supporting this research.

References

1. C. P. Bravoa, A. Cordtsa, B. Schulzeb, A. Spillera, Food Qual. Prefer. **28**,1 (2013)
2. R. M. Ness, M. Ness, M. Brennan, E. Oughton, C. Ritson, E. Ruto, Food Qual. Prefer. **21**, 1 (2010)
3. D. Pearsona , J. Henryks, H. Jones, Renew Agr. Food Syst. **26**, 2 (2011)
4. J. Chen, A. Lobo , N. Rajendran, International Journal of Consumer Studies **38**, 4 (2014).
5. U. Hjelmar, Appetite **56**,2 (2011)
6. P. Justin, R. Jyoti, Journal of Consumer Marketing **29**, 6 (2012)
7. L. Marian, , P. Chrysochou , A. Krystallis , J.Thøgersen, Food Quality and Preference **37**(2014)
8. A. Khanlari, Strategic Customer Relationship Management in the Age of Social Media .
9. P. Kriwy, R. A. Mecking, International Journal of Consumer Studies **36**,1 (2012)
10. M. Yazdanpanah, M. Forouzani, Journal of Cleaner Production **107**, 16(2015)
11. S. K. Pandey , A. Khare, Journal of Indian Business Research 7 ,4 (2015)
12. J. Hwang, Journal of Retailing and Consumer Services **28**(2016)
13. S. Halilovica, M. Cicica, Behaviour & Information Technology **32**,4 (2013)
14. C. L. Hsu, J.C. Lin,Electronic Commerce Research and Applications **24**,3 (2015)
15. Y. Sun, L. Liu, X. Peng, Y. Dong, Electronic Markets **24**, 1(2014)
16. C. L. Hsu, J.C. Lin,Electronic Commerce Research and Applications **24**,3 (2015)
17. P. K.Kopalle , D. R. Lehmann, J. M. R. **38**, 3 (2001)
18. Y. M. Cheng, Information Technology & People, **27**, 3 (2014)
19. S. Halilovica, M. Cicica, Behaviour & Information Technology **32**,4 (2013)
20. I. L. Wu, International Journal of Information Management **33**, 1(2013)
21. R. L. Oliver, J. Appl. Psychol. 62, 4 (1977)
22. R. L. Oliver, J. M. R. **17**,4 (1980)
23. W. E. Anderson, W. M. Sullivan, Marketing Sci. **12**, 2 (1993)
24. H. H. Huang, C. H. Liu, Taiwan J. M. S. **10**, 1 (2014)
25. W. E. Anderson, W. M. Sullivan, Marketing Sci. **12**, 2 (1993)
26. Y. Sun, L. Liu, X. Peng, Y. Dong, Electronic Markets **24**, 1(2014)
27. C. L. Hsu, J.C. Lin,Electronic Commerce Research and Applications **24**,3 (2015)
28. S. Walther, R. Eden , G. Phadke, E. Torsten, Lecture Notes in Business Information Processing **198**(2015)

Appendix

1.

$$\frac{\partial \mu_a}{\partial} L(\mu_a,\mu_b,\sigma_a{}^2,\sigma_b{}^2,\rho)$$
$$=\left(\frac{1}{2\pi wk\sigma_a\sigma_b\sqrt{1-\rho^2}}\right)^n \times$$
$$\left\{exp\, n\left[-\frac{1}{2(1-\rho^2)}\right]\right\}$$
$$\times\left[\left(\frac{\mu_a-\log w}{\sigma_a}\right)+n\rho\left(\frac{\log k-\mu_b}{\sigma_a\sigma_b}\right)\right]$$

2.

$$\frac{\partial \mu_b}{\partial} L(\mu_a,\mu_b,\sigma_a{}^2,\sigma_b{}^2,\rho)$$
$$=\left(\frac{1}{2\pi wk\sigma_a\sigma_b\sqrt{1-\rho^2}}\right)^n \times$$
$$\left\{exp\, n\left[-\frac{1}{2(1-\rho^2)}\right]\right\}$$
$$\times\left[n\rho\left(\frac{\log w-\mu_a}{\sigma_a\sigma_b}\right)+\left(\frac{\mu_b-\log k}{\sigma_b}\right)\right]$$

3.

$$\frac{\partial \sigma_a{}^2}{\partial} L(\mu_a,\mu_b,\sigma_a{}^2,\sigma_b{}^2,\rho)$$
$$=\left(\frac{1}{2\pi wk\sigma_b\sqrt{1-\rho^2}}\right)^n \times$$
$$\left\{exp\, n\left[-\frac{1}{2(1-\rho^2)}\right]\right\}$$
$$\times\left[\begin{array}{l} n\rho(1+n)\left(\dfrac{\log w-\mu_a}{\sigma_a{}^{n+2}}\right)\left(\dfrac{\log k-\mu_b}{\sigma_b}\right) \\ -\dfrac{(\log w-\mu_a)^2(8+4n)}{\sigma_a{}^{n+3}}-\dfrac{n(\log k-\mu_b)^2}{4\sigma_b{}^2\sigma_a{}^{n+1}}\end{array}\right]$$

4.

$$\frac{\partial\sigma_b{}^2}{\partial}L(\mu_a,\mu_b,\sigma_a{}^2,\sigma_b{}^2,\rho)$$

$$=\left(\frac{1}{2\pi wk\sigma_a\sqrt{1-\rho^2}}\right)^n\times$$

$$\left\{exp\ n\left[-\frac{1}{2(1-\rho^2)}\right]\right\}$$

$$\times\left[\begin{aligned}&n\rho(1+n)\left(\frac{\log w-\mu_a}{\sigma_a}\right)\left(\frac{\log k-\mu_b}{\sigma_b{}^{n+2}}\right)\\&-\frac{(\log k-\mu_b)^2(8+4n)}{\sigma_b{}^{n+3}}-\frac{n(\log k-\mu_b)^2}{4\sigma_a{}^2\sigma_b{}^{n+1}}\end{aligned}\right]$$

5.

$$\frac{\partial\rho}{\partial}L(\mu_a,\mu_b,\sigma_a{}^2,\sigma_b{}^2,\rho)$$

$$=\left(\frac{1}{2\pi wk\sigma_a\sigma_b}\right)^n\times exp\left\{n\left[-\frac{1}{2(1-\rho^2)}\right]\right\}$$

$$\times\left[\frac{np+n}{\left(\sqrt{1-p^2}\right)^n}-np(1-p)^2\right]$$

$$\times\left[\begin{aligned}&\left(\frac{\log w-\mu_a}{2\sigma_a}\right)^2-n\rho\left(\frac{\log w-\mu_a}{\sigma_a}\right)\left(\frac{\log k-\mu_b}{\sigma_b}\right)\\&+\left(\frac{\log k-\mu_b}{2\sigma_b}\right)^2\end{aligned}\right]$$