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A framework for variance analysis of customer equity based on a Markov chain model

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ABSTRACT

This study proposes a framework for variance analysis of customer equity (CE) based on a Markov chain model called the Leslie matrix, developed in mathematical biology. Because customer lifetime value represents the net present value of customer derived cashflow, CE can be characterized as a forward-looking measure. Numerous studies have addressed the use of CE for planning. However, few studies have utilized CE for control. When CE is used as a basis for control, variance analysis is indispensable. In the proposed framework, CE variance is divided into three parts: customer payoff variance, customer lifecycle variance, and customer state variance. Thereafter, customer lifecycle variance is further broken down into customer acquisition, retention, and expansion. The aforementioned framework was applied to membership customers of a Japanese resort hotel chain. The results revealed that customer retention was a major cause of CE variance, whereas customer acquisition and expansion had a smaller impact.

1. Introduction

This study proposes a framework for variance analysis of customer equity (CE) based on a Markov chain model. CE, defined as the total customer lifetime value (CLV) of current and future customers, can be characterized as a forward-looking measure. A forward-looking measure is helpful for avoiding short-term orientation when used to control marketing strategies. For instance, Wiesel, Skiera, and Villanueva (2008) presented an illustrative example in which CE deteriorated when a marketing manager attempted to improve current operating profits by gaining new customers at a low retention rate. Casas-Arce, Martínez-Jerez, and Narayanan (2017) claimed that when trying to avoid the short-term focus caused by backward-looking measures, forward-looking measures played an important role because they implicated future financial performances.

CLV entails customer retention (improving the retention rate of customers) and customer expansion (enhancing payoffs from customers). The summation of the CLVs of all current and future customers produces CE, which differs from CLV in that it also includes customer acquisition (increasing the number of new customers). CE is an estimate of firm value as it encompasses current and future customers. Accordingly, CE can evaluate the effects of marketing programs aimed at customer acquisition, retention, and expansion on firm value (Gupta et al., 2006). Although the present study addresses CLV, it focuses on CE as it is a broader concept.

The literature has indicated that CE is useful for planning marketing programs because it separately clarifies the financial effects of customer acquisition, retention, and expansion. Blattberg and Deighton (1996), the first proponents of CE, indicated that it could be used to optimize the resource allocation between customer acquisition and retention. Homburg, Steiner, and Totzek (2009) addressed customer expansion, revealing that the effects of offensive expansion (i.e., promoting profitability amelioration) and defensive expansion (i.e., preventing profitability deterioration) depended on the current levels of customer profitability. Although their focus is on CLV, their findings can readily be extended to CE by multiplying CLV by the number of customers.

When CE is used as a basis for controlling marketing programs, analysis of CE variance is indispensable. This is because such analysis can identify the causes of under- and overachievement of planned CE, such as customer acquisition, retention, and expansion. Although few studies have addressed the issue of variance analysis of CE, the flow statement of CE from current customers proposed by Wiesel et al. (2008) has potential for evolving into a variance analysis of CE.

Therefore, the present study proposes a variance analysis framework with a Markov-based CE model by developing Wiesel et al.'s study in two ways. The first development converts their flow statement framework that focuses on a *change* analysis between current and previous performance for *external* financial reporting into a *variance* analysis

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between budget and actual results for *internal* control of marketing programs. This conversion is divided into three parts: (1) focusing on the variance between budget and actual results, rather than on the change between previous and current performance; (2) incorporating the CE contribution of future customers (FCE) for controlling marketing programs, which is removed from the flow statement framework emphasizing CE contribution from current customers (CCE) for financial reporting;[1] and, (3) following an analysis procedure for providing attention-directing information to managers, rather than for providing decision-making information to investors, through identifying major causes of variance.

The second development replaces the *deterministic* CE model used in Wiesel et al. (2008) flow statement framework with a *probabilistic* CE model based on a Markov chain model. The deterministic model, when estimating CCE, assumes that the retention rate and customer (i.e., payoff per customer) are constant across customers and periods. It also estimates FCE, given that the number of newly acquired customers is constant in every future period (e.g., Pfeifer, 2011; Rust & Ming-Hui, 2014). On the other hand, the probabilistic CE model in this study categorizes customers into multiple heterogeneous states based on their lifecycle. It also allows customer transaction behavior to change over time in accordance with lifecycle transitions.

Although variance information based on the deterministic CE model may be useful for controlling marketing programs, it has two weaknesses. First, the deterministic CE model assumes that CE components, such as the number of future-acquired customers, customer retention rate, and customer payoff are constant over time. In other words, the deterministic CE model simply projects past customer acquisition, retention, and expansion into the future, making it difficult to reflect their future changes in the CE estimate. Second, the deterministic model provides unclear information on the impacts of customer acquisition, retention, and expansion. For example, the deterministic CE model assumes that the impacts of customer expansion are reflected in customer payoffs. However, these are influenced by the effects of customer expansion via upselling, upgrading, increasing usage, or cross-selling (Hogan et al., 2002) and the impacts of pricing and cost management.

This study addresses these issues by proposing the probabilistic CE model based on a Markov chain model called the *Leslie matrix*, developed in mathematical biology (Leslie, 1945). A Leslie matrix expresses the phases of an organism's lifecycle: its birth, growth, maturity, reproduction, and eventual death (Caswell, 2001). Mathematical biology uses this model to clarify the lifecycle phase that should be focused on to efficiently increase the population of a species in the long-term (Caswell, 1978). Because an organism's lifecycle can be interpreted as customer acquisition (organism's birth), retention (survival), and expansion (growth), the application of the Leslie matrix enables an analysis of the effect of each stage on CE. This feature can be used to trace CE variance to customer acquisition, retention, and expansion.

In the present study, the framework of variance analysis based on the probabilistic CE model is applied to a Japanese hotel chain company. The objective of the application is threefold: (1) to provide a possible specification of the probabilistic CE model in practice; (2) to show that the probabilistic CE model provides a better prediction accuracy of future performance than the deterministic CE model and backward-looking model through *k*-fold cross-validation; and, (3) to demonstrate that variance analysis based on the probabilistic CE model provides useful information for controlling marketing programs aimed at customer acquisition, retention, and expansion.

The remainder of this paper is organized as follows: Section 2 reviews the change analysis of CE based on the deterministic model. Section 3 explains the variance analysis of CE based on the deterministic model through an illustrative example. Section 4 develops a framework for the variance analysis of the probabilistic CE model based on the Leslie matrix, whereas Section 5 describes the application of the framework to a Japanese resort hotel chain. Finally, Section 6 presents a discussion and concluding remarks.

2. Change analysis based on the deterministic CE model

2.1. Deterministic CE model

CE was suggested in the 1990s for planning marketing programs to acquire new customers and retain current customers (Blattberg & Deighton, 1996). With the importance of CE being recognized, it has been applied using publicly available data on companies such as American subscription-based enterprises (Bonacchi, Kolev, & Lev, 2015): DISH Network and Sirius XM Holdings (McCarthy, Fader, & Hardie, 2017), Netflix (Schulze, Skiera, & Wiesel, 2012; Wiesel et al., 2008; Zhang, 2016), Overstock.com and Wayfair (McCarthy & Fader, 2018), and Sky Deutschl AG and DIRECTV (Rhouma & Zaccour, 2018). Furthermore, several studies estimated CE using internal data, which enable elaborated analyses. For example, CE was measured for a high-tech company (Kumar & Shah, 2009), an online retailing company (Song, Kim, & Kim, 2016), and a retailing company (Kumar & Shah, 2009; Libai, Narayandas, & Humby, 2002).

Some scholars recognize that CE is useful as a complement to backward-looking measures (Bonacchi et al., 2015). Wiesel et al. (2008) proposed a new form of performance report focusing on CCE for financial reporting. Although Wiesel et al. (2008) proposed the performance report form for external investors, with some modifications, it can also be used for managers to control marketing programs. Therefore, their framework is different from that in other CE studies as it can be used for controlling, rather than planning, marketing programs.

Wiesel et al. (2008) model is an extension of a simple deterministic CE model. CE is the total CLV of current and future customers, or CCE and FCE:

$$CE = CCE + FCE. \tag{1}$$

To obtain CCE and FCE, the deterministic model defines CLV assuming that customer payoff, retention rate, and discount rate remain constant over time (e.g., Bonacchi et al., 2015). Furthermore, customers are assumed to have an infinite lifetime. Given that customers make a transaction at the end of each survival period,

$$CLV = \sum_{s=1}^{\infty} p[r/(1+d)]^{s} = pr \Big/ (1+d-r), \tag{2}$$

where p denotes the customer payoff, d denotes the discount rate or cost of capital for the firm, and r denotes the probability that the customer will repeat purchases or remain as a "survival" in the process.[2] The effects of customer retention and expansion are represented by r and p in Equation (2), respectively.

Current customers are those retained at the end of time 0. Accordingly, CCE is given by

$$CCE = CLVc, \tag{3}$$

where c denotes the number of current customers. The *CLV* factor reflects the effects of current customers' retention and expansion.

[1] Pfeifer (2011) used the term CCE with the same meaning as the present study. Gupta and Lehmann (2006) pointed out that CCE is sometimes referred to as "static customer equity." Silveira, de Oliveira, and Luce (2012) defined static CE and dynamic CE as CCE and FCE, respectively.

[2] Wiesel et al. (2008) used a CLV model that includes the transaction at the end of survival period 0: $CLV = \sum_{s=0}^{\infty} p[r/(1+d)]^{s} = p(1+d)/(1+d-r)$. Equation (2) starts the estimation of CLV at the end of survival period 1 (e.g., Bonacchi et al., 2015). This emphasizes that CLV is purely forward-looking because the payoff of *current* customers at the end of survival period 0 is the interface between past and future.

CLV in Equation (2) must be adjusted when calculating FCE. Future customers make the first payoff when they are acquired, or at their survival period 0. Therefore, the first payoff must be added to the CLV of future customers. The deterministic CE model assumes that the number of new customers is constant over time (Pfeifer, 2011; Rust & Ming-Hui, 2014). Future customers are those acquired starting from the end of time 1Given that the company persists through time,

$$FCE = \sum_{s=0}^{\infty} p[r/(1+d)]^s \sum_{t=1}^{\infty} f \Big/ (1+d)^t = (p + CLV)f \Big/ d, \tag{4}$$

where f denotes the number of future customers newly acquired during each period. The first payoff of future customer acquisition is reflected in p, and successive future customer retention and expansion effects are summarized by the CLV. The right-hand side of Equation (4), f/d, means that acquiring f customers in each of all future periods corresponds to having f/d customers at the end of time 0.

Because the company's CE is an estimate of the operating value, adjusting it for the non-operating assets and debt reaches the company's shareholder value (Schulze et al., 2012), on which the present study does not focus.

2.2. Change analysis

The change analysis framework proposed by Wiesel et al. (2008) is applicable to any model. In the Netflix case study, the researchers applied the change analysis framework to the deterministic CE model. Wiesel et al. (2008) made a modification to both Equations (1) and (3) for financial reporting. First, they focused on CCE and omitted FCE from Equation (1). Second, Wiesel et al. proposed that c in Equation (3), the number of current customers at the end of time 0, should be divided into three customer segments: customers at the *beginning* of time 0, new customers, and lost customers during the same period. Given that CLV is the same in these three customer segments, CCE can also be decomposed into three parts:

$$CCE = BCE + NCE - LCE, \tag{5}$$

where BCE, NCE, and LCE are the CE contributions from customers at the beginning of time 0, new customers, and lost customers, respectively. The segment-by-segment CCE statement is called a *stock statement* because CCE indicates the value from customers at a certain moment in time. Furthermore, the comparison of the last and current stock statements is called a *flow statement*, which summarizes the changes in CCE between the last and current periods.

Wiesel et al. (2008) proposed that two kinds of flow statements should be provided to investors: flow statements from a *components viewpoint* and from an *effects viewpoint*. A flow statement from a components viewpoint shows the change in CCE on a segment-by-segment basis by simply comparing previous and current CCEs. In other words, the change in the total CCE is decomposed into the changes in BCE, NCE, and LCE. A flow statement from an effects viewpoint provides information on the impacts of customer metrics, such as customer payoff, retention rate, and the number of current customers, on the change in CCE. The sum of all the impacts is equal to the change in total CCE.

3. Variance analysis based on the deterministic CE model

3.1. From change analysis to variance analysis

Flow statements from the components and effects viewpoints analyze changes in CCE because they are designed to provide decision-making information to investors. To convert them into variance analysis report that provides attention-directing information to marketing managers, three revisions are needed. First, what should be analyzed is the variance between the budget and the actual results, rather than the change between the last and current results. Wiesel et al. (2008) emphasized the change between the last and current periods because their purpose was to propose a framework for financial reporting. However, what managers need for controlling marketing programs is variance information, because it shows whether the predetermined budget was achieved or not. The goal of variance analysis is to improve future performance by promoting organizational learning (Datar & Rajan, 2017, p. 286).

Second, CE variance analysis should incorporate not only CCE but also FCE. Since CE is the sum of CCE and FCE, acquiring, retaining, and expanding future customers could largely influence FCE and eventually CE. Wiesel et al. (2008) intentionally focused on CCE because they aimed to propose a framework for financial reporting. By focusing on CCE, companies can "avoid the challenges of forecasting the number of and outcomes from customers acquired in the future" (Pfeifer, 2011, p. 1). However, for control purposes, a variance analysis should include both CCE and FCE because the goal of marketing is to maximize CE.

Finally, CE variance analysis should provide attention-directing information through a sequential variance decomposition to identify major causes of over- or underachievement. In financial reporting, the information provider and the recipients are inside and outside the company, respectively. The purpose of information provision is to assist the recipients with further analysis and decision-making. Accordingly, financial reporting is oriented toward providing detailed information. In controlling marketing programs, on the other hand, both the information provider and recipients are inside the company. Analysis for controlling marketing programs emphasizes the identification of major causes of variance, directing the manager's attention to the area that requires corrective action. To efficiently identify the major causes of variance, a multilevel analysis is useful (Govindarajan & Shank, 1989; Shank & Churchill, 1977), in which the total variance is first calculated, and then complexity is added sequentially based on customer segments and customer metrics. This method integrates both the components and effects viewpoints of flow statements proposed by Wiesel et al. (2008). For example, CCE variance can be first decomposed into CLV and customer quantity (i.e., the number of customers) variances (the effects viewpoint), and then customer quantity variance can be broken into BCE, NCE, and LCE variances (the components viewpoint). By adding complexity sequentially, the effects and components viewpoints are integrated, assisting marketing managers in identifying the major causes of variance.

3.2. Illustrative example of variance analysis

To show how the three revisions convert change analysis into variance analysis, Table 1 shows almost the same numerical example on the deterministic CE model as the one in Wiesel et al. (2008). Notably, this illustration ignores acquisition costs when estimating FCE as they do not affect the core story from the results. First, Table 1 compares the budget and actual results to obtain the CE variance. This informs managers of the effectiveness of planned marketing programs, promoting organizational learning for future performance improvement.

Second, Table 1 estimates not only CCE but also FCE. As Wiesel et al. (2008) focused on financial reporting, they compared the total payoff as a backward-looking measure (row (6) in Table 1) and CCE as a forward-looking measure (row [10] in Table 1). The actual total payoff exceeds

Table 1
Illustrative example of CE estimation based on the deterministic model.

	Budget	Actual result	Variance/ budget
(1) Customer payoff (thousand yen)	10	12	20.0%
(2) Number of customers at the beginning of period	1000	1000	0.0%
(3) Number of new customers	150	300	100.0%
(4) Number of lost customers	100	200	100.0%
(5) Number of current customers = (2) + (3) – (4)	1050	1100	4.8%
(6) Total payoff = (1) × (5) (thousand yen)	10,500	13,200	25.7%
(7) Retention rate = [(2) – (4)] / (2)	0.90	0.80	−11.1%
(8) Discount rate	0.1	0.1	0.0%
(9)[a] CLV = (1) × (7) / [1 + (8) – (7)] (thousand yen)	45	32	−28.9%
(10) CCE = (9) × (5) (thousand yen)	47,250	35,200	−25.5%
(11) FCE = [(1) + (9)] × (3) × [1 + (8)] / (8) (thousand yen)	90,750	145,200	60.0%
(12) CE = (10) + (11) (thousand yen)	138,000	180,400	30.7%

[a] CLV, CCE, and FCE are estimated based on Equations (2), (3), and (4), respectively.

that of the budget by 25.7%, whereas the actual CCE is 10.2% less than that of budget. As will be described later, the major reason for this is that the actual retention rate (0.80) falls short of the budget (0.90) (row (7) in Table 1). However, the other part of CE, FCE (row [11] in Table 1), has further implications. The actual FCE surpasses that of the budget by 60.0%. This is caused by an overachievement of the number of new customers goal by 100%, leading to cash flow acceleration (row [3] in Table 1).[3] The favorable FCE variance fully complements the unfavorable CCE variance, which results in an overachievement of CE by 30.7% (row [12] in Table 1).

Finally, Fig. 1 analyzes the unfavorable CCE variance to show how variance analysis directs the manager's attention to major causes of underachievement. This approach starts with an overall comparison between the budgeted and actual CEs, and then sequentially adds complexity. A level 1 analysis produces a CCE variance of 12,050 thousand yen (U) by simply subtracting the budgeted CCE (CCE_{b1}) from the actual CCE (CCE_a). In a level 2 analysis, the flexible CCE budget (CCE_{b2}), in which the budgeted number of current customers is substituted for the actual result, is used to decompose the level 1 variance. The difference between CCE_a and CCE_{b2} is the CLV variance of 14,300 thousand yen (U). Subtracting CCE_{b1} from CCE_{b2} yields customer quantity variance of 2250 thousand yen (F). These results demonstrate that CLV underachievement is the cause of the unfavorable CCE variance. To identify causes of unfavorable CLV variance, a level 3 analysis further adds complexity through the use of another flexible budget, CCE_{b3}, which replaces the budgeted retention rate in CCE_{b2} with the actual result. The results show a customer payoff variance of 5,867 thousand yen (F) and retention rate variance of 20,167 thousand yen (U). Therefore, the most important cause of the unfavorable CCE variance is the underachievement in the retention rate.

Levels 1, 2, and 3 illustrate a variance analysis from the effects viewpoint. If the manager considers the major causes identified, then he/she can stop the analysis. However, if necessary, the manager can add more complexities to further explore the variance causes. In the additional analysis, both the components and effects viewpoints can be incorporated. For example, customer quantity variance of 2250 thousand yen (F) can be divided into the BCE variance of 0 yen, NCE variance of 6750 thousand yen (F), and LCE variance of 4500 thousand yen (U) (Level 3 components viewpoint). In addition, if the manager is interested in the causes of customer payoff variance, it can be broken into customer sales, cost of goods sold, and marketing cost variances (Level 4 components viewpoint). The customer sales variance can be further divided by product categories (Level 5 components viewpoint), which, in turn, can be decomposed into selling price and quantity variances (Level 6 effects viewpoint). The same approach can be applied to FCE variance.

[3] The customer base in the deterministic CE model converges to a constant value because the numbers of new and lost customers eventually become the same. In this example, both the actual and budgeted convergence customer base sizes are 1500 (300/[1 – 0.8] in the actual results and 150/[1 – 0.9] in the budget). Nevertheless, the actual CE largely exceeds the budgeted CE. This is because the actual customer base converges faster than the budgeted one, creating the effect of cash flow acceleration (Srivastava, Shervani, & Fahey, 1998).

3.3. *Weaknesses of variance analysis based on the deterministic CE model*

Variance analysis directs a manager's attention to major causes of variance and promotes organizational learning for future performance improvement. As indicated in the introduction, however, the deterministic CE model has two limitations that restrict the usefulness of variance analysis. First, the model assumes that the effects of customer acquisition, retention, and expansion are constant over time. However, it is more realistic to assume that the customer acquisition effect increases depending on the size of the customer base. This is because the company obtains money for customer acquisition investment from its current customer base. In addition, some customers become more loyal over time and their retention rate and payoff increase. Because CE is a forward-looking measure, its underlying model must be based on more realistic assumptions.

Second, variance analysis based on the deterministic CE model does not provide a clear picture of the customer acquisition, retention, and expansion effects. The customer acquisition effect is reflected both in the new customer variance in the CCE variance and in the FCE variance. In addition, the FCE variance includes not only the acquisition, but also the retention and expansion of future customers. The customer retention effect is also spread across the lost customer variance and retention variance in the CCE variance, and the retention variance in the FCE variance. Finally, the customer expansion effect emerges in the customer payoff variance in the CCE variance and that in the FCE variance. However, the customer expansion effect and the pricing and cost management effects are mixed within customer payoff variance.

A possible method for addressing the deterministic CE model limitations is to employ a probabilistic CE model based on the Leslie matrix, a Markov chain model developed in mathematical biology.

4. Variance analysis based on the probabilistic CE model

4.1. *Customer state*

Several discussions have focused on ways to identify customer lifecycle stages. The relationship development process proposed by Dwyer, Schurr, and Oh (1987) is one of the first models to categorize customer states. The model suggested five general phases in customer relationship development: awareness, exploration, expansion, commitment, and dissolution or defection. Reichheld and Sasser (1990), who regarded the financial effects of customer loyalty as critical, categorized customers as follows: new customers, loyal and non-loyal customers, and lost customers. Kotler and Kevin (2016) elaborated the *marketing funnel*, with eight stages for potential customer loyalty: target market, awareness, openness to trials, triers, recent users, regular users, customers using the brand the most often, and loyal customers.

Some scholars have proposed using customer behavior-based segmentation to identify customer loyalty states. Storbacka (1997) elaborated customer behavior-based measurements. These included customer revenue and cost, volume, profitability, and the combination of volume and profitability. Zeithaml, Rust, and Lemon (2001), who focused on the fact that loyalty differs among customers, proposed the *customer pyramid*, segmenting customers into four groups in order of profitability:

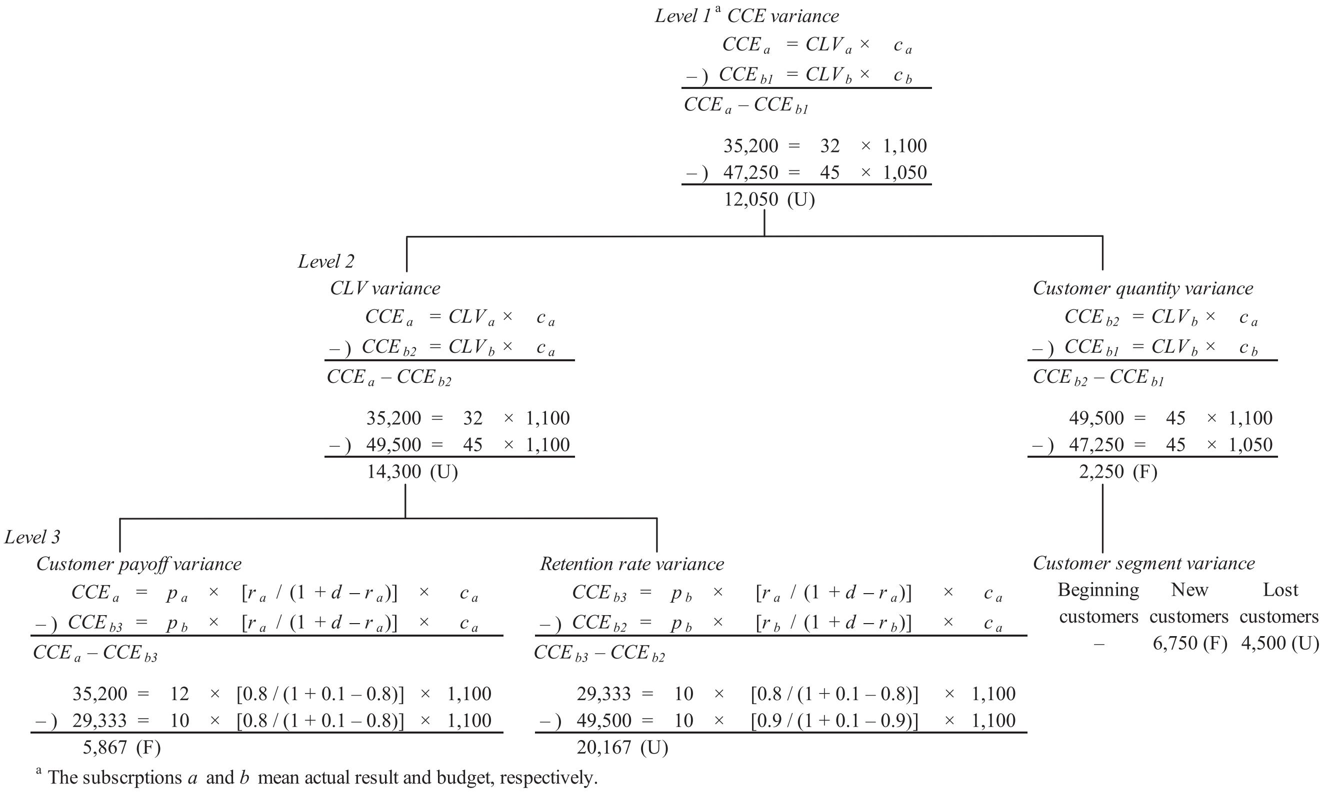

Fig. 1. Illustrative example of CCE variance analysis based on the deterministic model.

platinum, gold, iron, and lead. Ekinci, Ülengin, Uray, and Ülengin (2014) applied the idea of the customer pyramid to CLV estimation based on a Markov chain model.

This study uses two criteria to define customer states. The first criterion is relationship existence, which distinguishes between *new customers* and *lost customers*. For example, customers who have recently completed their first transaction with the firm are new customers, and those who have not made any transactions with the firm over a given period are lost customers. Other variables, such as cancellation of contract can be used as a criterion to help identify lost customers. These new and lost customer states are indispensable because they are necessary for capturing customer acquisition and retention effects.

The second criterion is customer behavior, which identifies the loyalty states of current customers who are neither new nor lost customers. Current customers must be categorized into multiple states based on a behavior criterion. Otherwise, the customer expansion effect cannot be measured. The number of customer behavior states is unlimited as long as more than one such state exists. For example, the application in Section 5 illustrates that the Japanese hotel chain categorized its current customers into four states based on a customer behavior criterion. For simplicity, the examples in this section divide current customers into only two states: *high-loyal* and *low-loyal*.

The four customer states are labeled as follows: new customers = 1, high-loyal customers = 2, low-loyal customers = 3, and lost customers = 4. Based on this labeling, let the number of customers in each state at the end of a period be c_1, c_2, c_3, and c_4. Then, the column vector for customer state distribution is

$$\boldsymbol{c} = \begin{pmatrix} c_1 \\ c_2 \\ c_3 \\ c_4 \end{pmatrix} \tag{6}$$

4.2. Customer lifecycle

The Leslie matrix depicts an organism's lifecycle using age-classified fertility and survival rates or death rates and estimates population and age distributions (Leslie, 1945). In the context of CE, fertility rate, survival rate, population, and age distribution represent acquisition rate, retention rate, customer base, and customer state distribution, respectively. Based on the original Leslie matrix, this section describes the *customer lifecycle matrix*, which is the sum of customer acquisition, retention, and expansion matrices (Matsuoka, 2019).

First, to construct the customer acquisition matrix, the acquisition rate should be defined. This study assumes that customer acquisition progresses at a constant ratio to the customer base. Customer acquisition programs, including advertisement and promotional campaigns, require investments, which can be written off in a lump. Therefore, for the company to make ends meet, investments in customer acquisition must be smaller than the profits made from the current customer base. Thus, the customer acquisition matrix is

$$\boldsymbol{A} = \begin{pmatrix} a & a & a & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}, \tag{7}$$

where the customer acquisition rate a is the ratio of the number of new customers in the next period to the number of current customers. Second, the customer retention matrix contains the retention rates that separate lost customers in the next period from the current customers:

$$\boldsymbol{R} = \begin{pmatrix} r_1 & 0 & 0 & 0 \\ 0 & r_2 & 0 & 0 \\ 0 & 0 & r_3 & 0 \\ 1 - r_1 & 1 - r_2 & 1 - r_3 & 0 \end{pmatrix}, \tag{8}$$

where each of the retention rates is defined as the probability that the current customer in question does not become a lost customer in the next period. Third, some of the retained customers become more loyal (i.e., positive expansion) or less loyal (i.e., negative expansion). As customers move to different customer states, the numbers of customers in their origin and destination customer states are adjusted accordingly. This is shown in the customer expansion matrix as follows:

$$\boldsymbol{E} = \begin{pmatrix} -r_1 & 0 & 0 & 0 \\ e_{12} & e_{22}-r_2 & e_{32} & 0 \\ e_{13} & e_{23} & e_{33}-r_3 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}, \tag{9}$$

where the expansion rates are defined as the transition probabilities of the current customers to another current customer state during the next period. Notably, the sum of the elements in each column of the expansion matrix is zero because the number of customers entering a destination state is the same as that of customers leaving the origin state.

Finally, summing the customer acquisition, retention, and expansion matrices gives the customer lifecycle matrix:

$$\boldsymbol{L} = \boldsymbol{A}+\boldsymbol{R}+\boldsymbol{E} = \begin{pmatrix} a & a & a & 0 \\ e_{12} & e_{22} & e_{32} & 0 \\ e_{13} & e_{23} & e_{33} & 0 \\ 1-r_1 & 1-r_2 & 1-r_3 & 0 \end{pmatrix} \tag{10}$$

All the elements in the last column are zero because lost customers do transit to any other state. The customer lifetime matrix captures customer acquisition, retention, and expansion in a single model. Equation (10) multiplied by Equation (6) generates the customer state vector at the end of the period. Therefore, when the customer lifecycle matrix, $\boldsymbol{L}$, is constant over time, the inner product of the t-th power of $\boldsymbol{L}$ from Equation (10) and $\boldsymbol{c}$ from Equation (6) yields the customer state vector after t iterations:

$$\boldsymbol{c}_t = \boldsymbol{L}^t\boldsymbol{c}. \tag{11}$$

4.3. Customer payoff

The information from a customer profitability analysis (CPA) can be used as the basic input for estimating CE (Niraj, Gupta, & Narasimhan, 2001). Customer payoff (i.e., payoff per customer) is defined as

$$p = Customer\ \ sales - Customer\ \ level\ \ costs. \tag{12}$$

Assuming a cost hierarchy, a CPA utilizing activity-based costing (ABC) enables the sophisticated allocation of customer-level costs, which include customer output unit-level costs, customer batch-level costs, and customer retention costs (Matsuoka, 2020). Customer acquisition costs are usually ignored in a CPA because they are written off in a lump, whereas acquired customers generate revenues in multiple periods (Niraj et al., 2001; Pfeifer, Haskins, & Conroy, 2005). When customer payoff is used as an input for CE estimation, customer acquisition costs should also be included in the calculation of customer payoff because CE encompasses future periods. Furthermore, one should adjust for the effects of expenses without cash outflows, such as depreciation and amortization costs on taxes, because CE estimation requires cash flows to be discounted.

Let $\boldsymbol{p}$ be the row vector of the payoff from each customer state:

$$\boldsymbol{p} = (\,p_1 \quad p_2 \quad p_3 \quad p_4\,), \tag{13}$$

where each p_i ($i = 1,\ldots,4$) shows the payoff from a customer in state i. Lost customers may create some cash inflows because they may make transactions during their final relationship period. For example, in a newspaper subscription setting, lost customers pay for the entire month in which they terminate their contract.

4.4. CE

Note that Equation (11) provides the number of customers in each customer state at time t. Thus, simply discounting the inner products of equations (13) and (11) for an infinite time horizon produces CE:

$$CE = \sum_{t=1}^{\infty}\boldsymbol{p}\left[\boldsymbol{L}(1+d)^{-1}\right]^t\boldsymbol{c} = \boldsymbol{pL}[\boldsymbol{I}(1+d)-\boldsymbol{L}]^{-1}\boldsymbol{c}. \tag{14}$$

Two modifications can yield CLV from the customer lifecycle matrix (Matsuoka, 2019). First, the customer lifecycle matrix ($\boldsymbol{L}$) in Equation (14) must be replaced by the composite matrix of the retention and expansion matrices ($\boldsymbol{R}+\boldsymbol{E}$) to eliminate the effects of the acquisition of future customers. Second, the customer state vector ($\boldsymbol{c}$) in Equation (14) must be omitted. These modifications in Equation (14) produce a row vector composed of state-by-state CLVs for current customers' survival time:

$$\boldsymbol{CLV} = \boldsymbol{p}\sum_{s=1}^{\infty}\left[(\boldsymbol{R}+\boldsymbol{E})(1+d)^{-1}\right]^s = \boldsymbol{p}(\boldsymbol{R}+\boldsymbol{E})[\boldsymbol{I}(1+d)-(\boldsymbol{R}+\boldsymbol{E})]^{-1}. \tag{15}$$

Multiplying CLV by the customer state vector,

$$CCE = \boldsymbol{CLVc}. \tag{16}$$

To obtain FCE, the number of future customers in each period must be determined. Combining the acquisition and customer lifecycle matrices, a row vector for the number of future customers acquired in period t ($\boldsymbol{f}_t$) can be defined as follows:

$$\boldsymbol{f}_t = \boldsymbol{AL}^{t-1}\boldsymbol{c}. \tag{17}$$

The future customers acquired in period t are retained and expanded for their survival time. In addition, future customers make the first payoff at their survival period 0, which must be added to their CLV. Therefore, their contribution to CE, or FCE_t, is given by

$$FCE_t = \sum_{s=0}^{\infty}\boldsymbol{p}\left[(\boldsymbol{R}+\boldsymbol{E})(1+d)^{-1}\right]^s\boldsymbol{f}_t(1+d)^{-t} = (\boldsymbol{p}+\boldsymbol{CLV})\boldsymbol{f}_t(1+d)^{-t}. \tag{18}$$

Assuming an infinite time horizon,

$$FCE = \sum_{t=1}^{\infty}(\boldsymbol{p}+\boldsymbol{CLV})\boldsymbol{f}_t(1+d)^{-t} = (\boldsymbol{p}+\boldsymbol{CLV})A[\boldsymbol{I}(1+d)-\boldsymbol{L}]^{-1}\boldsymbol{c}. \tag{19}$$

4.5. Variance analysis

Fig. 2 is a framework of variance analysis based on the probabilistic CE model. This model incorporates five customer metrics: the customer payoff vector; the customer acquisition, retention, and expansion matrices; and, the customer state vector. In accordance with a multilevel variance analysis procedure, rotating each factor sequentially from the budget to the actual results produces specific, separable impacts (Govindarajan & Shank, 1989). CE_{b1} and CE_a are the budgeted and actual CE, respectively. The level 1 analysis compares them and provides the CE variance.

In the level 2 analysis, the CE variance is decomposed using CE_{b2} and CE_{b5}. CE_{b2} is a flexible budget of CE that changes the customer state vector from the budgeted one to the actual result and keeps the remaining four metrics budgeted. CE_{b5} is a flexible budget calculated by further replacing the budgeted values in the customer lifecycle matrix ($\boldsymbol{A}+\boldsymbol{R}+\boldsymbol{E}$) in CE_{b2} with the actual results. Subtracting CE_{b1} from CE_{b2}, CE_{b2} from CE_{b5}, and CE_{b5} from CE_a produces the customer state variance, customer lifecycle variance, and customer payoff variance, respectively.

Finally, the customer lifecycle variance is decomposed in the level 3 analysis. This variance is the sum of the customer acquisition, retention, and expansion matrices. Thus, changing the elements of the three matrices from budgeted to actual results sequentially, estimating the flexible CE budgets, and comparing them produces the customer acquisition variance ($CE_{b3} - CE_{b2}$), customer retention variance ($CE_{b4} - CE_{b3}$), and customer expansion variance ($CE_{b5} - CE_{b4}$). A level 4 analysis or beyond can be conducted as appropriate. For example, the customer

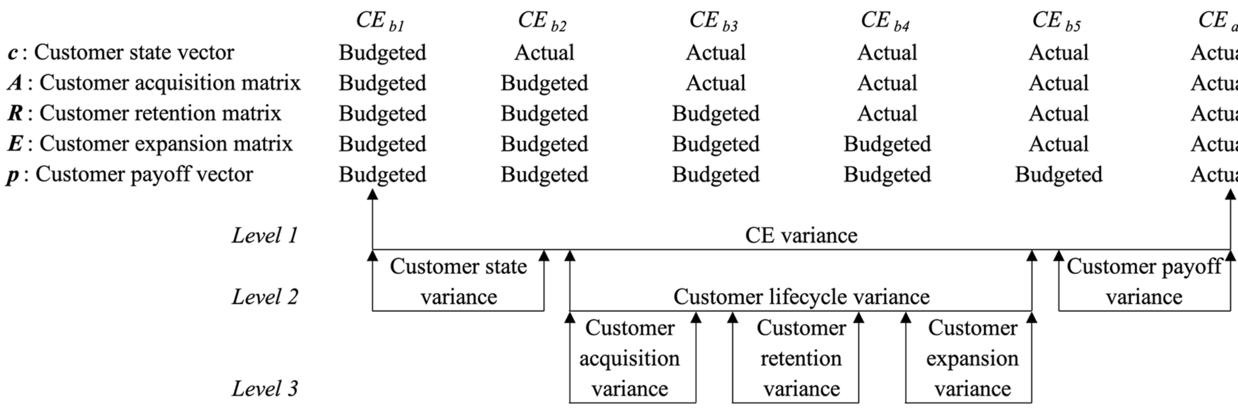

Fig. 2. Variance calculations using the dynamic CE model.

retention variance could be divided into variances of new customers, high-loyal customers, and low-loyal customers.

4.6. *Strengths of variance analysis based on the probabilistic model*

Variance analysis based on the probabilistic CE model overcomes two limitations of variance analysis based on the deterministic CE model. First, the probabilistic CE model allows the effects of the acquisition, retention, and expansion on CE to change over time. Second, the variance analysis based on the probabilistic CE model can provide a clearer picture of customer acquisition, retention, and expansion effects as the customer lifecycle matrix is the sum of the three matrices. Overall, the framework of variance analysis based on the probabilistic CE model is expected to provide useful attention-directing information for controlling marketing programs aimed at improving customer acquisition, retention, and expansion.

Scholars have been developing CLV and CE models based on Markov processes since CLV models incorporating the effects of changes in customer states over time were first proposed (Berger & Nasr, 1998; Dwyer, 1997). Pfeifer and Carraway (2000) established a CLV model based on Markov processes, and Libai et al. (2002) indicated that Markov processes could estimate CCE. These models, however, did not consider the effects of customer acquisition, and they did not address FCE. Rust, Lemon, and Zeithaml (2004) used a brand-switching matrix to develop a CE model that incorporated acquisition and retention rates. However, the model did not accommodate the effects of customer expansion. Based on these models, a range of applications associated with real business situations have been created (Aeron, Bhaskar, Sundararajan, Kumar, & Moorthy, 2008; Esteban-Bravo, Vidal-Sanz, & Yildirim, 2014; Haenlein, Kaplan, & Beeser, 2007; Homburg et al., 2009; Stahl, Heitmann, Lehmann, & Neslin, 2012; Tirenni et al., 2007).

Although a detailed comparison of all the models based on Markov processes is out of the scope of this study, it is worth emphasizing the importance of the framework developed here. Because the customer lifecycle matrix accommodates customer acquisition, retention, and expansion rates in a single model, variance information provides a useful input for controlling a company's marketing strategy. For example, it is relatively easy to relate the decomposed variances to changes in marketing programs, including advertisement and promotional campaigns (for customer acquisition); loyalty programs and service improvements (for customer retention); and, up-sell, upgrade, increased usage, and cross-sell programs (for customer expansion).

5. Application

5.1. *Objectives*

This section presents an application of the probabilistic CE model and the variance analysis based on it to a Japanese hotel chain. The objectives of this application are threefold. The first objective is to specify the customer state vector, customer lifecycle matrix, and customer payoff vector for a real company. The second aim is to compare, using real data, the backward-looking model and the two forward-looking models (i.e., the deterministic and probabilistic models). Finally, the application shows the results of a variance analysis based on the probabilistic CE model to illustrate that the framework is useful for controlling marketing programs aimed at customer acquisition, retention, and expansion.

The application to a Japanese hotel chain uses the same dataset reported in a conference paper (Matsuoka, 2019).[4] However, this study extracts new results, discussion, and conclusions by substantially improving the model used in the conference paper. First, the probabilistic CE model in this study assumes that noncustomer-level costs should not be allocated to customers when calculating customer profitability, because such allocation could distort a CE estimate. Second, the probabilistic CE model in this study removes payoffs of current customers at time 0 from a CE estimate, because the initial transactions refer to past, rather than future, performance. This enables the comparison between total payoff at time 0 as a backward-looking measure and CE (i.e., present value of total payoff since time 1) as a forward-looking measure. Third, this study shows that CCE and FCE can be separately modeled and claims that not only CCE but also FCE, should be considered when estimating CE. Finally, this study proposes a comprehensive framework for CE variance analysis. Matsuoka (2019) did not indicate customer payoff variance and customer lifecycle variance, which are encompassed in the framework of this study.

5.2. *Research site*

As described by Matsuoka (2019), the research site was a Japanese resort hotel chain that operates nearly 20 facilities in Japan and whose main customer targets were families and couples. The average hotel size was approximately 60 rooms, and the average daily rate was approximately 30,000 yen. Note that the ADR included restaurant revenues in addition to room rates because most of the company's customers spent nights and had dinner and breakfast at the hotel. The company sold membership rights and divided its customers into two groups: members and non-members. Members differed from non-members in that they obtained a range of benefits such as cheaper room rates and priority reservations in return for purchasing a membership and paying the annual membership fees. The membership sales and the hotel operation departments were separated, and each compiled their own profit-and-

[4] I would like to thank Dr. Susumu Ueno, the Chair of the Board of Directors of the Asia-Pacific Management Accounting Association, for the permission to use the data from the conference paper.

loss statements as independent profit centers.

This study provides a twofold focus on members. First, the relationship management of members is considered the most crucial success factor for this Japanese resort hotel chain. The scope of the company's relationship marketing strategy is evaluated through the customer acquisition, retention, and expansion variances in the customer lifecycle model. Second, the detailed longitudinal transaction data necessary for estimating the customer lifecycle matrix can only be obtained for members. Further, the membership enrollment and cancellation dates can be specified for individual customers. Furthermore, a customer's behavioral loyalty stage can be identified by examining the transaction history. Thus, the members of this Japanese resort hotel chain are suitable for this study.

5.3. Description of the data

The data required to estimate the customer lifecycle matrix (***L***) were collected for the three fiscal year periods from April 1, 2014, to March 31, 2017. In order to create one customer lifecycle matrix, two fiscal year data should be required. Thus, the three consecutive fiscal year data enabled two customer lifecycle matrices to be formed. The corresponding data were gathered for the initial customer state vector (***c***) and the customer payoff vector (***p***). The discount factor (*d*) was simply set to 10%.

A budget has two functions: a planning function through budget preparation, and a control function through variance analysis. The budget must be prepared before the variance analysis and is decided based on the company's current resources. Therefore, budget preparation starts by referring to the company's previous performance, and then expected future changes in external and internal environments are considered (Anthony, Govindarajan, Hartmann, Kraus, & Nilsson, 2014, p. 344). The focus of this study is on the control, rather than the planning, function of a budget. Therefore, for brevity, in this application, the company's actual results in FY2015 were regarded as the budget for FY2016.

Details on the collected data are provided below. The calculated numbers in this application were subject to a rounding error because they were accomplished using Microsoft Excel without rounding or truncation.

5.3.1. Customer state vector

Customers were segmented based on the existence of a relationship between them and the company and on their behavior-based loyalty. The existence of a relationship was identified by the enrollment and withdrawal dates on the membership list. To measure profitability, the annual number of rooms booked per member was used because it was not susceptible to revenue management, a popular dynamic pricing method in the hotel industry.

No definite threshold existed for behavior-based loyalty segmentation. Therefore, in this application, a decile analysis was employed to obtain the distribution of the number of rooms customers book in a year. Thus, 9 thresholds that evenly divided customers into 10 groups were used (Table 2). The patterns were quite similar for the data from FY2014, FY2015, and FY2016. Therefore, for the segmentation, the threshold modes of the three years were used. To reduce customer states into manageable lots, the customers of every two groups starting from the top were combined. The bottom three groups, which included no customers, were combined into one group. Thus, four customer states were created:

Tier I = customers who booked eight or more rooms annually
Tier II = customers who booked between three and seven rooms annually
Tier III = customers who booked one or two rooms annually
Tier IV = customers who did not book any rooms annually.

Table 2
Decile analysis of the number of rooms.

Percentile	Thresholds for the number of rooms			
	FY2014	FY2015	FY2016	Mode
10	0	0	0	0
20	0	0	0	0
30	0	0	0	0
40	1	1	1	1
50	2	2	2	2
60	3	3	4	3
70	5	5	5	5
80	8	7	8	8
90	14	12	12	12

Source: Adapted from Matsuoka (2019).

The customer state vectors for the budget and actual results for FY2016 are presented in Table 3. The budgeted total number of customers at the end of FY2016 (that is, the actual total number of customers at the end of FY2015) was set to 1000 for confidentiality reasons. However, this did not influence the patterns in the results. The total number of customers included those who defected in the previous year. Therefore, to obtain the budgeted number of *current* customers at the end of FY2016, the number of lost customers should be removed from the total number of customers.

5.3.2. Customer lifecycle matrix

Table 4 presents the customer lifecycle matrix for the budget and actual results for FY2016. As previously noted, the budgeted customer lifecycle matrix was derived from the actual results in FY 2015. The customer acquisition rate slightly exceeded from 5.6% in the budget to 6.6% in the actual results. Overall, the customer retention rates overachieved their budget, except for the one in Tier III. The largest deviation occurred in Tier IV, where the rate improved from 86.1% (1–0.139) in the budget to 92.9% (1–0.071) in the actual results. Approximately, the customer expansion rates exhibited similar patterns in both of the customer lifecycle matrices. However, some probabilities varied significantly. For example, the expansion rates from new to Tier I were 23.8% in the budget and 35.8% in the actual results. Similarly, the expansion rates from Tier I to Tier I (i.e., the probability of customers not expanding to any other state) were 59.6% in the budget and 68.4% in the actual results. These differences in the customer acquisition, retention, and expansion rates revealed the necessity of variance analysis to identify the key causal factors of CE variance.

5.3.3. Customer payoff vectors

The membership business of the hotel chain had three sources of payoffs: enrollment, membership, and hotel (Table 5). The calculation of the enrollment payoff was somewhat complicated. The membership sales department was responsible for customer acquisition and therefore, costs in the department were considered to be customer acquisition costs. Profits in the membership sales department were affected by depreciation costs. Therefore, they were added back to profits after taxes. Fixed costs, including depreciations, were assigned to each

Table 3
Number of customers by customer states at the end of the year.

	Budget	Actual result
New	56	61
Tier I	185	195
Tier II	244	247
Tier III	158	173
Tier IV	286	272
Lost	71	42
Total	1000	990
Current customers	929	948

Table 4
Customer lifecycle matrices (%).

		Budget						Actual result					
		Beginning states						Beginning states					
		New	Tier I	Tier II	Tier III	Tier IV	Lost	New	Tier I	Tier II	Tier III	Tier IV	Lost
Ending states	New	6.0	6.0	6.0	6.0	6.0	0.0	6.4	6.4	6.4	6.4	6.4	0.0
	Tier I	21.7	57.6	17.9	5.7	1.8	0.0	33.5	66.9	16.3	5.3	1.6	0.0
	Tier II	26.1	26.6	45.2	31.1	8.5	0.0	20.9	25.0	48.1	27.5	10.1	0.0
	Tier III	14.8	7.2	18.6	33.6	13.4	0.0	12.1	3.8	21.2	35.5	17.9	0.0
	Tier IV	28.6	5.3	13.9	25.3	62.4	0.0	27.2	2.2	11.5	27.5	63.3	0.0
	Lost	8.9	3.4	4.5	4.3	13.9	0.0	6.3	2.2	3.0	4.3	7.1	0.0

Table 5
Payoff calculations.

	(i) Enrollment payoff	(ii) Membership payoff	(iii) Hotel payoff
(1) Revenues	Enrollment sales	Annual membership sales	Hotel sales
(2) Costs	Cost of goods sold and S&GA costs of the membership sales dept.	–	Cost of goods sold of the hotel operation dept.
(3) Taxes	30%	30%	30%
(4) Depreciation	Depreciation costs of the membership sales dept.	–	–
(5) Cashflow	[(1) – (2)] × [1 – (3)] + (4)	(1) × [1 – (3)]	[(1) – (2)] × [1 – (3)]

customer because they were variable in the long term. The membership payoff simply represents the annual membership sales. Some sales and general administration expenses in the hotel operation department should be allocated to membership sales. Unfortunately, the company did not have a sophisticated costing system (e.g., ABC), and the portion of S&GA expenses to be attributed to membership sales could not be determined. Therefore, no S&GA expense was allocated to membership sales. Furthermore, the hotel payoff equals the gross profit margin after taxes. A certain amount of S&GA expenses should be assigned as service costs for retaining customers. However, due to the absence of ABC, it was not possible to allocate S&GA expenses to the hotel payoff.

Table 6 shows budgeted and actual customer payoffs for FY2016. The budgeted customer payoffs were calculated based on the actual results in FY 2016. The payoff from new customers was much larger because they generated enrollment sales. Tier IV customers, who did not spend any nights at one of the company's hotels during the year, generated membership payoffs.

5.4. Model comparison

5.4.1. Customer payoff and CLV

Table 6 indicates that, on the whole, customer payoffs were below budget. Only the customer payoff of new customers overachieved its budget. However, after excluding enrollment payoffs, it underachieved its budget (76.5 for the budget and 70.5 for the actual result).

Table 6
Customer payoff (i.e., payoff per customer) and CLV (thousand yen).

	Customer payoff		Deterministic CLV		Probabilistic CLV	
	Budget	Actual result	Budget	Actual result	Budget	Actual result
Retained[a]	89.3	85.3	465.2	571.1	–	–
New[b]	612.4	668.0	–	–	501.5	613.6
Tier I	170.2	160.0	1242.8	1293.6	634.1	743.4
Tier II	92.6	87.0	629.2	663.3	543.3	619.8
Tier III	64.1	61.8	447.7	432.0	493.1	556.3
Tier IV	48.2	45.3	209.9	271.5	382.2	491.4
Lost	62.3	61.1	0.0	0.0	0.0	0.0

[a] Customer payoff of retained customers is the weighted average of tiers I to IV.

[b] The deterministic CLV of new customers is not estimated because the deterministic model does not identify to which tier they will transit during the remainder of their survival period.

Table 6 also presents the CLV estimates, showing the opposite pattern to customer payoff. Because the Japanese hotel chain customers make payoffs during the year they defect, the deterministic CLV model in Equation (2) is revised as follows:

$$CLV = \sum_{s=1}^{\infty}\left[p_r r^s + p_l r^{s-1}(1-r)\right] \Big/ (1+d)^s$$
$$= \left[p_r r + p_l(1-r)\right] \Big/ (1+d-r), \tag{20}$$

where p_r and p_l are payoff from retained (i.e., tiers I, II, III, and IV) and lost customers, respectively. The actual result of the deterministic CLV (571.1 thousand yen) of retained customers (i.e., customers in tiers I, II, III, and IV) exceeded the budget (465.2 thousand yen), reflecting the overachievement of the customer retention rate from 0.925 for the budget (based on Table 3, 1–71/ [1000–56]) and 0.955 for the actual result (1–42 / [990–61]).

The probabilistic CLV model in Equation (15) was employed to obtain the state-by-state CLVs. Each CLV exceeded the budget because of retention and expansion effects. Revised CLVs, obtained by reinserting the retention matrix in the budgeted CLV in the actual retention matrix, exceeded the budgeted CLV in each customer state (retention effect, not reported in Table 6). For example, the CLV of Tier I increased from 634.1 thousand yen to 715.6 thousand yen. Replacing the budgeted retention and expansion matrices in the budgeted CLVs with the actual results further improved CLVs compared to the revised CLVs (expansion effects). For instance, the CLV of Tier I rose from 715.6 thousand yen to 788.3 thousand yen. Subtracting the re-revised CLVs from the actual CLVs yielded a customer payoff effect. In Tier I, it was −45.0 thousand yen (743.4–788.3).

Finally, by removing an expansion matrix from Equation (15), a segment-based deterministic CLV model ($\boldsymbol{pR}[\boldsymbol{I}(1+d)-\boldsymbol{R}]^{-1}$) was employed to clear the effects of customer expansion (Table 6). The results show that the budget achievement pattern approximates that of the probabilistic model. Although the CLV in Tier III slightly underachieved its budget, CLVs in tiers I, II, and IV overachieved their budgets. However, the level of CLV was largely different between the segment-based deterministic and probabilistic models. The segment-based deterministic model overestimates CLV in Tier I and underestimates it in Tier IV. The same finding is also presented by Homburg et al. (2009). For example, the segment-based deterministic model estimated the actual CLV of Tier I to be 1.74 times larger (1293.6/743.4) than that of the probabilistic model. This is because the segment-based deterministic model assumes the high customer payoff and retention rate in Tier I to be constant over time. If the supposition that customers change their loyalty and behaviors over time is more realistic (e.g., Campbell & Frei, 2004; Malthouse & Blattberg, 2005), the probabilistic CLV model, which considers expansion effects, may provide better information on the relative importance of customers.

5.4.2. Prediction accuracy of future total payoff

How different is the predictive accuracy of different models at the aggregated level, rather than at the customer level? To answer this question, two methods can be used: holdout samples and *k*-fold validation (Malthouse & Blattberg, 2005). The former is applicable to larger samples, whereas the latter is suitable for smaller samples. This study used thousands of customer data points; however, these cannot be considered as *big data*. Accordingly, *k*-fold validation was selected as a suitable method. First, *k*-fold validation randomly divides the observations into *k* groups. The present study divided the customers into 10 groups, following Malthouse and Blattberg (2005).

Second, the parameters were estimated based on the data after the first group was excluded. Future total payoffs (the product of customer payoff and number of customers) based on the backward-looking model ($\widehat{TP}_{bt+1}$), deterministic model ($\widehat{TP}_{dt+1}$), and probabilistic model ($\widehat{TP}_{pt+1}$), are estimated using the following equations:

$$\widehat{TP}_{bt+1} = p_n c_{nt} + p_r c_{rt}, \tag{21}$$

$$\widehat{TP}_{dt+1} = p_n c_{nt} + [p_r r + p_l(1 - r)]c_{rt}, \text{ and} \tag{22}$$

$$\widehat{TP}_{pt+1} = \boldsymbol{pLc}_t, \tag{23}$$

where the subscriptions *n*, *r*, and *l* indicate new customers, retained customers, and lost customers, respectively. Customer payoffs (p_n, p_r, and p_l), retention rate (r), a customer payoff vector ($\boldsymbol{p}$) composed of six customer payoffs, and a lifecycle matrix ($\boldsymbol{L}$) consisting of one acquisition rate, five retention rates, and 20 expansion rates are parameters estimated from training data. Test data were used to obtain the customer state vector at time *t* ($\boldsymbol{c}_t$) as well as the numbers of new customers (c_{nt}), retained customers (c_{rt}), and lost customers (c_{lt}) at time *t*. Third, the estimated parameters were applied to the first group to predict the total payoff in the next period. Fourth, the estimated total payoff and the actual results in the first group were compared to calculate AD (absolute deviation) and APE (absolute percentage error). Repeating the second, third, and fourth steps to the tenth group, the mean AD and APE were obtained.

Table 7 shows the results of the 10-fold validation, in which parameters were estimated using 2015 data (period *t*). The mean APEs of the backward-looking model, deterministic CE model, and probabilistic CE model are 10.3%, 10.1%, and 9.6%, respectively. Although the probabilistic model employs 32 parameters (six payoffs in the customer payoff vector and 26 rates in the customer lifecycle matrix), it shows only a slight improvement compared to the deterministic model with four parameters (p_n, p_r, p_l and r). Interestingly, the backward-looking model based on only two parameters (p_n and p_r) indicates a comparable predictive accuracy with the forward-looking models. The results suggest that, although the different models provide different information at the customer level, there is almost no difference between the three models in terms of predictive accuracy at the aggregated level.

Table 7
Results of 10-fold cross validation.

	Backward-looking model		Deterministic model		Probabilistic model	
	AD[a]	APE[b]	AD	APE	AD	APE
1	3886	12.7	4660	15.2	4187	13.7
2	8414	22.7	8345	22.5	782	2.1
3	693	2.0	199	0.6	1718	5.0
4	1276	3.7	636	1.8	107	0.3
5	1766	4.4	770	1.9	3858	9.7
6	210	0.6	497	1.5	1730	5.2
7	12,684	28.0	11,936	26.3	12,779	28.2
8	711	2.1	1549	4.5	273	0.8
9	4071	11.1	3261	8.9	5030	13.7
10	5023	15.7	5818	18.2	5633	17.6
Mean	3873	10.3	3767	10.1	3610	9.6

[a] AD is absolute deviation.
[b] APE is absolute percentage error.

5.4.3. Performance report

To confirm how the different models provide different performance information, Table 8 presents the budgets, actual results, and variances, based on the backward-looking, deterministic, and probabilistic models. The backward-looking model simply provides the total payoff as performance information, while the deterministic and probabilistic models offer CE, CCE, and FCE for performance evaluation.

First, the total payoff (row (1) in Table 8), a backward-looking measure, shows a small favorable variance of 2280 thousand yen (2.0% above budget), while the CEs based on the deterministic and probabilistic models (rows (2) and (5) in Table 8) exhibit large favorable variances of 226,520 thousand yen (20.9% above the budget) and 535,938 thousand yen (52.9% above the budget), respectively. Therefore, both CE models imply that the Japanese resort hotel chain achieved great performance in the long-term, even though the backward-looking measure signaled that it simply achieved the budget.

Next, the difference in CE variance between the deterministic and probabilistic models was 309,418 thousand yen (535,938–226,520). Since the CCE variance did not show a substantial difference between the deterministic and probabilistic models, FCE variances caused this difference: FCE overachievements are 139,410 thousand yen in the deterministic model and 435,732 thousand yen in the probabilistic models.

The FCE differences between the deterministic and probabilistic models are relatively substantial. One reason for this is that the probabilistic FCE model supposes that new customers are acquired at a certain ratio to the customer base, while the deterministic FCE model assumes the number of customers to be constant over time. The incorporation of acquisition rate into the deterministic FCE model is useful to confirm the impact of this difference. The number of future customers at period *t* (f_t) can be determined based on acquisition rate *a*:

Table 8
Budgets and actual results (thousand yen).

	Budget	Actual result	Variance	Variance/Budget
Backward-looking model[a]				
(1) Total payoff	116,737	119,016	2280 (F)	2.0%
Deterministic CE model[b]				
(2) CE	1,084,903	1,311,423	226,520 (F)	20.9%
(3) CCE	462,914	550,024	87,110 (F)	18.8%
(4) FCE	621,988	761,398	139,410 (F)	22.4%
Probabilistic CE model[c]				
(5) CE	1,013,772	1,549,710	535,938 (F)	52.9%
(6) CCE	465,184	565,390	100,206 (F)	21.5%
(7) FCE	548,588	984,320	435,732 (F)	79.4%

[a] Total payoff is the inner product of the customer payoff vector in Table 6 and the customer state vector in Table 3.
[b] Deterministic CE, CCE, and FCE are estimated based on Equation (2). CCE is the product of the CLV of retained customers (Table 6) and the number of current customers (Table 3). FCE covers CLV as well as the first payoff of new customers (p_n) at survival period 0 ("New" row of "Customer payoff" column in Table 6). The number of new customers is obtained from Table 3. CE is the sum of CCE and FCE.
[c] Probabilistic CE, CCE, and FCE are estimated based on the equations (12), (13), and (14), respectively. The data are obtained from Table 3 (customer state vector), 4 (customer lifecycle matrix), and 6 (customer payoff).

$$f_t = a(a+r)^{t-1}c. \tag{24}$$

Combining Equation (24) with Equation (20) yields the revised deterministic FCE:

$$FCE = (p_n + CLV)\sum_{t=1}^{\infty} f_t \bigg/ (1+d)^t = (p_n + CLV)ac \bigg/ (1+d-a-r). \tag{25}$$

Notably, p_n must be included in Equation (25) to accommodate the first payoff by new customers at their survival period 0. Budgeted and actual FCEs based on the revised deterministic model were 537,358 thousand yen and 932,527 thousand yen, respectively. Therefore, the results approximate those of the probabilistic FCEs.

Finally, it should be noted that FCE contributes considerably to CE in both the deterministic and probabilistic models. Looking at the actual results, FCEs based on the deterministic and probabilistic models constituted 58.1% (761,398/1,311,423) and 63.5% (984,320/1,549,710) of the CE, respectively. This supports the findings of the study by Schulze et al. (2012) that FCE constitutes a major part of CE. In the Japanese hotel chain, new customers generated enrollment payoffs, which may amplify the customer acquisition effect. The actual customer payoff of new customers without enrollment payoff was 70.5 thousand yen. Following the removal of enrollment payoffs, the actual FCEs, based on the deterministic and probabilistic models, were 396,923 thousand yen and 525,423 thousand yen, respectively. The same calculation was performed using the budgeted data, and the results showed a similar pattern.[5] Therefore, while enrollment payoffs certainly augmented FCE, there remained a large impact on CE.

5.5. Variance analysis

Fig. 3 shows the results of the variance analysis using the framework based on the management-oriented approach. In level 1, a CE variance of 535,938 thousand yen (F) was obtained, and in level 2, this was decomposed into three parts: a customer payoff variance of 18,547 thousand yen (U), a customer lifecycle variance of 528,896 thousand yen (F), and a customer state variance of 25,589 thousand yen (F). The results indicate that the favorable CE variance was created by the favorable customer lifecycle variance, which far exceeded the unfavorable variances of customer payoffs.

The overwhelming favorable variance of customer lifecycle implies that marketing programs aimed at customer acquisition, retention, and/or expansion performed much better than their budgets. The variance analysis in level 3 clarifies that the favorable variance was decomposed into three parts: a customer acquisition variance of 59,161 thousand yen (F), a customer retention variance of 367,291 thousand yen (F), and a customer expansion variance of 102,444 thousand yen (F). Therefore, the most impactful factor generating the favorable customer lifecycle variance was customer retention. This is supported by the results in Table 4. The last row of the two customer lifecycle matrices shows the defection rates or 1–retention rates. The improvements in the defection rates were 2.6, 1.2, 1.5, and 6.8 percentage points for new, Tier I, Tier II, and Tier IV customers, respectively.

Customer expansion was less influential than customer retention, it indicated a significant favorable variance of 107,081 thousand yen. Strategies for customer expansion are categorized into two types: defensive and offensive (Homburg et al., 2009). In this application, because there are 20 expansion rates in a customer lifecycle, the focus here is on the defensive strategy for Tier I (most loyal customers) and the offensive strategy for Tier IV (least loyal customers). The improvements in the expansion rates from Tier I to Tiers II, III, and IV were 1.6, 3.4, and 3.1 percentage points, respectively. Therefore, the defensive strategy for Tier I customers was more successful than that budgeted. Although the expansion rate from Tier IV to I decreased by 1.2 percentage points, the expansion rates from Tier IV to Tiers II and III increased by 1.6 and 4.5 percentage points, respectively. These results suggest that, overall, the offensive strategy for Tier IV was better than that budgeted. To reiterate the above, the defensive and offensive strategies together contributed to a favorable variance of customer expansion.

The customer acquisition variance exhibited a less favorable result than customer retention and expansion. The first row of each customer lifecycle matrix in Table 4 shows the acquisition rates. The Japanese hotel chain overachieved the budgeted acquisition rate slightly by 0.4 point. However, the customer acquisition variance constituted 5.8% of the budgeted CE (59,161/1,013,772). This implies that a significant CE variance could be caused by only a slight deviation from the budgeted acquisition rate. Therefore, the Japanese resort hotel chain should pay attention to customer acquisition as well as customer retention and expansion.

6. Discussion and conclusions

This study proposed a variance analysis of CE, a forward-looking measure. Scholars have discussed the fact that a forward-looking measure is useful for avoiding short-term behaviors caused by the use of a backward-looking measure. This study applied the variance analysis of CE to a Japanese resort hotel chain to observe how a forward-looking measure could provide useful information. The customer lifecycle matrix integrated customer acquisition, retention, and expansion—the crucial goals of marketing programs—into a single model using the Leslie matrix. Previous Markov chain models for CE or CLV considered customer acquisition and retention rates (Rust et al., 2004) or customer retention and expansion rates (Homburg et al., 2009) simultaneously. To the best of the present author's knowledge, no model has thus far simultaneously utilized customer acquisition, retention, and expansion.

6.1. Theoretical implications

This study has theoretical and practical implications. From a theoretical perspective, this study presents a framework of variance analysis from the viewpoint of the *customer lifecycle*. Variance analysis originated in management accounting, where profit variance is analyzed in terms of *products*. Product-oriented variance attributes profit variance into selling prices, sales mix, market shares, and market size (e.g., Anthony et al., 2014; Datar & Rajan, 2017). On the other hand, variance analysis of CE splits variance into customer payoff, lifecycle, and state, and the customer lifecycle variance is further decomposed into customer acquisition, retention, and expansion. Because the latter three elements are crucial in marketing, this customer-oriented variance analysis was suitable for evaluating the performance of marketing programs.

This study also addressed the new research frontier of controlling marketing programs on the basis of forward-looking measures. Control functions are traditionally assumed to be based on a variance analysis of backward-looking measures (e.g., profit, sales, and costs), whereas forward-looking measures (e.g., net present value and internal rate of return) play an important role in planning. As shown in the case of the Japanese resort hotel chain, backward-looking measure variances cannot be consistent with those based on a forward-looking measure. Accordingly, backward-looking control could cause short-term behaviors that would deteriorate future performance (Casas-Arce et al., 2017; Wiesel et al., 2008). A promising way to avoid this conflict is to use the same forward-looking measure in both the planning and controlling phases, as was demonstrated in the application of the CE variance analysis to the Japanese resort hotel chain.

[5] Budgeted customer payoff of new customers without enrollment payoff was 76.5 thousand yen. Budgeted FCEs without enrollment payoffs were 321,884 thousand yen in the deterministic model and 284,654 thousand yen in the probabilistic model.

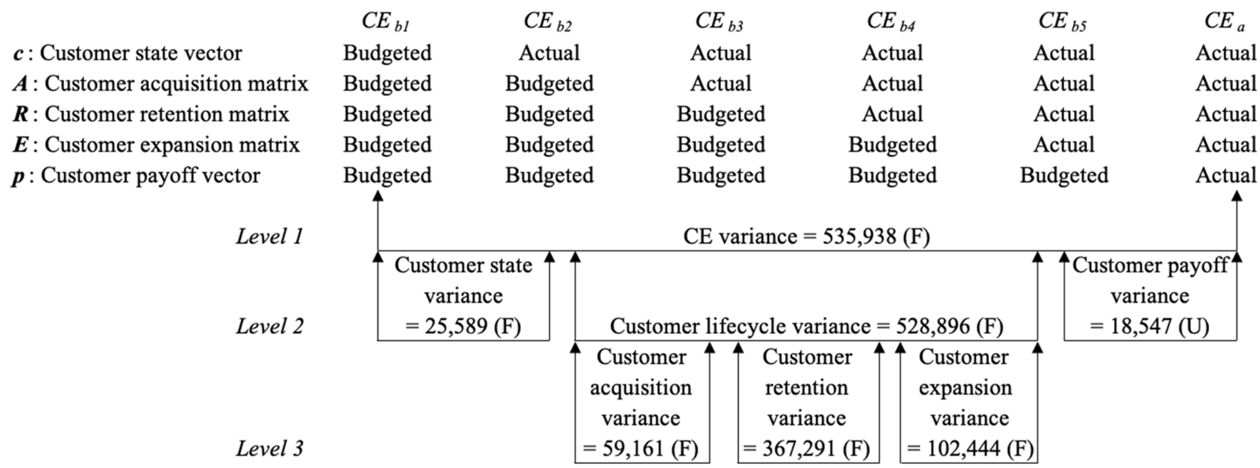

Fig. 3. Results of variance analysis (thousand yen).

6.2. *Practical implications*

Any sweeping generalization from a single case study must be avoided. Nevertheless, the application shows an important practical implication: customer acquisition, retention, and expansion differently impact CE. Their magnitudes should, therefore, guide decision-making regarding the planning and control of marketing programs. Although this study focused on variance analysis as a tool for control, standard planning tools can also be employed. For example, a sensitivity analysis can reveal ways to prioritize customer acquisition, retention, and expansion in the order of CE impacts. Furthermore, Monte Carlo simulations based on the customer lifecycle matrix can identify factors causing uncertainty in the CE estimates.

Further, a variance analysis of CE is helpful for seamlessly controlling planned programs because both planning and control are based on the same measure. This enables the company to discover the main cause of over- or underachievement of CE and to determine the required corrective actions. For example, the variance analysis performed for the Japanese resort hotel chain exhibited the unexpected result that a slight improvement in customer acquisition generated a significant favorable variance. Although customer retention protects the current customer base from shrinking, it is insufficient for promoting customer base growth, which requires customer acquisition. A CE variance analysis stimulates learning about the importance of customer acquisition, retention, and expansion.

6.3. *Conclusions*

Using the CE model based on the customer lifecycle matrix involved several technical issues. First, categorizing customer states was important. The application employed a decile analysis to obtain the distribution of rooms booked and somewhat subjectively grouped them into four states. This subjective segmentation entailed a risk of distorting the results. Therefore, in future research, a sophisticated method of customer state categorization, such as a hidden Markov model, should be further adapted to the customer lifecycle matrix (Netzer, Lattin, & Srinivasan, 2008). Second, the application of the Japanese resort hotel chain focused only on CE from customers with a membership. The present author was required to estimate non-member-derived CE to capture the overall CE of the company. Although the transaction histories of individual non-members were unavailable, a survey method for CE estimation seems to be a promising way to address this issue (Rust et al., 2004; Stahl et al., 2012).

This study introduced a single case study. The development of digital technologies has enabled companies to collect volumes of customer data. Therefore, CE estimation using internal data is expected to be increasingly applicable. More applications to different industries that would provide different practical implications are expected in future research.

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Declaration of Competing Interest

None.

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