Forward-Looking Metrics for Marketers
Application of Customer Lifetime Value (CLV) to Fast-Moving Consumer Goods

Debra Parcheta, Blue Marble Enterprises, Inc.

Abstract: Customer Lifetime Value (CLV) has been used for some time as a forward-looking performance metric for contractual and account-based products and services. The forward-looking nature of CLV also appeals to marketers of fast-moving consumer goods (FMCG), as an alternative to short-term, backward-looking performance metrics such as sales and market share. Furthermore, aggregating CLVs for a brand’s current and new customers produces a forward-looking brand value metric called Customer Equity (CE). This pilot study of the application of CLV to FMCG, initiated by the Marketing Accountability Standards Board (MASB) and undertaken by three marketers, academic leaders and analytics firms, had two primary objectives: to demonstrate that the CLV construct and models can be reliably applied to FMCG products and to determine whether CLV reveals differential responses across differing target markets.

Results of this pilot study found that CLV concepts can be applied to transaction-level FMCG data to anticipate the directional trend in future customer equity for the brand. For the six brands studied, the predicted CE trend was mirrored by a similar, though lagged, trend in the actual sales of the brand. The study also helps identify the limitations and requirements to produce a useful predictions of trends for brands. Marketing tactics at the transaction and weekly levels were also evaluated to see if they affected CE – a first step toward using CLV to identify marketing tactics that will build FMCG brand success for the long term.

Key Words: Customer Lifetime Value, CLV, Customer Equity, CE, FMCG
Authors:

Debra Parcheta is the CEO and Chief Engineer at Blue Marble Enterprises, Inc., a database systems company known for its metrics databases and analysis, 14456 E Evans Ave, Aurora CO 80014, (Email: dparcheta@blue-marble.com, phone (1) 303-750-9610 Ext 1) and Instructor, University of Colorado at Denver, Computer Science and Engineering.
Application of Customer Lifetime Value (CLV) to Fast-Moving Consumer Goods

Debra Parcheta, Blue Marble Enterprises, Inc.

Advances in computing speed and storage capacity over the last two decades have made possible the collection and storage of detailed, consumer-level, product-level and firm-level data about brand sales, category trends and marketing impacts for fast-moving consumer goods (FMCG) marketers. As analytical methods have evolved, “big data” has fueled marketers’ knowledge of how mass marketing drives sales and customer behavior. However, marketers in the FMCG sector do not rely on contract or account-based relationships with their end users, making it harder to predict how targeted customers will purchase brands in the future.

These FMCG marketers continue to become more proficient at using historical data to plan and execute short-term marketing strategies and to calculate resulting marketing-effectiveness metrics and indicators. Current metrics for brand success, which remain primarily backward-looking and short-term focused, are not limited to but include response elasticity, ROI, past sales trends, purchase frequency, and market share. Hence, marketing managers are now more likely to make the “right” tradeoffs to deliver required short-term ROI and market share gains.

However, marketing and financial managers recognize that short-term effects do not necessarily anticipate brand success for the long term. In fact, Yoo, Hanssens & Kim (2012)\(^1\) demonstrated that some marketing choices could erode brand success in the long term by causing customers to change their purchasing habits in ways that are not easily changed back. For example, offering sales promotions at frequent and predictable intervals can create “strategic” consumer behavior; that is, consumers wait to purchase until the next promotion cycle, thereby reducing the brand’s profit contribution from their purchases.

A brand’s success depends on much more than achieving quarterly or weekly sales goals or short term ROI. If FMCG marketers add future-focused metrics, they would be better able to build brands with fore-knowledge of marketing program outcomes and prevent unintentional brand erosion. In 2012, Yoo, Hanssens & Kim expanded on the 2005 work of Fader, Hardie and Lee to test the application of CLV and CE on a data set of customer transaction-level data for competing brands of ketchup and yogurt, with encouraging results. From such metrics, the long-term impacts of marketing tactics and tradeoffs can be modeled, allowing marketers to better manage brands for the long-term. The promise of CLV for an FMCG brand is to measure current purchase behavior, household-by-household, and anticipate the brand’s future CE trend, which provides a prediction of the net present value (NPV) of cash flows resulting from marketing-driven changes in the brand’s relationships with its customers.

CLV and CE have proven to be valuable metrics for marketers who have contractual customer relationships. In these CLV evaluations, the length of the contract is known, so the duration and size of the expected profit stream from each customer is known. At any point in time, these CLV calculations can be summed to obtain CE. Successive evaluations can show how CE might change over time from the acquisition and retention of contracted customers. These CLV/CE metrics are relatively easy to calculate based on current customer behavior, known contract prices and profits, and known contractual time frames. Past and present contracts and past and present rates of acquisition and retention are readily used to calculate the expected financial return going forward.

**Defining CLV for FMCG products**

Fast-moving consumer goods, on the other hand, are bought frequently by customers at grocery, convenience and chain stores at relatively low prices. It is not unusual for customers to buy multiple brands in a category, either in one shopping trip or on subsequent trips. These goods are usually consumed within days or weeks, which makes the frequency and size of purchases parameters not found in contractual businesses. Though individual profits from fast-moving consumer goods are small, the volume resulting from high turnover rate and frequent purchases makes cumulative profits quite substantial. For FMCG marketers, the ability to determine the net present value of a customer’s future purchases necessitates calculating the probability of whether or not a new customer will be gained (acquisition), an existing customer will be retained and will periodically repurchase the brand (retention), or whether an existing customer has become inactive and needs to be re-acquired.

To calculate the probability of being active, the price paid, purchase amount, and frequency of the customer’s future expected transactions need to be estimated using stochastic models derived from the basic elements of probability and statistics. Stochastic modeling is a tool that uses probability to model real-world situations in which uncertainty exists. The model reveals each customer’s patterns of behavior in the transaction data and assigns probabilities of being active in the next week to those customers. In turn, the probabilities from the model are used to determine expected average numbers of future transactions, units per transaction and price per unit for the modeled brand. (Figure 1.)
The CLV calculations for FMCG brands study

The Marketing Accountability Standards Board (MASB) of the Marketing Accountability Foundation (MAF) assembled a project team to conduct a pilot test of the CLV mathematics and concepts used by Yoo, Hanssens & Kim (2012). Six FMCG brands from three major marketers,
marketing practitioners and academic members formed a team to develop software applying these CLV concepts to determine the practicality of the application to FMCG brands.

The three FMCG marketers and their data vendor supplied static panel data at the household transaction-level for a three-year period. A database system was built to apply the Beta Geometric/Negative Binomial Distribution (BG/NBD) method\(^2\) to the marketers’ customer-level transaction and marketing data to calculate CLV and CE values.

The probability of a customer repurchasing a brand in a given week and all the expected future transactions predicted from both acquisition and retention customers in the data set were calculated. The transactions from the first year of the data set were used as an initialization set to determine each customer’s rate of purchasing and patterns from his/her purchasing habits. Purchasers were classified as “retention customers” if their probability of being active was greater than or equal to 50%. Customers with a probability less than 50% were either new customers with no purchase history and therefore a low probability of being active, or existing customers whose behavior suggested that they may need to be reacquired. Those customers were classified as “acquisition customers” for the analyses (Figure 2.)

From the initialization set, it was possible to compute a probability of each customer being active each week in the future. The remaining 2 years of data were used, week by week, to iterate the CLV calculations for each customer. Summing customer CLV calculations provides a future CE prediction from each week’s change in customer behavior.

For each week, the CE metric is calculated by summing CLV predictions across customers based on past 52 week purchasing patterns (frequency, size, and price) and incorporating a discount rate to represent the future value of money given the time value of money principle which recognizes that the purchasing power of money declines over time. Summing the CLVs of all customers each week results in a CE trend line that projects a week-by-week future NPV for the brand.

\(^2\) It is also possible to use Beta Geometric/Beta Bernoulli [BG/BB] methods to perform these calculations, with very similar results. BG/BB does not use acquisition and retention assumptions.
Plotting the CE values from each week’s successive calculation results in a prediction of trend, based on past and present customer behavior. This predicted trend suggests whether the brand sales will be stable, rising or declining (Figure 3.) Assuming the brand is currently profitable, a stable CE suggests future profitability given the same marketing strategies. A rising CE indicates that the current marketing strategies will yield higher future profitability. Declining CE suggests a decline in future profitability which should prompt a change in the current marketing strategy to avert the decline.

![Graphs of Brand A to F showing CE trend](image)

**Figure 3:** Customer equity from both the acquisition and retention customer groups is plotted separately to show how each group of customers might be influencing the CE trend. For example, rising customer equity for Brand B comes from the retention customers group, while falling customer equity for Brand A or Brand C is driven by falling CLVs in the acquisition customer group.

**Results**

After the calculation of the CE trend, mix-modeling techniques can be used to determine if...
marketing tactics were drivers of the CE trend. These models are considered “equity response models,” as they can enable managers to choose marketing tactics based on the expected impact on future success of the brand. Marketers of FMCG brands can add a forward-looking, long-term indicator of how marketing choices are expected to influence future brand success to their decision-making tools.

The study was conducted on brands in very different FMCG categories to verify that the CLV and CE metrics can be applied across a wide variety of FMCG brands. To test the validity of the CE prediction, the green CE line (Figure 4) was plotted week-by-week predicting the future profits from the brand. The study participant for Brand B also provided the actual sales for the time frame to validate whether the prediction foreshadowed the actual changes in sales in the future.

![Figure 4](image)

**Figure 4:** For Brand B, the CE prediction from the panel set indicated 4 changes in the future health of the brand with a lag time of 6 months before a similar pattern of slope changes appeared in the actual sales trend of the brand.

CLV and CE analyses were also applied to demographically-targeted sets of customers for each brand and to competing brands in the same categories. For all of the different panel sets and subsets, CLV could be calculated and a resulting CE trend was graphed. A stable metric emerged with a clear trend line that was compared to actual future sales of the brands. (Figures 5a and 5b.)
Figure 5a: Trends in customer equity predictions were mirrored by actual sales of the brand in the future with a lag of 4 – 8 months in time between the prediction and the actual sales trend.
Figure 5b: Trends in customer equity predictions were mirrored by actual sales of the brand in the future with a lag of 4 – 8 months in time between the prediction and the actual sales trend.
**Discussion**

During the course of the pilot test, certain limitations and refinements were identified that could improve the accuracy of results in the future. Using transaction-level data from a rolling static panel or another data source that better incorporates customers that are new-to-category could prevent routine declines in projected behavior toward the end of the time frame modeled. Using consumer panels that do not experience panel fatigue would be desirable as well for the same reason. Unlinked\(^3\) panel data is of interest because CLV/CE works at a customer level and could be sensitive to patterns from customers that would not normally be included in linked panel data. More investigation needs to be done on smaller marketing target groups. The pilot test concluded with a rigorous evaluation of the 6 brands, but did not have the latitude to explore the demographics of customer sub-groups within each brand.

At the conclusion of the pilot test, the CLV and CE metrics were submitted to the Marketing Metric Audit Protocol at MASB. MASB’s mission is to set standards and processes necessary for evaluating marketing measurement in a manner that insures credibility, validity, transparency and understanding. The Marketing Metric Audit Protocol (MMAP) process\(^4\) for CLV applied to FMCG showed that the metric was relevant, objective, transparent, and subject to audit. The metric resulted in clear general implications (change/don’t change).

The team identified future work to be conducted to develop and refine the metric for industry application. While CLV for FMCG provides a financial change projection, future trials will be needed to determine whether it can predict future sales. The metric recognizes short- and long-term effects from marketing and can also highlight when these effects are not directionally consistent. For the pilot study, analyses were conducted using a common retention probability to categorize acquisition and retention customers. The test also used a common contribution margin for all brands. Proprietary analyses will incorporate brand-specific thresholds and actual margins, making the metric more accurate for the brand being analyzed.

MASB has also approved a subsequent commercial test of CLV and CE for FMCG brands using single-source data, which provides larger sets of reliable data from which more comprehensive customer patterns can be seen.

**Conclusion**

By examining CLV and CE, marketers and financial managers can incorporate a forward-looking, long-term financial performance projection that anticipates the future success of the brand, based on their past and present marketing actions. Beyond the objectivity provided by short-term metrics, CLV and CE provide long-term perspective to aid in optimizing the use of marketing tactics.

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\(^3\) “Linked” panel data requires that a certain customer be reported in a certain number of months throughout the entire panel time frame. For example, in a 10/12 linked static panel set of transactions, a panel member is only included in the data set if he/she reported purchases in 10 out of 12 months in all 3 years of the time frame. An “unlinked” set would not exclude panel members who were less frequent reporters of their purchases, who were new to market after the initial 2 months of the time frame or who disappeared during the time frame.
The benefits of extending the CLV/CE model to FMCG are numerous. Because these metrics are based on projecting each customer’s CLV, FMCG marketers will be better able to study segments of consumers. The CLV and CE metrics can predict future net present value for different subsets of a brand’s business, thereby assisting with the decisions for optimizing marketing budgets to acquire and retain the most profitable customers. In other words, CLV and CE identify for marketers which marketing activities to select and manage to provide the greatest long-term value.
References
