Paper Title: The impact of assumptions in CLV estimation: An initial discussion and verification
Track: Marketing Management
Key-words: Customer Equity, Customer Lifetime Value, Marketing strategy

Introduction

Customer lifetime value (CLV) and Customer Equity (CE) appeared as a central metric for marketing in the last years, especially in a time where marketing accountability is challenged and instigates a more profound marketing-finance interface. However, this growing importance did not come without its theoretical and empirical shortcomings. This paper is an initial effort to identify and suggest some improvements in CLV/CE assumptions, as well to evaluate the results of different CLV/CE models by simulating changes in some variables of each model.. We did a literature review (check the appendix for the list of journals), covering the period of 1974-2016. There were 54 articles that dealt with 29 different CE/CLV estimation methods and we found five different issues with respect to CLV/CE: CLV forecasting methods; customer behavior approaches; the contractual/noncontractual controversy; retention rates estimation; the impact of different variables on CLV/CE and on decision making. Much discussed here is in line with the latest questions that Peter Fader and Bruce Hardie are trying to introduce in CLV estimation but still little explored by the literature.

On the remaining of this paper we present a short review of the definitions of CLV and CE and analyze the five issues mentioned above. The first four issues we dealt briefly on a theoretical basis. The last one – the impact of different variables on CLV/CE and decision making – we used simulation techniques to perform the analysis.

Customer Equity and Customer Lifetime Value

Customer lifetime value (CLV) appeared first as “long run customer profitability” on a seminal Journal of Marketing article by Philip Kotler in 1974. Fifteen years later Donald Jackson, in 1989, tried to demonstrate a method for calculating the expected financial contribution of a customer. In the same year, Dwyer published an article entitled “Customer Lifetime Valuation to Support Marketing Decision Making” on the Journal of Direct Marketing. This article was the starting point of a central stream of research for marketing. Since then, many methods and models were developed to verify the potential of customers as assets that generate cash flows, from simple NPV models and Bayesian models to stochastic and portfolio allocation models.

CLV was defined by Kotler as ‘The present value of the future profit stream expected given a time horizon of transacting with the customer’ (KOTLER, 1974). Little has changed since then: present value of all future profits generated from a customer (Gupta and Lehmann, 2003); net profit or loss to the firm from a customer over the entire life of transactions of that customer with the firm (Jain and Singh, 2002); The main idea was to figure out the customer contributions, by using the net present value principle, in the same way as financial assets.

Customer Equity (CE) was introduced by Blattberg and Deighton (1995) in their paper "Manage marketing by the customer equity test". The authors did not define CE explicitly, but we can understand that CE is more a method to determine the optimum level of acquisition and retention spending than a proper verification of customer expected contribution. The optimized expending would then reveal the maximum individual CE.

CE suffered an important change in its formal definition by the 2000s, when became the sum of all firm's CLV. Now it is common to define CE as "The sum total of lifetime value of all customers of the firm represents the CE of the firm" (Kumar and Shah, 2009). The underlying logic is to assume that the firm customer base represents an asset that yields revenues over time, in the same way financial assets do. Therefore, the "equity" is not the individual CLV but the sum of the CLVs of all customers.

Regardless the formal definition of CE/CLV, this stream of research generated a series of results that can help business to better allocate resources for creating and enduring customers relationships. It allows, for example, to identify profitable customers and to avoid expending on unprofitable relationships (GUPTA et al., 2004). More sophisticated methods include measuring CE impact on the firm market capitalization (KUMAR and SHAH, 2009), customer portfolio management (TARASI et al., 2011), CLV stochastic forecast (FADER and HARDIE, 2009), among others. This effort to link marketing and finance came in a period of skepticism about marketing's ability to create value and lack of metrics, amongst other factors such as marketing's low bargaining power in corporate boards, increasing costs/competition, and data abundance.

First Issue: CLV forecasting

One important difference between CLV models is how to estimate the future contribution of a customer. As a forward-looking metric (KUMAR, 2008), CLV forecasts will show how firms will perform on the future and the future value of the customer base (CE). An expected increase in CE will always be preferable over a future decrease. However, that projection has been somewhat arbitrary with little argument about the best estimation method. Gupta et al. (2004) forecasted the future number of customers but did not incorporate the future CE. Kumar and Shah (2009) used 36 months as upper bound, and Schulze et al. (2012) argues that infinity is the best method for determining CE, among other approaches. Since modern CLV estimation methods use NPV, CLV is highly sensitive to the time span chosen. As Fader and Hardie (2014b, pp. 1-2) put it:

> "The upper bound of summation is T. Unless we are planning to terminate our relationship with the customer at that future point in time, this will not give us a true estimate of the customer's (expected) lifetime value; it is ignoring the residual value of the customer beyond that point in time. Now, there is nothing wrong with cutting off the calculation at T; just don't call it lifetime value"

What would be the appropriate solution? Fader argues that infinity would represent the true lifetime, in line with Schulze et al. (2012). If project infinity is not viable, a high upper bound summation will be very close to the infinity solution (T = 100 or higher). Up to now, however, there are not enough papers discussing the best way to address this question.

Second Issue: Customer behavior

A common assumption about the underlying customer behavior for CLV estimation: the lost-for-good versus always-a-share. This dichotomy was first proposed for the B2B setting by Jackson (1985) and reaffirmed in past and recent works on CLV/CE – eg. Dwyer (1989) and Kumar and Shah (2009). Always-a-share assumes that the customer will transact but won't have total commitment with a firm (several vendors at same time); on the other hand, lost-for-good states that once the customer becomes "dead", he will never transact again. This concept becomes confusing when combined with contractual/noncontractual settings. Rust et al. (2004) defended that noncontractual and always-a-share can be treated as equal. Kumar and Shah (2009, p. 123) said "For contractual settings, firms can employ the "lost-for-good" approach to compute the CLV". However, Jackson's classification is an extreme and do not account for intermediary positions, as the author herself admitted. Contractual and noncontractual settings say nothing about customer behavior, that is, deriving one from another is not theoretically possible nor empirically proved. Fader and Hardie (2014a, pp. 10) brings attention to this in customer base analysis:

> "We prefer the contractual versus noncontractual classification to the lost-for-good versus always-a-share classification as it is agnostic when it comes to the issue of competition and, more importantly, brings to the fore the issue of the observability of customer attrition, which has obvious implications for the types of marketing metrics and statistical models the analyst should use when analyzing a given customer database."

This discussion might seem viewed as purely conceptual but it has implications for estimation. Using Jackson's approach to choose CLV methods may induce wrong decisions about model development and specification. It is possible to argue that the always-a-share and lost-for-good dichotomy does not help at all in pursuing better CLV/CE models.

Third Issue: Contractual/noncontractual relationships

If one do not use Jackson's dicothomy, the other option for CLV estimation could be the transaction setting: contractual or noncontractual. On the first case, the time when the customer stops transacting ("death") is clearly observed – it can be an absence of renewal or contract break. The second case do not have a visible "death" because the seller never knows if the customer is dormant or really finished his relationship. In fact, the great majority of customer transactions are noncontractual.

The consequence for estimation is as follows: the lack of a retention rate on noncontractual settings means that the conceptually correct parameter is the probability of being active, that cannot be derived from the customer base in the same way retention rates are (even when retention rates is a kind of probability). Moreover, in contractual settings cohort analysis become central, as retention rates can be significantly diverse across customers (and, in consequence, CLV/CE) (FADER and HARDIE, 2010). The central question is to know if customers will continue to transact or not. If this is true, then Fader and Hardie (2014a, p. 8) ends the issue:

> "It is now standard to use the term "contractual" to characterize a relationship when the death of a customer is observed by the firm, and the term 'noncontractual' to characterize a relationship where the death of a customer is unobserved by the firm."

Fourth Issue: Retention rate heterogeneity

In general, retention rates on CLV estimation are assumed constant, calculated from the total customer base (and ignoring the contractual/noncontracual controversy). Some models are capable of cohort estimation with diverse rates (FADER and HARDIE, 2010), but the majority will use one and only rate for all customers and time periods. However, some works (FADER and HARDIE, 2014) shows that retention rate in contractual settings is different and mutating as time and cohorts goes by, resulting in CLV overestimation of newly acquired customers. As Fader and Hardie (2014b, pp. 2) puts it:

> "[…]when we track a cohort of customers (i.e., a group of customers acquired at the same time) over time, we do not observe a constant retention rate; rather, we find that the retention rates tend to increase as a function of customer tenure. Clearly the expected residual lifetime value of a customer who has made several renewals will be greater than the expected lifetime value of an as-yet-to-be-acquired customer."

Some models already include or indicate the possibility of cohort estimation but the consequence is still little explored. Only 3 works contains any discussion about it (BRAUN e SCHWEIDEL, 2011; FADER e HARDIE, 2010; SCHULZE et al., 2012). Underestimating this issue will cause CE to be biased and can compromise decision-making.

Fifth Issue: Variables impact on CLV estimates

Some works indicate the magnitude of variable manipulation on the CLV/CE estimation, but no one did a more comprehensive analysis between models. What is the sensibility of the variables? Would this sensibility impact decision-making on marketing resources? Can CLV/CE bias marketing strategy?

To start exploring these questions we choose 5 five models and simulated alterations in its variables: Blattberg and Deighton (1995) – two equations; Berger and Nasr (1998) and Gupta and Lehmann (2003) – two equations. These models were chosen because they are straightforward to apply by marketers and require less information than more complex modeling. Equations are listed below.

Table 1– Models choosen

Authors	Code	Model
Berger and Nasr (1998)	BN1	$CLV = \left(m * \sum_{t=0}^{n} \frac{r^t}{(1+d)^t}\right) - \left(M * \sum_{t=1}^{n} \frac{r^{t-1}}{(1+d)^{t-0.5}}\right)$
	BN2	$CLV = \sum_{t=0}^{n} \pi(t) * [\frac{r^t}{(1+d)^t}]$
Gupta and Lehmann (2003)	GL1	$CLV = m(\frac{r}{1+d-r})$
	GL2	$CLV = m\left(\frac{r}{1+d-r(1+g)}\right)$
Blattberg and Deighton (1996)	BD	$CE = a * m - A + a\left(m - \frac{M}{r}\right)\left[\frac{r'}{(1+r')}\right]$

To estimate CLV in these models the variables needed are:

1. *n* – time window;
2. *r* – retention rate;
3. *r´* – *r*/(1+*d*);
4. *d* – discount factor;
5. *m* – contribution margin;
6. *M* – retention spending;
7. *π(t)* – estimated profit;
8. *g* – growth rate of *m*;
9. *A* – Acquisition cost;
10. *a* – acquisition rate at *A*;

Simulation Results

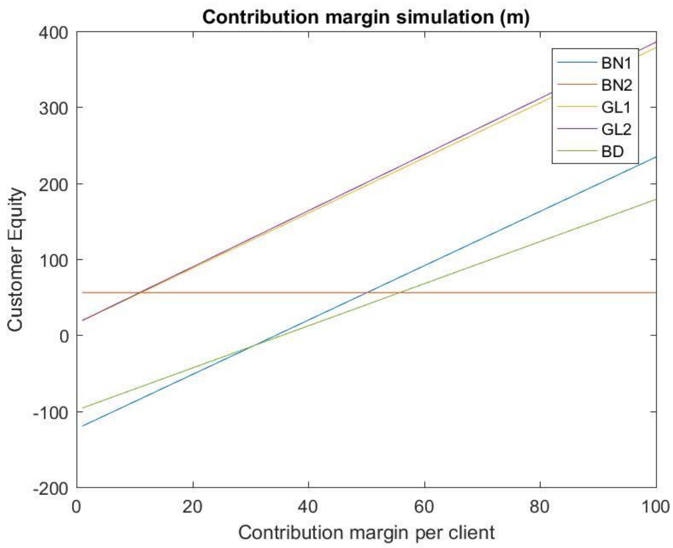
To find the CLV value some initial conditions were assumed: 1) ten periods of time (n); 2) retention rates (r) equal to 70%; 3) discount factor (d) set on 7%; 4) contribution margin (m) set to 100 monetary units (mu); 5) retention spending (M) on 30 mu.; 6) profit estimate (*π(t)*) on 30 mu.; 7) margin growth rate (g) on 1%; 8) Acquisition cost (A) equal to 70 mu.; 9) Acquisition rate (a) at 50%. Moreover, the analysis were done at the customer level, enabling to consider CLV and CE interchangeably. Results from this initial condition are in below (Table 2).

Table 2 - Estimated *Customer Equity* for the five models

Model	*CE*
BN1	47,96 mu
BN2	55,94 mu
GL1	189,19 mu
GL2	192,84 mu
BD	34,05 mu

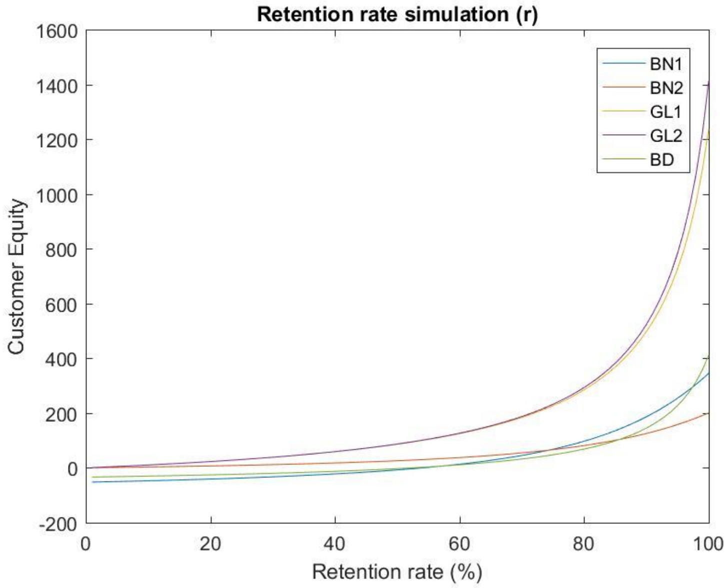
The first conclusion is that values differ substantially between models, in line with some expected outcomes proposed by KUMAR and GEORGE (2004). This "raw" estimate is not the main concern right now but the variable sensibility on the different models. From these initial results, changes in retention rate and contribution margin were simulated. The following graph (Figure 1) shows that contribution margin increases CE in a linear fashion, the exception of BN2, which does not include margins but profits per customer – margin and profit cannot be directly related.

Figure1



Retention rates operate exponentially, as the following graphs (Figure 2) show. It worth notice that for retention rates above 80% GL1 and GL2 have an explosive behavior. The other three models are less sensible. That means, if those models evaluate the customer base, CE can be much higher in a high retention rate scenario. These issues must be discussed with caution when deciding what kind of effort to use for increasing CE.

Figure 2



The next series of graphs compares the combined impact of margins and retention rates. For low values, margins cause an increase greater than retention, but as we move into the extreme right axis, retention overcomes margins in CE estimation. That could impose a question: is it better to improve margins or concentrate efforts to achieve higher retention rates? The two objectives requires diverse marketing strategies and one would say that is not possible to implement both at the same time. If we consider scarce resources for marketing expenditures this is clearly a trade-off. Moreover, in BN1 retention spending has great impact on CE, so it would be important to keep this cost low.

Figure 3

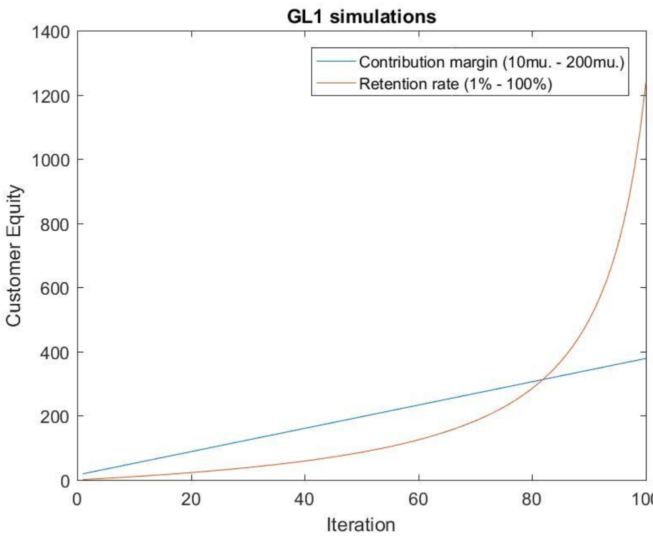


Figure 4

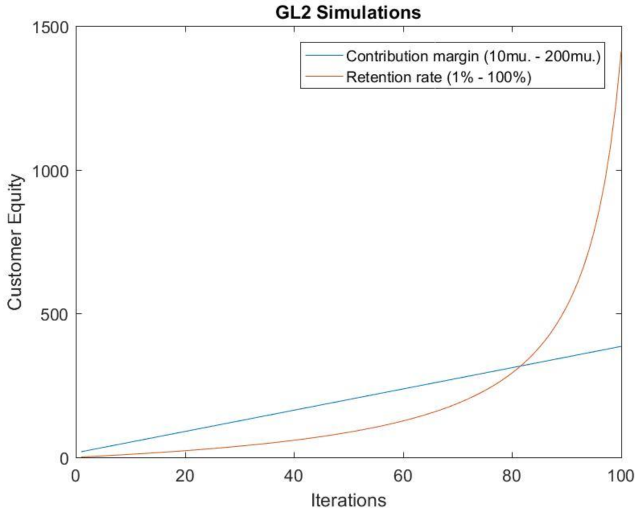


Figure 5

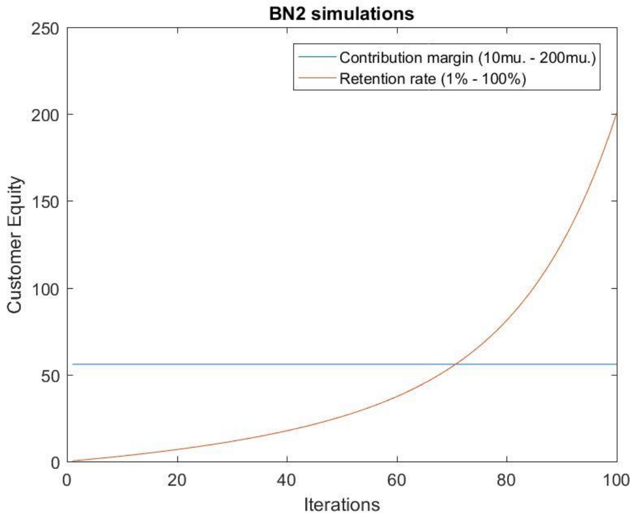
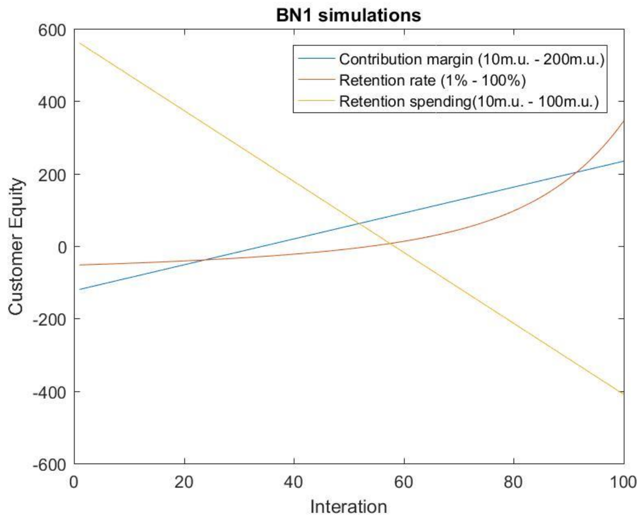


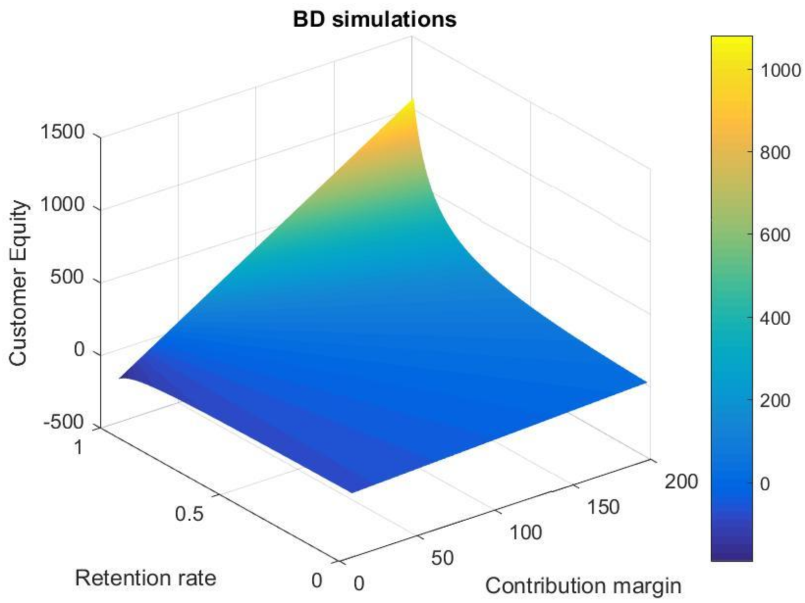
Figure 6



The next series of graphs shows which variable can increase CE more rapidly. Again, retention rate and margins were considered because they are the most common parameters in CLV modeling.

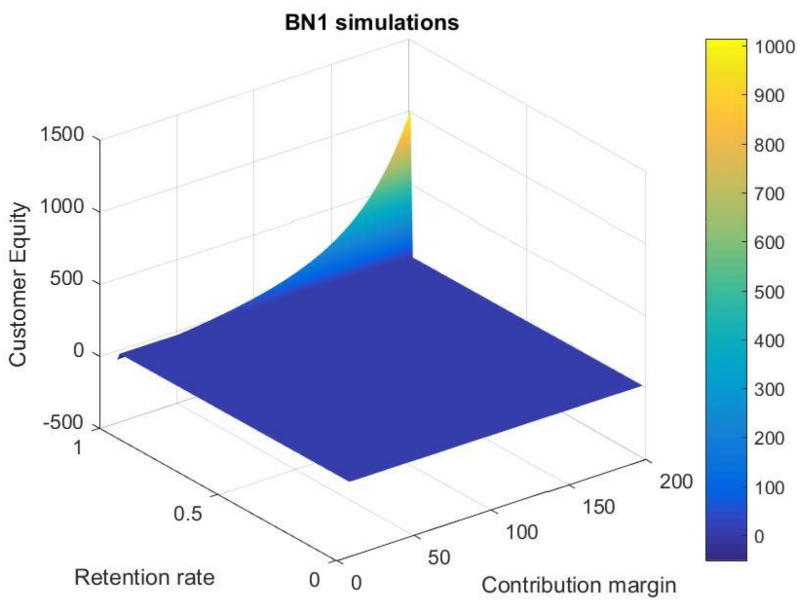
In BD (Figure 7) model margins will have an impact greater than retention and, depending on the context, seeking higher retention rates may not be worth at all.

Figure 7



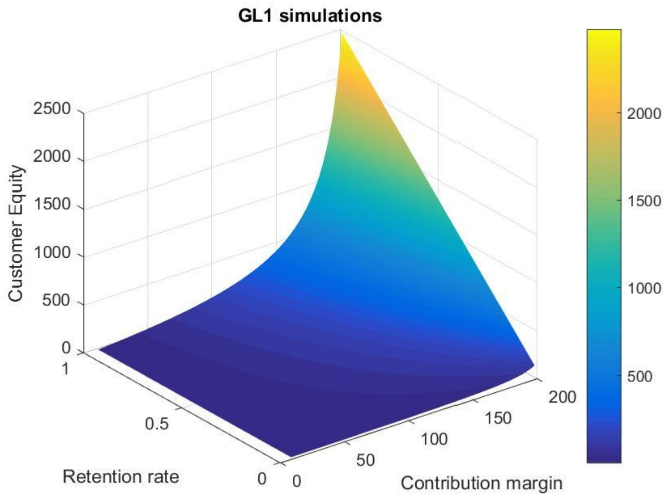
This graph (Figure 8) reveals that in BN1 margins are insignificant for CE creation in low levels of retention, impacting only with extreme values. Thus, this implies that a customer base who has a high churn will result in low CE even when margins are high.

Figure 8



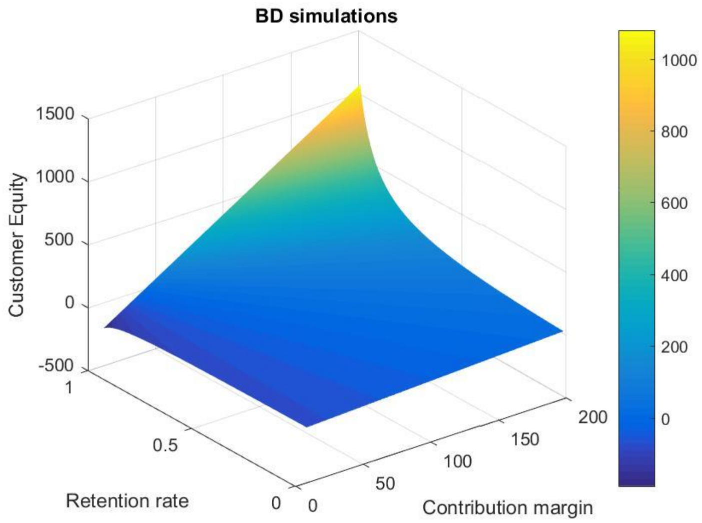
In GL1 (Figure 9) margins will have decreasing gains that retention rate, which have an almost explosive behavior in the higher end. In this model, it is better to pursue better margins than high retention. However, on the long run, retention can make big difference in CE creation.

Figure 9



BD (Figure 10) has the opposite behavior than GL1: margins affects CE in a greater extent than retention. This is an initial evidence that choosing one model can direct marketing efforts in a specific way. In other words, it is possible that decision-making based on CLV will be biased towards the model chosen.

Figure 10



Conclusion

It's a fact that Customer Equity and Customer Lifetime Value had a great impact on marketing research and practice, especially on a context of doubt about the real marketing contributions and the seek for marketing accountability. Moreover, they strengthen the marketing-finance interface and opened a new and growing area of research. However, this growth revealed some shortcomings, both theoretically and managerial. This short investigation aimed to address some of these questions, not by offering answers but highlighting and presenting an initial exploration on the main issues. The revision of literature indicated controversy regarding CLV forecasting, customer behavior, contractual/noncontractual transactions, and retention estimates. Empirically, simulations bring initial evidence that CLV modeling can influence marketing strategy, by conditioning efforts in some way or another (for example, margins versus retention). Since 54 publications resulted in more than 20 models, it is central to deepen research about CLV assumptions and methods, so better studies can be made both academic and managerial. More research comparing CE estimation can shed light on those issues.

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Appendix – List of Analyzed Papers

Author	Metric	Journal	Year
Kotler	CLV	Journal of Marketing	1974
Dwyer	CE	Jounal of Interactive Marketing	1989
Keanand and Wang	CLV	Journal of Direct Marketing	1995
Blattberg and Deighton	CE	Harvard Business Review	1996
Bitran and Mondschein	CLV	Management Science	1996
Berger and Nasr	CLV	Journal of Interactive Marketing	1998
Pfeifer and Carraway	CLV	Journal of Interactive Marketing	2000
Reinartz and Kumar	CLV	Journal of Marketing	2000
Verhoef and Donkers	CLV	Decision Support Systems	2001
Berger and Nasr	CE	Omega	2001
Libai, Narayandas and Humby	CE	Journal of Service Research	2002
Jain and Singh	CLV	Journal of interactive Marketing	2002
Berger, Weinberg, and Hann	CLV	The Journal of Database Marketing & Customer Strategy Management	2003
Drèzand and Bonfrer	CLV	Quantitative Marketing and Economics	2003
Gupta and Lehmann	CLV	Journal of Interactive Marketing	2003
Reinartz and Kumar	CLV	Journal of Marketing	2003
Rosset, Neumann, Eick, and Vatnik	CLV	Data Mining and Knowledge Discovery	2003
Gupta, Lehmann, and Stuart	CLV	Journal of Marketing Research	2004
Rust, Lemon, and Zeithaml	CLV	Journal of Marketing	2004
Venkatesan and Kumar	CLV	Journal of Marketing	2004
Fader, Hardie, and Lee	CLV	Marketing Science	2005
Lewis	CLV	Journal of Marketing	2005
Malthousand and Blattberg	CLV	Journal of Interactive Marketing	2005
Pfeifer and Bang	CLV	Journal of Interactive Marketing	2005
Ryals	CLV	Journal of Marketing	2005
Kumar, Shah, and Venkatesan	CLV	Journal of Retailing	2006
Lewis	CLV	Journal of Marketing	2006
Donkers, Verhoef, and Jong	CLV	Quantitative Marketing and Economics.	2007
Fader and Hardie	CLV	Journal of Interactive Marketing	2007
Fader, Hardie, and Jerath	CLV	Journal of Interactive Marketing	2007
Tirenni et al.	CE/CLV	Marketing Science	2007
Haenlein, Kaplan, and Beeser	CLV	European Management Journal	2007
Aeron et al.	CLV	Database Marketing & Customer Strategy Management	2008
Borle, Singh, and Jain	CLV	Management Science	2008
Kumar, Venkatesan, Bohling, and Beckmann	CLV	Marketing Science	2008
Villanueva, Yoo, and Hanssens	CE	Journal of Marketing Research	2008
Ryals	CLV	Journal of Database Marketing	2008
Wiesel and Skiera	CLV/CE	Journal of Marketing	2008

Kumar and Shah	CLV/CE	Journal of Marketing	2009
Pancras	CE	Journal of Interactive Marketing	2009
Fader and Hardiand	CLV	Marketing Science	2010
Fader, Hardie, and Shang	CLV	Marketing Science	2010
Braun and Schweidel	CLV	Marketing Science	2011
Chan, Wu and Xie	CLV	Marketing Science	2011
Neslin	CLV	Journal of Interactive Marketing	2011
Rust, Kumar, and Venkatesan	CLV	International Journal of Research in Marketing	2011
Schmitt, Skiera and Bulte	CLV	Journal of Marketing	2011
Wiesel, Skiera and Villanueva	CLV/CE	Journal of Marketing	2011
Skiera, Bermes and Horn	CLV/CE	Journal of Marketing	2011
Schulze, Skiera and Wiesel	CLV/CE	Journal of Marketing	2012
Tukel and Dixit	CLV	Journal of Business & Industrial Marketing	2013
Ekinci, Uray and Ulengin	CLV	European Journal of Marketing	2014
Klein and Kolb	CLV/CE	Omega	2015
Jerath, Fader and Hardie	CLV	European Journal of Operational Research	2016

Source: Elaborated by the author.