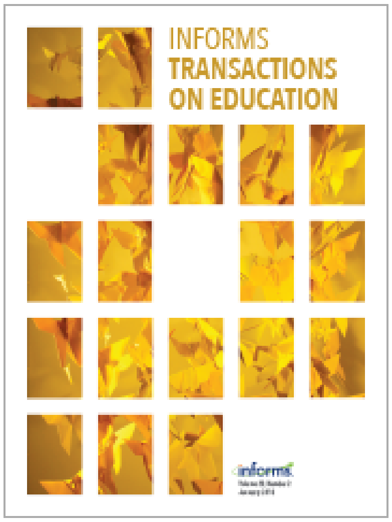

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Using Simulation to Model Customer Behavior in the Context of Customer Lifetime Value Estimation

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This article illustrates how simulation can be used in the classroom for modeling customer behavior in the context of customer lifetime value estimation. Operations research instructors could use this exercise to introduce multiperiod spreadsheet simulation models in a business setting that is of great importance in practice, and the simulation approach to teaching this subject could be of interest also to marketing and accounting instructors. At Babson College, the spreadsheet simulation exercise is part of an integrated one-case teaching day of the marketing, accounting, and operations research disciplines in the full-time MBA program, but the exercise is directly transferable to stand-alone courses as well. In our experience, students have felt empowered by the ability to incorporate their ideas about customer behavior directly into customer lifetime value models, and have appreciated the ease with which simulation enables them to obtain intuition about the sensitivity of their estimates to different assumptions.

Key words: customer lifetime value models; spreadsheet simulation models; cross-disciplinary integration; sensitivity analysis; intuition
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1. Introduction

The problems of estimating lifecycle costs and the economic value of a customer appear in numerous business settings. They are an essential component of marketing courses in business schools, and draw on concepts from multiple areas, such as managerial cost accounting and decision support systems. This *interdisciplinary* nature of customer lifetime value models prompted marketing, accounting, and operations research faculty teaching in the integrated core of the full-time MBA program at Babson College to create a joint one-case day in which we address the business aspects of the problem of customer lifetime value estimation, and the implications of different assumptions on the bottom line for the firm. This article focuses on the decision support systems (DSS) part of the class discussion, which consists of building spreadsheet simulation models. The goal is to make business students aware of the impact of different assumptions about customer behavior on the estimate of customer value, and to provide them with a concrete tool for sensitivity analysis. While the learning experience of this one-case day is substantially enhanced by the integrated three-discipline perspective on the business problem, we believe that the idea of using simulation to improve student intuition about these issues can be helpful to operations research, marketing, and accounting faculty at business schools in stand-alone classes as well. For operations research faculty, customer lifetime value estimation provides a rich context for introducing multiperiod simulation modeling and emphasizing the advantages of Monte Carlo simulation in business applications. For accounting and marketing faculty, using in-class exercises involving spreadsheet simulation makes the lecture interesting and entertaining for the students. Furthermore, it enables students to test their own ideas of customer behavior, and study the impact of these assumptions on variables of interest.

Customer lifetime value (LTV) is generally defined as the present value of all future profits obtained from a customer over its lifetime relationship with the firm. Expected customer LTV can be computed as follows (see Gupta et al. 2006, for example):

$$\mathrm{LTV} = \sum_{t=1}^{T} \frac{(p_t - c_t) r_t}{(1+i)^t} - \mathrm{AC} \tag{1}$$

where

p_t is the price paid by the customer at time t;

c_t is the cost of servicing the customer at time t;

i is the discount rate or cost of capital for the firm;

r_t is the "retention rate," or the probability that the customer will stay with the firm (stay "current" or "alive") through time period t;

AC is the acquisition cost;

T is the time horizon for estimating the LTV.

Note that the customer LTV analysis explicitly considers the probability that a customer will defect. Typically, LTV analysis is done at the individual customer level, as opposed to aggregating and averaging cash flows over all customers, to allow for differentiation between customers who are more profitable than others.

The concept of customer LTV estimation is easy to grasp, but is very difficult to implement effectively. There are several important parameters in Equation (1) (e.g., the discount rate, the retention rate, and the acquisition cost) that need to be estimated from data or chosen subjectively. The literature provides closed-form expressions for customer LTV based on various assumptions about the underlying random processes (for a comprehensive review, see Gupta et al. 2006, for example). Some such assumptions include (a) at each time period, a customer is either "current" ("alive") or has left for good; and (b) the length of the time period is "small" and customer departures follow a Poisson process, which implies that each customer's lifetime is exponentially distributed (see Smittlein et al. 1987, one of the first probabilistic models of customer LTV).

Although computationally convenient, closed-form customer LTV formulas only provide point estimates, and thus ignore two important practical issues. First, they do not consider the *risk* in estimating the LTV, as seen in its probability distribution. Second, closed-form formulas typically do not allow for incorporating assumptions about changing customer behavior over time.

From a teaching perspective, closed-form customer LTV models are difficult to explain to business students if the students have little or no background in advanced quantitative methods. While students may appreciate the usefulness of the mathematical models, they cannot necessarily obtain intuition about the sensitivity of the models with respect to the different assumptions that are made. Simulation modeling allows for incorporating flexible assumptions that enrich the conclusions obtained from traditional customer LTV calculations. More importantly for teaching purposes, simulation is intuitive and easy to implement with today's user-friendly software. Interestingly, while a case has been made for using simulation in the practice of customer lifetime value modeling (see Raab 2005, Cannon et al. 2005, for example), we have not seen many instances in which it is used in the classroom in this particular context. As we were completing this article, we became aware of spreadsheet simulation models of customer loyalty suggested in Albright et al. (2006). The idea of those models is similar to the models we describe, but in this article we attempt to bring in some additional considerations in the teaching of the concept of customer LTV with simulation. Namely, we incorporate different features in the model, present a specific teaching plan for an integrated multidisciplinary approach, and suggest points of discussion that allow for obtaining managerial insights beyond simple interpretation of the output from the simulation. This kind of discussion is particularly important for justifying the presence of DSS in the business curriculum.

We use the case "Virgin Mobile USA: Pricing for the Very First Time" (McGovern 2004) as a basis for discussion; however, any teaching case that involves a customer lifetime value model can be used. The background for the Virgin Mobile case is that a new network provider (Virgin Mobile) is trying to evaluate different options for pricing mobile phone plans. In deciding on a pricing structure, the network provider needs to study the behavior and the value of a typical service subscriber.

The rest of this article discusses our teaching approach in greater detail. We begin by explaining the business setting. We then describe the base simulation model and its extensions, and discuss the output and implications for managerial action. We conclude with a summary of the learning outcomes of the class.

2. The Context: A Customer LTV Model for a Wireless Phone Service Provider

The case concerns Virgin Mobile, a U.K.-based company, at a time when Virgin Mobile is considering entering the U.S. market. The company is targeting young customers and is trying to decide on its pricing and service subscription contract structure. The options available to Virgin Mobile include (a) cloning the industry prices with some differentiated applications such as better customer service, (b) pricing below the competition, and (c) a radically new pricing plan that shortens or eliminates subscription contracts altogether and introduces pre-paid arrangements. The appendix contains the joint teaching plan of the three disciplines (marketing, accounting, and decision support systems) for the day.

After the marketing and the accounting faculty guide the students through understanding the appeal, the shortcomings, and the costing of the different options (items 1–5 in the teaching plan in Appendix A), an important issue emerges. In the end, the company is driven by considerations for profitability, and the profitability is highly dependent on Virgin Mobile's estimate of the value of a customer. A classical calculation of the lifetime value, as explained earlier, is

$$\mathrm{LTV} = \sum_{t=1}^{T} \frac{(M_t) r_t}{(1+i)^t} - \mathrm{AC},$$

where $M_t = p_t - c_t$ is the margin the customer generates in month t. In the Virgin Mobile case, it is assumed that all new customers stay with the phone service provider for the first month, and that the probability that a customer departs in any particular time period is constant. This means that the (cumulative) retention rate r_t in time period t can be written as r^{t-1}, where r is the retention rate in a single period, so we use the expression

$$\mathrm{LTV} = \sum_{t=1}^{T} \frac{(M_t) r^{t-1}}{(1+i)^t} - \mathrm{AC}$$

instead. If the monthly margin M_t is assumed constant and the time horizon is infinite, one can compute a closed-form expression for the customer LTV using infinite geometric series (see Gupta and Lehmann 2005, for example):

$$\mathrm{LTV} = \frac{M}{1-r+i} - \mathrm{AC}. \tag{2}$$

The derivation is straightforward and may be of interest to the students, depending on their background:

$$\begin{aligned}
\mathrm{LTV} &= \sum_{t=1}^{\infty} \frac{(M_t) r^{t-1}}{(1+i)^t} - \mathrm{AC} \\
&= \frac{M}{(1+i)}\left(1 + \frac{r}{(1+i)} + \frac{r^2}{(1+i)^2} + \cdots\right) - \mathrm{AC} \\
&= \frac{M}{(1+i)}\left(\frac{1}{1-r/(1+i)}\right) - \mathrm{AC} \\
&= \frac{M}{(1+i)}\left(\frac{(1+i)}{1+i-r}\right) - \mathrm{AC} \\
&= \frac{M}{(1+i-r)} - \mathrm{AC}.
\end{aligned}$$

The industry average values cited in the case are:

- The monthly cost of servicing a customer is \$30, and the average monthly customer charge equals \$52 (thus, the margin generated per month by a single customer is $M = \$22$);
- The retention rate r, assumed constant over the life of a customer, is 98% for customers with contracts (i.e., the "churn" rate, or the rate of customer turnover, is 2% per month);
- The discount rate i is estimated at 5% per year compounded annually, i.e., $(1.05)^{1/12} = 0.4074\%$ per month;
- The acquisition costs (AC) are about \$370, and include advertising costs, sales commission costs, and the cost of a handset subsidy.

Based on this information, the lifetime value of a single customer can be computed to be \$543.84. It is easy to see that the time to break even is approximately $\mathrm{AC}/M = 370/22 = 16.82$ months. This explains why many wireless service subscription contracts have a length of two years.

3. Spreadsheet Simulation Models

For business students with some quantitative background, the calculation in the previous section makes sense. However, we have found that it is easier to illustrate the validity of the mathematical expression for computing customer LTV with a spreadsheet example. It not only helps to illustrate the concept of computing the present value of a sequence of future cash flows, but also sets up the simulation exercise that follows.

3.1. Illustrating the Simulation Approach in the Case of Constant Churn Rate

The Worksheet "LTV Static 1" in the file VMSimulation-InClass-@RISK.xls[1] illustrates the calculation of the LTV if the customer churn rate is 2% per month and the time horizon is 360 months, or 30 years, which is more time than one would expect a customer to remain with the wireless phone service provider. The LTV is computed in Cell B10. The instructor can use this worksheet to show that the computed customer LTV from the spreadsheet is equivalent to the one computed with Equation (2), because the time horizon is long. For easy comparison, we provide the LTV with the infinite time horizon assumption from Equation (2) in Cell B11. The instructor can also use this worksheet to demonstrate how much the estimate of the LTV changes if the churn rate is slightly higher (e.g., 6%, which the case cites as the industry average for customers without contracts).

Worksheet "LTV Static 2" (in VMSimulation-InClass-@RISK.xls) allows the instructor to illustrate how much the LTV changes if a customer leaves early. The lifetime value of a customer is computed as the present value of the sum of the customer contributions only during the number of months specified in Cell B7. Changing the value of the time horizon in Cell B7 automatically modifies the entries in the column starting in Cell D12, entitled "Current Cus-

[1] This Excel spreadsheet file can be found and downloaded from http://ite.pubs.informs.org/.

tomer?" The values in the latter column are 1 at the beginning, and become 0 if the month number in the corresponding row is higher than the specified time horizon in Cell B7. Consequently, the received customer monthly margin in the column starting in Cell F12 is nonzero only for months in which the customer is "current." The total customer LTV in Cell B10 is computed as the sum of the received discounted monthly margins. This worksheet allows students to develop intuition about the fact that Equation (2) can significantly overestimate the actual LTV for realistic values of the customer life.

Having discussed the sensitivity of the customer profitability estimates to the assumptions about the churn rate and the life of a customer, the instructor can make a natural transition to a discussion of an automated way to incorporate multiple scenarios in the LTV estimation framework. Moreover, it is important for students to realize that the churn rate and the life of a customer are directly related. A high churn rate leads to a short customer life in a concrete way. In particular, a constant churn rate implies a geometric lifetime, so the sensitivity analysis of the LTV should be done by modeling these two parameters simultaneously.

Worksheet "LTV Sim" (in VMSimulation-InClass-@RISK.xls) contains an example of a simulation in which the churn rate is linked to the calculation of customer life, and scenarios are linked directly to the computation of the customer LTV. This is the spreadsheet used by DSS faculty to introduce simulation into the calculation of customer LTV. At the point in the semester at which this case is taught, the students have had one class in which spreadsheet simulation was introduced as a concept. Students have seen how to enter probability distributions and how to read simulation output in class, but have not had a chance to practice the technique in a real-life application. We use @RISK as our add-in spreadsheet simulation tool (http://www.palisade.com), but the spreadsheet models we provide can be easily changed for use with other widely used spreadsheet simulation packages such as Crystal Ball (http://www.crystalball.com). Instructors who do not have access to these spreadsheet simulation packages can use the file VMSimulation-InClass-Excel.xls, which implements the same basic model using only functions available with Excel, such as the random number generator function RAND( ). Excel's own capabilities for simulation are limited, so not all of the analysis that follows can be illustrated easily, but instructors can still cover the main topic. We provide more detail on the Excel-only simulation implementation in §3.4.

Next, we detail the simulation model in the Worksheet "LTV Sim" (in VMSimulation-InClass-@RISK.xls).

In Column D ("Current Customer? 1 = Yes, 0 = No"), we model the event of departure of a customer. For example, in the first time period, a customer is certain to stay, so the customer is "current," and the entry in that cell is 1. In the second time period, a customer leaves with probability equal to the churn rate, or stays with probability (1 − churn rate), which in @RISK is described by the formula =RiskDiscrete({0, 1}, B14:C14). The latter formula simulates a number from a discrete distribution, and takes as inputs two arrays: the first array ({0, 1}) contains the discrete values of the random variable, and the second array (in this case, B14:C14) contains the probabilities of the corresponding values in the first array. While listing the churn and retention rate for each month in columns B and C appears redundant at this point, it is a good idea to keep these columns in the spreadsheet, because they facilitate the student simulation exercise later in the class.

In the third time period (Cell D15) we need to check whether a customer has already left. If the customer has not left yet, we simulate another binary random variable with the formula =RiskDiscrete({0, 1}, B15:C15). If the customer has left already, the status should remain "not current." In this case, there is an entry of "0" in at least one of the cells above the current cell in the same column, and therefore the minimum value of those cells is 0. The MIN function and the IF statement in Excel allow us to set the value of the current cell to 0, which preserves the "not current" status. So, for example, the expression for Cell D15 (the third month) is =IF(MIN($D$13:D14) = 1, RiskDiscrete({0, 1}, B15:C15), 0).

The customer contributions in each month are computed in Column F, based on whether the customer has left or is still "current" in Column D. For example, in Month 3 (row 15), the expression in Cell F15 for whether the monthly margin from Cell B5 has been received is =IF(D15 = 1, $B$5/E15, 0), where Cell D15 contains the realization of the random variable deciding whether a customer has stayed or has left.

The actual life of a customer (in months) is easily computed by counting the number of cells containing "1" in Column D. We keep track of the realized customer life in Cell B11, and make it an output cell for @RISK, which is specified by entering =RISKOUTPUT("Actual Customer Life")+ before the formula in that cell. Note that in very rare instances, a customer may survive longer than the time horizon of 360 months specified in the spreadsheet. Our implicit assumption is that such customers automatically leave at the end of the 360 months.

In addition to the realized customer life, we keep track of the LTV in Cell B10, which is computed as =RiskOutput("Lifetime Value") + B8 − B9.

Table 1 **Output Summary Statistics: Static and Simulated Values for Customer LTV Over 10,000 Scenarios**

Outputs	Lifetime value	Actual customer life
Worksheet	LTV sim	LTV sim
Statistics/cell	$B$10	$B$11
Minimum	−$348.09	1
Maximum	$3,780.51	360
Mean	$552.47	50.47
Standard deviation	$764.52	49.24

After running the simulation in class (we use 10,000 trials so that it does not run too long), we briefly discuss the simulation output (see Table 1 and Figures 1–2, as well as Worksheets "Output Stats Report" and "Output Graphs" in VMSimulation-InClass-@RISK.xls). The average lifetime value of a customer (about $552) is close to the value estimated without simulation (this follows from the constant margin assumption), and the average life of a customer is close to the value one can estimate analytically, about 50 months with an exponential decay function assumption ($1/0.02 = 50$). However, we now also have a lot of additional information, in particular about the variability of the output variables of interest. For example, it is clear from the output that the LTV is very volatile (standard deviation of $764.52), and that the probability that the LTV will be negative is quite large, 28.89% (see Figure 1). Similarly, while a customer stays with the provider for approximately 50 months on average, as expected, there is a substantial variability in customer lifetime as well (standard deviation = 49.24 months), and a substantial probability (27.49%) that the customer will stay with the provider for less than 16.82 months—the time needed to make up for the large customer acquisition costs.

Figure 1 **Output Distribution for Customer LTV Per Month and Probability that the LTV Will Be Positive, for a Constant Churn Rate of 2%**

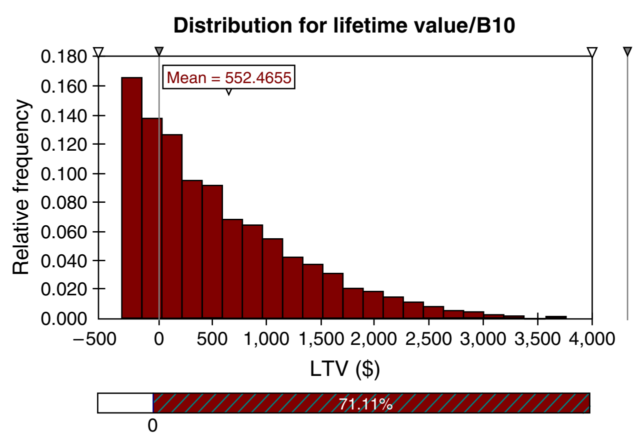
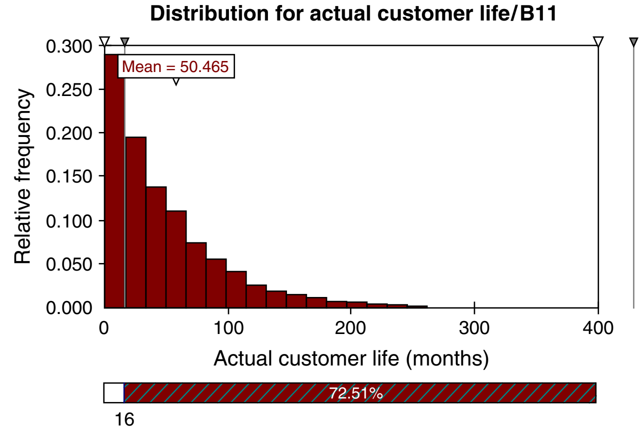


Figure 2 **Output Distribution for the Actual Life of a Customer and Probability that the Actual Life Will Be Greater than 16.82 Months, the Number of Months Necessary to Break Even, for a Constant Churn Rate of 2% Per Month**



3.2. Illustrating the Advantage of Using Simulation in the Case of Non-Constant Churn Rate

Simulation can be used to address another important aspect of the LTV estimation model. The assumption of a *constant* retention rate over the life of the relationship with the customer is questionable. For example, one may argue that a particular group of customers (those in the 16–24 age group) are more likely to stay with the company for the first year, but are highly likely to switch to another provider once this new hip wireless service provider is no longer fashionable. Alternatively, one may argue that customers become inert over time, and if they have stayed with a phone service provider for a long time, they are less likely to leave. These kinds of considerations lead to more challenging computations for the expected LTV and its variability, and most business students with non-quantitative backgrounds cannot create sophisticated analytical models that compute a closed form expression for the LTV or the length of time a customer may stay with the phone service provider given such assumptions.

We ask students to offer their own ideas for how customers would behave, and a lively discussion usually ensues. We then divide the students into groups and ask them to implement different customer behavior assumptions in a simulation model. Given the limited class time (we have about 45 minutes for the break-out exercise), we structure the exercise by distributing a handout with instructions, VMSimulation-StudentHandout.pdf, and template Excel spreadsheets VMSimulation_1.xls and VMSimulation_2.xls.[2] Two

[2] The instruction handout and Excel spreadsheet files can be found and downloaded from http://ite.pubs.informs.org/.

Figure 3 Distribution of LTV, Case 1

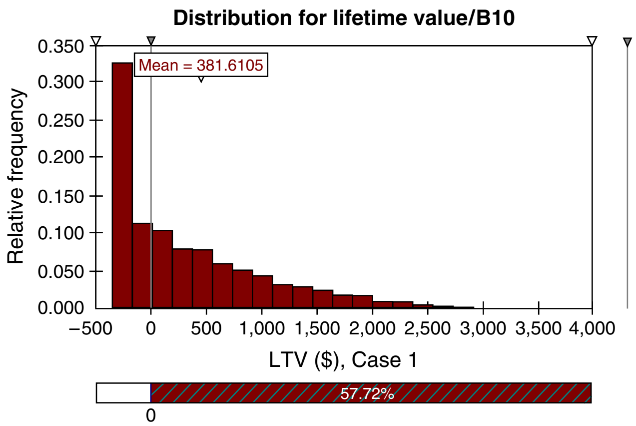
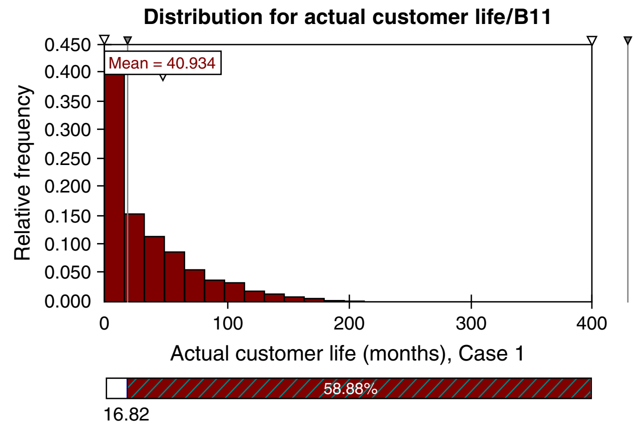


Figure 4 Distribution of Actual Customer Life, Case 1



possible sets of assumptions on customer behavior are as follows:

- Case 1: The customer is more likely to switch to another carrier during months 2–6 (with probability 6% per month), but if he or she has stayed with Virgin Mobile for 6 months, the probability of switching to another carrier decreases to 2% for subsequent months; or
- Case 2: The customer is unlikely to switch to another carrier in months 2–3 (the probability of switching is only 1%), but the probability increases to 6% for the following 12 months, and to 30% after that.

Half of the student groups implement the assumptions in Case 1, and half implement the assumptions in Case 2. When the students report back with results 45 minutes later, we ask one team to present the results for each case, so that the whole class can see the difference in LTV estimates resulting from the different assumptions. The solutions are provided in the file VMSimulation-StudentSolution.xls.[3] For example, if one assumes that customers who have stayed with the company for six months are less likely to leave after that, one obtains the distributions for lifetime value and customer life in Figures 3 and 4, respectively. The estimated average LTV is positive ($381.61). There is a 57.72% probability that the LTV will be positive, and a large probability (58.88%) that the life of the customer will be sufficient to pay back the acquisition cost.

This is not the case when one assumes that after staying with the company for a given amount of time, a customer (especially a young customer, which is the target customer for Virgin Mobile) will be more likely to leave because the fashion will change (see Figures 5 and 6). The LTV is negative on average (−$112.13), and the proposition no longer seems appealing. In addition, the probability that the customer would stay long enough to justify the acquisition costs is only 22.97%.

[3] This Excel spreadsheet file can be found and downloaded from http://ite.pubs.informs.org/.

Figure 5 Distribution of LTV, Case 2

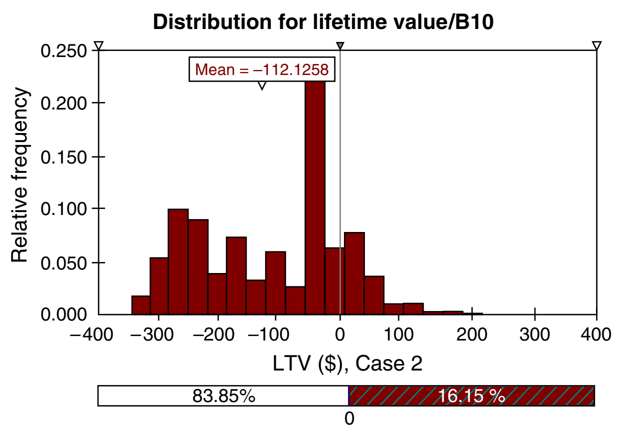
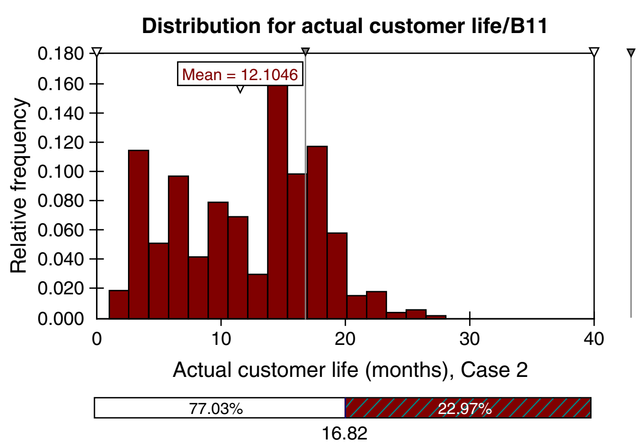


Figure 6 Distribution of Actual Customer Life, Case 2



3.3. Extensions

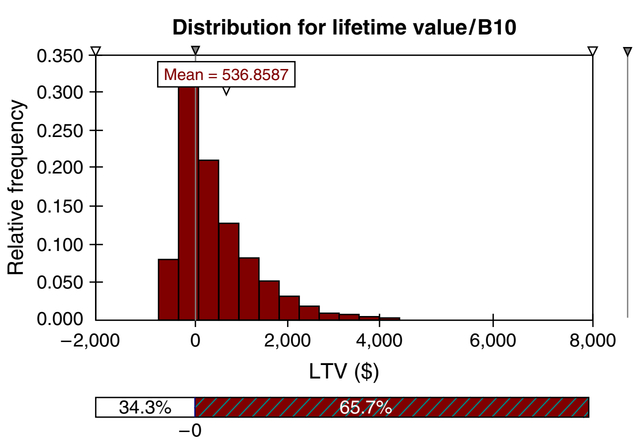
While we did not have time to incorporate simulation of additional uncertain inputs in our class, instructors whose primary goal is to discuss spreadsheet simulation models can easily allow, for example, the acquisition costs, the monthly charge to a customer, or the discount rate to vary in the spreadsheet model.

The estimates of these inputs to an LTV model are typically averages or subjective guesses, not exact values, so there is good justification for modeling these inputs as random. For example, the estimate of the acquisition cost includes an estimate of the advertising cost per customer. This advertising cost is typically determined by dividing a fixed advertising budget by the assumed number of new customers to sign up after the company's advertising campaign ends. In particular, Virgin Mobile allocated $60 million to advertising, and expected 1 million new subscribers, so their estimated advertising cost per subscriber was $60. Obviously, if fewer or more customers sign up than planned, the acquisition cost estimate per customer used in the static LTV model can be substantially different.

An example of modeling multiple inputs as random variables is provided in the Worksheet "LTV Sim Multiple Factors" in the file VMSimulation-InClass-@RISK.xls. It builds upon the base case model presented in class (Worksheet "LTV Sim"). We modeled the monthly charge to a customer (Cell B3) as a normal random variable with mean equal to the industry average of $52 and standard deviation of $10, and the acquisition cost (Cell B9) as a uniform random variable on the interval [$200, $540]. In @RISK, these distributions are represented as =RiskNormal(52, 10) and =RiskUniform(200, 540), respectively.

The additional variability in the base case model does not change the actual customer life (because we did not change the churn rate assumption), but it does change the distribution of the customer LTV (see Figure 7 and Worksheets "Output Stats Report" and "Output Graphs" in the file VMSimulationInClass-@RISK.xls). While the average LTV value remains statistically the same as in the base case, there is higher variability (the standard deviation is $922.21), and the probability that the LTV will be negative has increased to 34.30%.

Figure 7 **Distribution of the LTV When the Churn Rate Is Constant at 2%, Monthly Margin Per Customer Is a Normal Random Variable with Mean $52 and Standard Deviation $10, and Acquisition Costs Per Customer Follow a Uniform Distribution on [200, 540]**



The impact of the variability of the individual inputs on the variability in the estimate of customer LTV is easy to evaluate by using the sensitivity analysis tools of @RISK. (Other specialized Excel simulation add-ins, such as Crystal Ball, have similar capabilities.) In particular, "tornado graphs" in @RISK allow one to identify the input variables whose variability contributes the most to the variability in the output variable. There can be different types of tornado graphs. For help on how to use and interpret tornado graphs, see the online tutorials at http://www.palisade.com/training/, for example. The tornado graph for LTV in Figure 8 presents the standardized slope coefficients of a regression of the sampled input variable values in the simulation against the values of the output variable (LTV). The size of a bar is a measure of the impact of the input variable on the output variable, and the direction of the bar indicates whether the relationship with the output variable is positive or negative. According to Figure 8, LTV is impacted most significantly by the monthly customer charge, and an increase in the monthly customer charge leads to an increase in the LTV (top bar in the tornado graph). An increase in acquisition costs leads to a decrease in the LTV, which agrees with intuition (third bar from the top). The value of the random variable in Cell D14, which is the first month in which a customer can leave the wireless service provider, also has a substantial impact on LTV (second bar from the top). By comparison, the effect of each of the other random inputs on LTV is small.

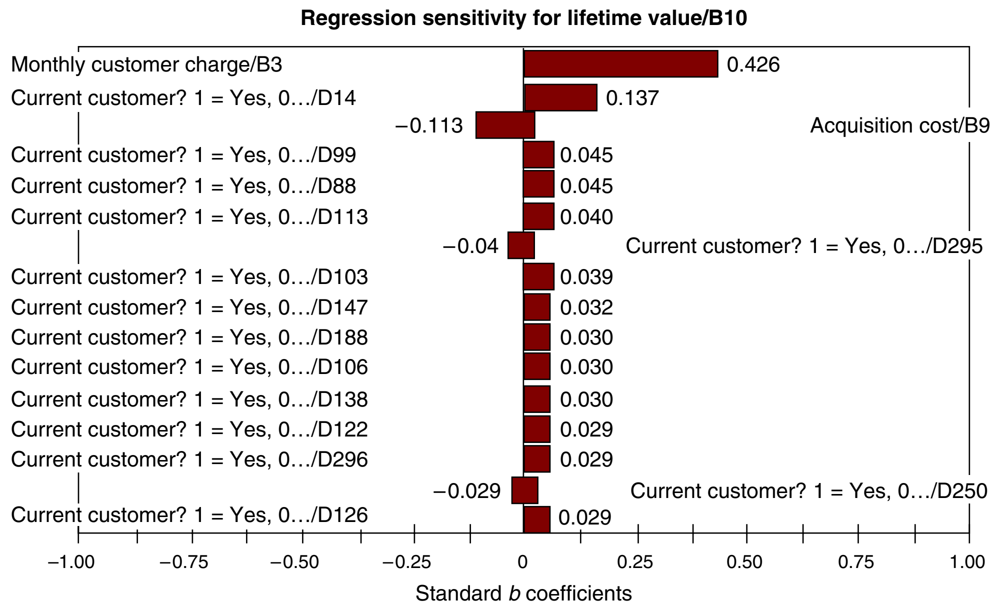
3.4. A Note on Excel-Only Implementation of the Simulation Models

As we mentioned earlier, the analysis in §3.2 can be performed using only Excel functions, such as the random number generator function RAND( ). The file VMSimulation-InClass-Excel.xls[4] contains an example of how this can be done.[5] RAND( ) draws a random number on the interval [0, 1]. The general setup of the simulation is the same, except that instead of the RiskDiscrete function for simulating a discrete random variable in Column D, we use an IF statement. If the realized value of RAND( ) is less than the churn rate (which happens with the probability reflected in the churn rate), then the assigned value is 0 and the customer "leaves;" otherwise the customer stays. So, the formula for the third month, for

[4] This Excel spreadsheet file can be found and downloaded from http://ite.pubs.informs.org/.

[5] We thank the associate editor for suggesting and outlining the Excel-only simulation framework.

Figure 8 A Tornado Graph for LTV



example (in Cell D15 of Worksheet "LTV Sim"), is =IF(MIN($D$13:D14) = 1, IF(RAND( ) < B15, 0, 1), 0).

Excel does not have the same capabilities as specialized simulation add-ins to keep track of simulation output and create graphs, so the output of the simulation needs to be handled manually. In the right hand side of the Worksheet "LTV Sim," we have created data tables that calculate the LTV and the actual lifetime of a customer over 1,000 scenarios. The simulated data in these columns (Cells I13:I1012 for LTV and Cells L13:L1012 for actual customer life) can be used to plot the probability distributions of the outputs using Excel's Chart Wizard, and to determine the average values, standard deviations of estimates, and probabilities of interest. A word of caution: Since the number of random numbers that need to be generated is large, Excel may take a significant amount of time to re-compute and update the worksheet whenever a small change to the spreadsheet is made. We recommend that instructors select the manual recalculation option in Excel, and press F9 if they need to generate new scenarios. It may also be useful to "freeze" the simulation output by coping the simulated values in the data table, and pasting them as values by selecting "Paste Special."

If an instructor is interested in incorporating multiple random inputs in the model, as we discussed in §3.3, the Excel function RAND( ) can be used in combination with other Excel functions to simulate random variables from different probability distributions. For example, to simulate a normal random variable with mean 52 and standard deviation 10 (the input distribution we used for monthly charge per customer in Cell B3), one would enter the formula =NORMINV(RAND( ), 52, 10). To simulate a uniform random variable between 200 and 540 (the input distribution we used for the acquisition cost per customer in Cell B9), one would enter = 200 + (540 − 200) ∗ RAND( ).

4. Managerial Insights

An important strategy for ensuring the success of this class for business students is to conclude with a transition from the descriptive to the prescriptive. Simulation allows us to analyze the sensitivity of our customer profitability estimates to our assumptions on customer behavior and other important parameters. Once we have studied the effect of these assumptions, we can use the insights we have gathered to create strategies for generating particularly desirable patterns of customer behavior. For example, if the simulation tells us that the LTV estimate would be considerably higher if we are able to retain customers between their 6th and 12th month with the company, we could plan promotions that entice customers to stay for those months without putting too much effort into trying to retain them forever. Or, if there is a specific customer profile that produces a higher LTV or a lower risk based on the simulation results, we can target that kind of customer, or try to motivate that desirable behavior in existing customers by using special pricing structures and incentives.

5. Concluding Remarks

We believe that using spreadsheet simulation modeling to incorporate different assumptions for customer behavior in the context of teaching customer lifetime value estimation has had multiple benefits. First, it has allowed us to introduce material that may be mathematically challenging to some students in a very intuitive fashion. Second, it has helped us to integrate the mechanics of spreadsheet modeling with a discussion of managerial implications. Third, while thinking about the simulation model, students revisit important Excel functions, such as IF and SUM, and learn how to build relatively sophisticated Excel models. From the perspective of operations research instructors, the exercise reviews several important statistical, modeling, and spreadsheet simulation software concepts, such as probability distributions, risk, confidence interval estimates for population parameters (such as the true mean customer lifetime value), multiperiod simulation modeling, and nesting @RISK functions in Excel functions. Many of these concepts would have remained a footnote in cases discussed in business programs, but simulation has allowed them to feel real, tangible, and useful. We hope that this simulation exercise will be helpful to and enjoyed by other instructors and students as well.

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Appendix

Teaching Plan and Study Questions
Session 1 (MARKETING, 45 minutes total):

1. What is the state of the US mobile telephone market at the time of the case study?
2. Do you agree with Virgin Mobile's target market selection? What are the risks associated with targeting this segment?
3. What do you think of Virgin Mobile's value proposition? What do you think of its channel and merchandising strategy?
4. Does the way Virgin Mobile define the pricing options make sense to you? Are all three viable? Are there other options?

Session 2 Plus Break Out Session (ACCOUNTING and DSS, 90 minutes total):

5. (ACCOUNTING, 35 min) Walk students through the computations of lifetime value for a new customer. Do you agree with the financial analysis done by Virgin Mobile to establish the financial viability of their model?
6. (ACCOUNTING and DSS, 10 min) Incorporate variability in the model (Worksheets "LTV Static 1" and "LTV Static 2" in file VMSimulation-InClass-@RISK.xls). Ask questions such as:
   - What is a major assumption for computing the lifetime value of a customer?
   - How does a change in the assumed monthly churn rate impact the estimate of financial viability?
   - Do you agree with the assumption of a constant churn rate? What are other reasonable assumptions? (Write a couple of the suggestions on the board.)
7. (Break out session, 45 min) Split the class into groups and ask them to implement these assumptions as part of a simulation model. (Distribute the handout, VMSSimulation-StudentHandout.pdf with detailed instructions in Appendix B and the template files, VMSimulation_1.xls and VMSimulation_2.xls).

Session 3 (ACCOUNTING and DSS, 45 minutes total):

8. (ACCOUNTING and DSS, 15 min) Ask a couple of student teams to present their results.
9. (ACCOUNTING, 30 min) How would you go about conducting a customer analysis to help determine a go-to-market configuration of the Virgin Mobile offering?

Session 4 (Plenary Session: MARKETING, ACCOUNTING and DSS, 30 min total)

10. Final Comments and Wrap Up.

References
Albright, S. C., W. Winston, C. Zappe. 2006. *Data Analysis and Decision Making with Microsoft Excel*, 3rd ed. Thomson South-Western, Mason, OH.

Cannon, H., J. Cannon, M. Schwaiger. 2005. Simulating customer lifetime value: Implications for game design and student performance. *Developments Bus. Simulation and Experiential Learn.* **32** 54–64.

Gupta, S., D. R. Lehmann. 2005. *Managing Customers as Investments*. Wharton School Publishing, Philadelphia.

Gupta, S., D. Hanssens, B. Hardie, W. Kahn, V. Kumar, N. Lin, N. Ravishanker, S. Sriram. 2006. Modeling customer lifetime value. *J. Service Res.* **9**(2) 139–155.

McGovern, G. 2004. *Virgin Mobile: Pricing for the Very First Time*. Harvard Business School Press, Case Number 9-504-028.

Raab, D. 2005. Customer value models. *DM Review* (September), http://www.dmreview.com/issues/20050901/1035611-1.html.

Schmittlein, D., D. Morrison, R. Colombo. 1987. Counting your customers: Who they are and what will they do next? *Management Sci.* **33**(1) 1–24.