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It is increasingly apparent that the financial value of a firm depends on off-balance-sheet intangible assets. In this article, the authors focus on the most critical aspect of a firm: its customers. Specifically, they demonstrate how valuing customers makes it feasible to value firms, including high-growth firms with negative earnings. The authors define the value of a customer as the expected sum of discounted future earnings. They demonstrate their valuation method by using publicly available data for five firms. They find that a 1% improvement in retention, margin, or acquisition cost improves firm value by 5%, 1%, and .1%, respectively. They also find that a 1% improvement in retention has almost five times greater impact on firm value than a 1% change in discount rate or cost of capital. The results show that the linking of marketing concepts to shareholder value is both possible and insightful.

Valuing Customers

Recently, there have been many calls for marketing accountability, measurement of marketing productivity, and better marketing metrics. Much of this stems from the dual realities of crumbling functional boundaries, as evidenced by the growing roles of design in new product development as well as operations and information technology in customer relationship management, and the increasing pressure to relate marketing to stock market performance. This article relates the key focus of marketing effort, the customers, to the key measure of a firm's financial success, its market value.

Traditional accounting has focused on measuring tangible assets, and the resulting data presented in annual reports, 10-Ks, and so on has formed the basis of firm valuation. However, intangible assets (e.g., brand, customer, and employee equity) are critical and often dominant determinants of value (Amir and Lev 1996; Srivastava, Shervani, and Fahey 1998), yet financial analysts at best tangentially cover these critical determinants. Moreover, the dot-com bubble has been attributed *post hoc* to the use of "too much marketing" (i.e., large advertising budgets and reliance on questionable marketing metrics, such as eyeballs and click-throughs), which suggests that market-based measures may be in danger of being rejected en masse.

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We merge traditional financial valuation methods based on discounted earnings with the key marketing concept of the value of the customer to a firm. Specifically, we show how a disciplined analysis of value based on customers and their expected future earnings (1) provides insights not possible at the traditional more-aggregate level of analysis, (2) facilitates projections for new and growing businesses, and (3) provides an explanation for the dot-com bubble. The basis of this approach is customer lifetime value, which is the discounted future income stream derived from acquisition, retention, and expansion projections and their associated costs. In essence, we extend the concept of customer lifetime value and the works of several researchers (e.g., Blattberg, Getz, and Thomas 2001; Niraj, Gupta, and Narasimhan 2001; Reinartz and Kumar 2000; Rust, Zeithaml, and Lemon 2001) to the arena of financial valuation.

VALUING HIGH-GROWTH BUSINESSES

In general, it is relatively easy to value stable and mature businesses. For these types of companies, the cash flow stream is relatively easy to predict. Therefore, financial models such as discounted cash flow (DCF) work reasonably well. In contrast, the valuation of high-growth businesses is complex, because these businesses have limited history to draw on for future projections. They also typically invest heavily in the early periods, which results in negative cash flows. Consequently, traditional financial methods are not useful for evaluating these businesses; it is difficult to use a price-to-earnings (P/E) ratio for a company that has no earnings or negative earnings or to use the DCF approach when a firm has negative cash flow. This difficulty became evident during the height of the dot-com bubble, when many innovative valuation methods emerged.

A popular measure that emerged in 1999–2000 is the number of customers, or eyeballs. This metric is based on

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the assumption that growth companies need to acquire customers rapidly to gain first-mover advantage and to build strong network externalities, at times regardless of the cost involved (*The Wall Street Journal* 1999). Academic research in accounting also has provided validation for this assumption. For example, Trueman, Wong, and Zhang (2000) combine financial information from company statements with nonfinancial information from Media Metrix for the period September 1998 to December 1999 for 63 Internet firms. A regression of market value on these components reveals that though bottom-line net income has no relationship to stock price, unique visitors and page views add significant explanatory power. In a related study, Demers and Lev (2001) use similar data for 1999–2000 for 84 Internet companies in order to examine the relationship between market value and nonfinancial measures during and after the Internet bubble. They find that nonfinancial measures, such as reach (i.e., number of unique visitors) and stickiness (i.e., site's ability to hold its customers), explain the share price of Internet companies, both before and after the bubble burst.

Note that these studies are correlational and assume that the market value represents the true intrinsic value of the firm at any time, which is an efficient market argument. However, even if the markets are efficient in the long run, recent history suggests that significant deviations exist in the short run. In other words, the value of the dependent variable in these studies is likely to change significantly over time, which may alter conclusions about the value of customers. Partly because of this, financial analysts are now quite skeptical of nonfinancial metrics, especially number of customers. For example, an article criticized the Wall Street icon Mary Meeker for relying too much on eyeballs and page views and even putting them ahead of financial measures (*Fortune* 2001b).

Our Approach

The mood on Wall Street suggests that customer-based metrics not only are irrelevant to firm valuation but also can be misleading. We argue against this view. We suggest and show that value based on customers can be a strong determinant of firm value. The premise of our customer-based valuation approach is simple: If the long-term value of a customer can be estimated and the growth in number of customers can be forecast, it is easy to value a company's current and future customer base. To the extent that the customer base forms a large part of a company's overall value, it can provide a useful proxy for firm value. We demonstrate our approach for one well-established firm for which traditional financial methods work well. In addition, we use our approach to estimate the value of four Internet firms for which traditional financial methods may not work well.

We also show that it is not necessary to obtain detailed proprietary information (as is typically done in database marketing and customer lifetime value research) to apply our approach. Except for retention rate, we use only published information from firms' annual reports and other financial statements to estimate the value of their customer base. Therefore, our approach can be valuable for external constituencies, such as investors, financial analysts, and acquirer companies, which may not have access to detailed internal data.

The closest parallel approach to our own is that of Kim, Mahajan, and Srivastava (1995), who use a DCF method to estimate the value of a business in the wireless communications industry. Our work differs from their approach in several important ways. First, our approach focuses on the company level (rather than the industry level), and we apply our method to multiple firms. Second, we do not need to make any assumption about the time when growth ends. We explicitly model growth in customers and firm value. Third, we incorporate customer retention, which has a significant substantive and methodological impact. For example, industry reports show that the annual churn rate in the telecommunications industry (which Kim, Mahajan, and Srivastava examine) is more than 20%. The industry estimates that this churn rate reduces firms' value by several billion dollars. Our analysis confirms that customer retention has a large impact on firm value. The inclusion of customer retention requires us to account for different customer cohorts that change the model conceptually and mathematically. Finally, the inclusion of customer retention and acquisition in the model provides insights for managers about potential marketing levers that are available to them for improving customer and firm value.

In summary, the key contribution of our approach is the provision of an estimate of the value of the current and future customer base of a firm, which in turn forms a proxy for the value of high-growth firms for which traditional financial methods do not work well. Our main contributions lie in three areas: (1) providing a better method for forecasting the future stream of income when it is not possible to simply extrapolate the historical (negative) earnings of a firm, (2) providing insights about marketing levers (e.g., retention) that can help managers improve firm value, and (3) suggesting that customers are indeed assets, and therefore customer-related expenditures should be treated as investments rather than expenses.

MODEL

Conceptually, the value of a firm's customer base is the sum of the lifetime value of its current and future customers. We build a model for the lifetime value of a cohort of customers, aggregate the lifetime value across current and future cohorts, and then construct models to forecast the key input to the model (e.g., the number of customers in future cohorts).

We begin with a simple scenario in which a customer generates a margin m_t for each period t, the discount rate is i, and the retention rate is 100%. In this case, the lifetime value of the customer is simply the present value of the future income stream:

$$\text{LV} = \sum_{t=0}^{\infty} \frac{m_t}{(1+i)^t}. \tag{1}$$

This is identical to the DCF approach of valuing perpetuity (Brealey and Myers 1996). When we account for the customer retention rate r, the formulation is modified as follows:[1]

$$\text{LV} = \sum_{t=0}^{\infty} m_t \frac{r^t}{(1+i)^t}. \tag{2}$$

[1]We recognize that retention rates may not be constant; however, we make this simplified assumption for the ease of modeling and empirical application. Our data for Ameritrade supports our assumption.

Many researchers have debated the appropriate duration over which lifetime estimates should be based (Berger and Nasr 1998). We build our model for an infinite time horizon for several reasons. First, we do not need to specify arbitrarily the number of years that a customer will stay with the company. Second, the retention rate accounts for the fact that over time, the chances of a customer staying with the company decrease significantly. Third, the typical method for the conversion of retention rate to expected lifetime and then calculation of present value over that finite time period overestimates lifetime value.[2] Fourth, both retention and discount rates ensure that earnings from the distant future contribute significantly less to lifetime value. Finally, models with infinite horizons are significantly simpler to estimate.

To estimate the lifetime value of the entire customer base of a firm, we recognize that the firm acquires new customers in each time period. Each cohort of customers goes through the defection and profit pattern shown in Table 1, which shows that the firm acquires n_0 customers at time 0 at an acquisition cost of c_0 per customer. Over time, customers defect such that the firm is left with n_0r customers at the end of Period 1, n_0r^2 customers at the end of Period 2, and so on. The profit from each customer may vary over time. For example, Reichheld (1996) suggests that profits from a customer increase over that customer's lifetime. In contrast, Reinartz and Kumar (2000) find that this pattern does not hold for noncontractual settings.

Therefore, the lifetime value of Cohort 0 at Time 0 is given by

$$LV_0 = n_0 \sum_{t=o}^{\infty} m_t \frac{r^t}{(1+i)^t} - n_0 c_0. \tag{3}$$

Cohort 1 follows a pattern similar to that of Cohort 0, except that it is shifted in time by one period. Therefore, the lifetime value of Cohort 1 at Time 1 is given by

$$LV_1 = n_1 \sum_{t=1}^{\infty} m_{t-1} \frac{r^{t-1}}{(1+i)^{t-1}} - n_1 c_1. \tag{4}$$

It is easy to convert this value at Time 0 by discounting it for one period. In other words, the lifetime value of Cohort 1 at Time 0 is

$$LV_1 = \frac{n_1}{1+i} \sum_{t=1}^{\infty} m_{t-1} \frac{r^{t-1}}{(1+i)^{t-1}} - \frac{n_1 c_1}{1+i}. \tag{5}$$

In general, the lifetime value for the kth cohort at Time 0 is given by

$$LV_k = \frac{n_k}{(1+i)^k} \sum_{t=k}^{\infty} m_{t-k} \frac{r^{t-k}}{(1+i)^{t-k}} - \frac{n_k c_k}{(1+i)^k}. \tag{6}$$

The value of the firm's customer base is then the sum of the lifetime value of all cohorts:

$$\text{Value} = \sum_{k=0}^{\infty} \frac{n_k}{(1+i)^k} \sum_{t=k}^{\infty} m_{t-k} \frac{r^{t-k}}{(1+i)^{t-k}} - \sum_{k=0}^{\infty} \frac{n_k c_k}{(1+i)^k}. \tag{7}$$

Although it is easier to conceptualize the model in discrete terms, in reality customer acquisition and defection is a continuous process. Schmittlein and Mahajan (1982) show that estimation of an inherently continuous process, such as a Bass (1969) diffusion model, with a discrete version produces biases. Furthermore, we model key input (e.g., n_k) as a continuous function. Therefore, we use a continuous version of customer value.

If the annual discount rate is i and we continuously compound m times a year, the discount rate at the end of the year is $1/[1 + (i/m)])^m$. As m approaches infinity, the discount rate becomes e^{-it} (Brealey and Myers 1996). Similarly, it is easy to show that $r^t/(1 + i)^t$ is equivalent to $e^{-[(1 + i - r)/r]t}$. Therefore, the continuous version of Equation 7 is

$$\text{Value} = \int_{k=0}^{\infty} \int_{t=k}^{\infty} n_k m_{t-k} e^{-ik} e^{-\left(\frac{1+i-r}{r}\right)(t-k)} dt\,dk - \int_{k=0}^{\infty} n_k c_k e^{-ik} dk. \tag{8}$$

Equation 8 provides customer value before any tax considerations. Consistent with financial models, we use the after-tax value as a proxy for firm value. Here, we use a corporate tax rate of 38% for all firms. Before building models of n_k and so on, we turn to data in our empirical application to

[2]For example, consider a situation in which the annual margin from a customer is \$100, the retention rate is 80%, and the discount rate is 12%. Using Equation 2, we estimate the lifetime value of this customer to be \$250. An alternative approach would suggest that the 80% retention rate implies that this customer is expected to stay with the company for five years. The present value of the \$100 stream of income for five years is \$360, an overestimate of approximately 44%.

Table 1

NUMBER OF CUSTOMERS AND MARGINS FOR EACH COHORT

	Cohort 0		*Cohort 1*		*Cohort 2*	
Time	*Customers*	*Margin*	*Customers*	*Margin*	*Customers*	*Margin*
0	n_0	m_0				
1	n_0r	m_1	n_1	m_0		
2	n_0r^2	m_2	n_1r	m_1	n_2	m_0
3	n_0r^3	m_3	n_1r^2	m_2	n_2r	m_1
.	.	.	n_1r^3	m_3	n_2r^2	m_2
.	.	.	.	.	n_2r^3	m_3
.	.	.	.	.	.	.

Notes: We have assumed that each customer cohort follows the same pattern of margins (m_0, m_1, m_2, ... m_n). Although it is possible to make this pattern vary across cohorts, this increases the model complexity significantly. In addition, literature lacks theoretical justification for a specific pattern. Finally, most data sets are insufficient to validate a specific pattern empirically.

understand the nature of available information. The available data, their empirical patterns, and theory guide us in our selection of appropriate models for these input variables.

APPLICATION

Data

We estimated our model using data from five companies: one traditional firm (Capital One) and four Internet companies (Amazon.com, Ameritrade, eBay, and E*Trade). We used a traditional firm to show that similar to standard financial models, our approach is capable of providing good estimates of firm value. We used four Internet companies to show the usefulness of our approach when standard financial models may not apply well because of low or negative cash flows. We based our choice of companies on the availability of public data.

We used quarterly data from annual reports, 10-K and 10-Q statements, and other company reports for the period from 1996–1997 to March 2002. The data for each quarter include number of customers, margin, and marketing costs. Using these data, we estimated the acquisition cost and quarterly margin per customer. A summary of the data is provided in Table 2.

Number of customers. Figure 1 shows the growth in number of customers for each of the five firms. The data show a remarkable consistency with classical diffusion theory. A natural candidate for estimation of the number of customers in future periods is the Bass (1969) diffusion model. The continuous Bass model (p. 218) is based on the solution to a nonlinear differential equation, and the resulting sales or number of customers' equation is quite complex. The discrete analog model is simpler but still poses challenges in our context, because sales or number of new customers are functions of either cumulative sales or customers. This recursive relationship makes the integration (or summation) more complex.

Therefore, we modeled customers using an S-shaped function that is similar to the Bass (1969) diffusion model but is mathematically more convenient in our context. Specifically, we suggest that the cumulative number of customers N_t at any time t is given by

$$N_t = \frac{\alpha}{1 + \exp(-\beta - \gamma t)}. \tag{9}$$

The number of customers reaches α as time approaches infinity. The parameter γ captures the slope of the curve. The number of new customers acquired at any time is

$$n_t = \frac{dN_t}{dt} = \frac{\alpha\gamma \exp(-\beta - \gamma t)}{[1 + \exp(-\beta - \gamma t)]^2}. \tag{10}$$

This model, also called the technological substitution model, has been used by several researchers to model innovations and to project the number of customers (e.g., Fisher and Pry 1971; Kim, Mahajan, and Srivastava 1995). Bass, Jain, and Krishnan (2000) suggest that estimates from this model are comparable to those from the Bass model.

Margin. It is relatively straightforward to obtain the quarterly revenues for a firm from financial statements. However, the assessment of costs poses challenges because firms do not report direct costs in a consistent manner. For example, although fulfillment cost (i.e., shipping and handling) is a large portion of Amazon.com's operating expense, the firm does not include it in calculating its margin. We included these costs in our estimate of the margin. Similarly, a major expense for the credit card company Capital One is the salary of its employees. We included salaries as a direct cost to arrive at margins for two reasons. First, Capital One (2001, p. 22) explicitly states in its annual report that its "salaries and associate benefits expense increased 36% as a direct result of the cost of operations to manage the growth in the company's accounts." Second, to separate fixed and variable cost, we ran a regression between employee expenses and the number of customers (Anthony, Hawkins, and Merchant 1998), which produced an R^2 of .974, with almost all the cost allocated as variable. In other words, as a direct marketing company, an increase in the number of customers for Capital One is directly associated with an increase in employee expenses. We followed a similar process for the other firms.

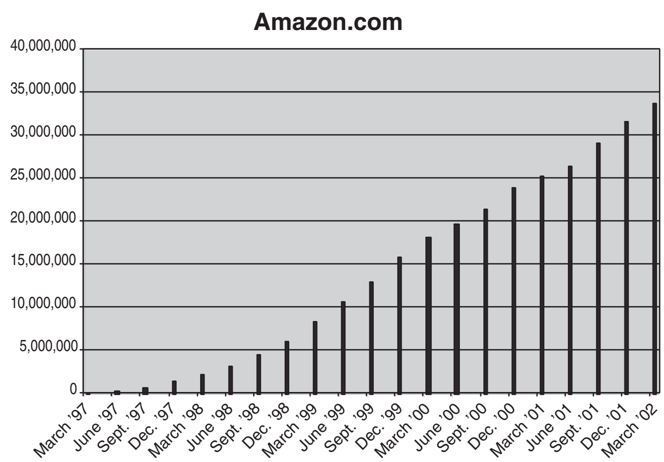
After we determined total margin for a quarter, we estimated quarterly margin per customer by dividing the total margin by the number of current customers in that quarter. Unlike the number of customers, there is no systematic trend in margins. We confirmed this by running a regression. The lack of a systematic pattern echoes the debate among researchers in this area. For example, Reichheld (1996) finds that the longer a customer stays with a company, the more the customer buys. Reichheld also suggests that the company has the potential to cross-sell its products to its customer base. In addition to increased revenue, Reichheld finds that the longer a customer stays with a company, the lower is the cost of doing business with the customer. However, Reinartz and Kumar (2000) challenge these findings and show that duration of stay is not necessarily related to increased margin.

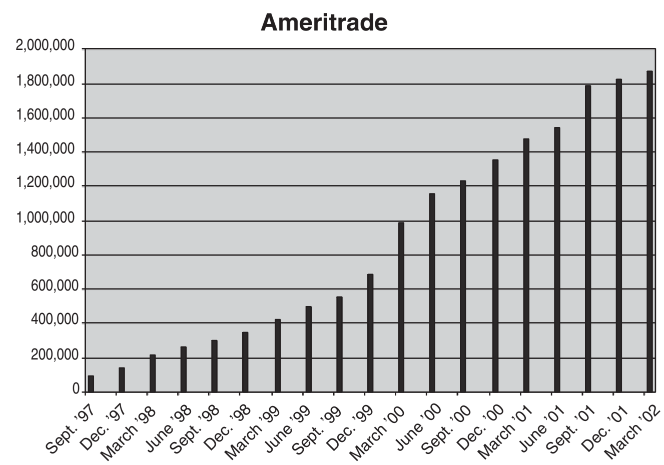
Table 2
DESCRIPTIVE DATA

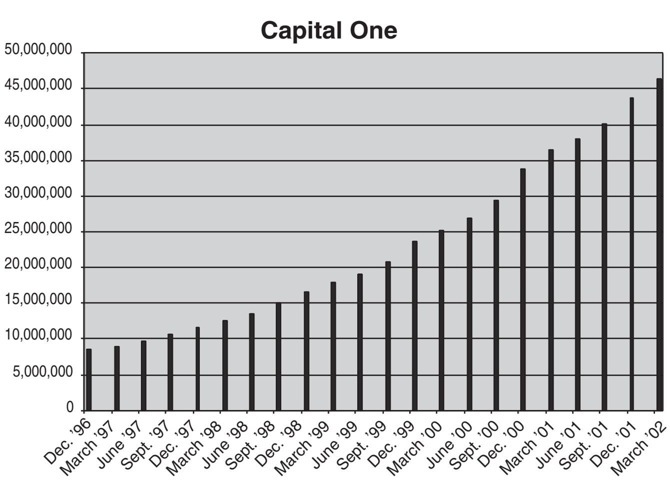
Company	Data Period: From	Data Period: To	Number of Customers	Quarterly Margin	Acquisition Cost	Retention Rate
Amazon.com	March 1997	March 2002	33,800,000	$ 3.87	$ 7.70	70%
Ameritrade	September 1997	March 2002	1,877,000	50.39	203.44	95%
Capital One	December 1996	March 2002	46,600,000	13.71	75.49	85%
eBay	December 1996	March 2002	46,100,000	4.31	11.26	80%
E*Trade	December 1997	March 2002	4,117,370	43.02	391.00	95%

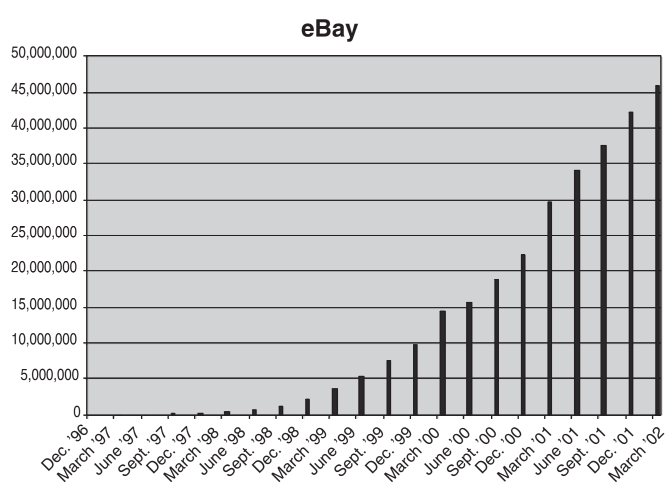
Notes: Number of customers is as of the end of March 2002. Quarterly margin is per customer based on the average of the previous four quarters. Acquisition cost is per customer based on the average of the previous four quarters.

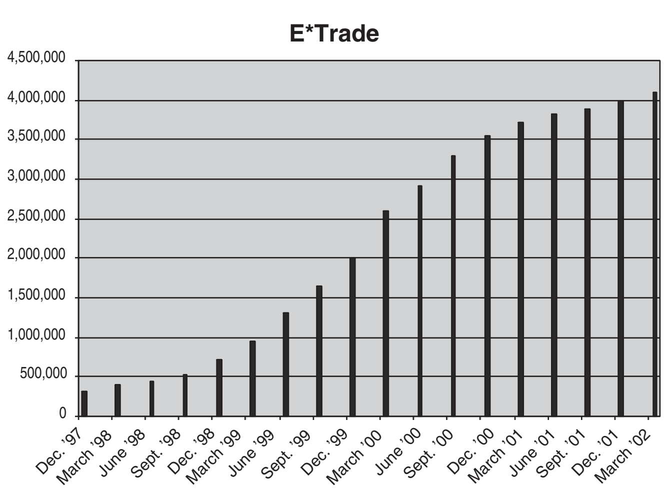
Figure 1
NUMBER OF CUSTOMERS











In addition to the debate about the pattern of margins over time *within* a cohort, the issue is further complicated in our case because our aggregate data combine margins *across* several cohorts, each of them at a different life cycle stage. As a company expands its customer base, it tends to draw more marginal customers who do not spend as much with the company as its original customers did. Consequently, average revenue per customer may decline over time. This is especially true if a company's customer base expands rapidly, thereby changing its customer mix. For example, CDNow's revenue per customer fell from $23.15 to $21.16 in 1998. In the first quarter of 1999, it acquired its competitor N2K, which further contributed to the decline in its revenue per customer from $18.15 in the first quarter of 1999 to $14.42 in the second quarter of 1999 (Kaufman 1999).

Given conflicting evidence in research and the lack of any systematic pattern in our data, we used the average of the last four quarters as the margin for future periods.[3] We performed sensitivity analysis to determine how customer and firm values change with changes in margins.

Acquisition cost. Although acquisition cost is easy to define, it is difficult to estimate precisely in an empirical setting. Companies use different accounting and management practices to define the costs that should be included in this measure. Consequently, some marketing studies (e.g., Reinartz and Kumar 2000) do not include acquisition cost in the analysis.

We operationalized acquisition cost by dividing the total marketing cost by the number of newly acquired customers for each time period. Although some of the marketing cost is incurred for retention purposes as well, we did not have information to separate the two costs. However, this simplification is not likely to have significant impact on our results for several reasons. First, the firms in our data set were in the growth stage of their life cycle, and thus customer acquisition was a dominant factor. Second, several studies show that, in general, customer acquisition costs are significantly higher than customer retention costs (Reichheld 1996). For example, Thomas (2001) estimates acquisition cost per customer to be $26.94 and retention cost per customer to be $2.15. Finally, our estimates of acquisition costs are quite similar to estimates published in various industry reports.

As with profit margins, there is no systematic trend in acquisition costs. We confirmed this by running a regression. There are two opposing forces that affect acquisition costs. As competition intensifies and a company acquires marginal customers (i.e., customers to whom the firm's products and services are less convincing), its acquisition cost increases. This is most evident in the telecommunications industry, in which the acquisition cost per subscriber dramatically increased from $4,200 when AT&T bought TCI and MediaOne to $12,400 when Vodafone acquired Mannesmann. However, as a company increases its customer base and reputation in the market, word of mouth and branding power make it easier to attract new customers. It is difficult to know how these two forces counterbalance each other. Because our data show no significant patterns in the acquisition costs over time, we used the previous four quarters' average as the cost for future customer acquisitions.[4] We also assessed the sensitivity of our results to changes in acquisition costs.

Retention. Customer retention is one of the most critical variables that affect customers' lifetime profit, yet most companies do not make it publicly available. Therefore, we estimated retention rates from several sources.

For Ameritrade, we obtained detailed account information from Salomon Smith Barney that shows Ameritrade's account retention rates to be 95.0% for fiscal year 1999, 96.2% for 2000, 95.7% for 2001, and 94% (annualized) for the quarter ending March 2002. These figures show two things. First, 95% is a good estimate for Ameritrade's average retention rate. Second, over time, this retention rate has not changed significantly. We were unable to obtain any specific information about E*Trade. Given its similarity to Ameritrade, we used a 95% retention for E*Trade.

For Capital One, we obtained retention-rate estimates from an industry expert, who suggested that the retention rate for North American credit card companies is in the range of 85% to 88%. According to the expert, there are many factors that contribute to retention (e.g., credit quality, pricing, customer service). He further suggested that Capital One scores slightly worse than many other companies (e.g., MBNA) on some of these factors, and its retention rate was in the range of 84% to 86%. Therefore, we used the average of 85% as our best estimate for Capital One's customer retention rate.

Amazon.com has changed the way it reports its number of customers in financial statements. Previously, Amazon reported cumulative customers (both active and inactive), but now it reports only active customers (retroactively from fourth quarter of 1999). Using data on active and cumulative number of customers for 2000–2001, we estimated Amazon's retention rate to be in the range of 65.3% to 74.6%, with an average of approximately 70%. This estimate is similar to Amazon's self-stated retention rates and slightly less than the 78% retention rate suggested by some consultants (Seybold 2000).

EBay does not provide estimates of its retention rate. In the absence of any data, we used an 80% retention rate for eBay, which is the average observed among U.S. firms (Reichheld 1996). For all companies, we also conducted sensitivity analysis.

Discount rate. Standard financial methods (e.g., capital asset pricing model) can be used to estimate discount rates. Damodaran (2001) estimates the cost of capital for Amazon to be 12.56%. In general, finance texts suggest a range of 8% to 16% for the annual discount rate. Therefore, we used the average of 12% for our analysis. We also show the sensitivity of our results to different rates of discount.

Estimation

For each company, we have historical data on the actual number of customers. These numbers are a net effect of all customers who ever tried the services of the company minus the defectors. For example, if a company has 100,000 customers in Period 0 and 130,000 customers in Period 1 and its retention rate is 80%, it acquired 50,000 customers from Period 0 to Period 1. Therefore, the cumulative number of

[3]Four-quarter average, also known as trailing 12-month average, is also a common practice among financial analysts.

[4]A firm has already incurred acquisition costs for its existing customers. Therefore, this cost is sunk and is not considered in valuation.

customers who ever tried the company's services is 100,000 in Period 0 and 150,000 in Period 1. In our valuation model, n_t is the number of customers acquired during time t, not the number of net (i.e., acquired minus defected) new customers. Therefore, we model number of customers who ever tried a firm's services (i.e., N_t). When the parameters of the model have been estimated, it is easy to obtain n_t by using Equation 10. We estimated the model for forecasting number of customers using nonlinear least squares, as Srinivasan and Mason (1986) suggest. We then used parameters of this model as well as estimates of acquisition cost, retention rate, margin, and discount rate as input to the valuation model in Equation 8. We then evaluated the model using Mathematica.

Note that the procedure we described previously assumes that all customers (both active and inactive) potentially affect the future growth of number of customers. It is possible to modify this assumption and to construct alternative, and potentially complex, models of diffusion. For example, an alternative model is to assume that whereas active and inactive customers define the remaining market potential, only currently active customers spread positive word of mouth to affect future customer growth. This model is similar to a diffusion model that incorporates replacement purchases (Kamakura and Balasubramanian 1987). We estimated this model for Amazon.com and found that its results are similar to those obtained from our model. For example, this model projected that the total market potential for Amazon was 71.8 million, and our model estimated total market potential to be 67 million. Further research should investigate alternative models of customer growth, such as a model that assumes negative word of mouth from defectors and positive word of mouth from currently active customers.

Results

We report results for the number of customers and then discuss results for the value of a firm's customer base as of March 31, 2002.

Number of customers. Table 3 provides parameter estimates and fit statistics for each of the five companies. We report mean absolute deviation (MAD) and mean squared errors (MSE) as measures of fit, because traditional measures such as R^2 are not appropriate for nonlinear regression modeling (Bates and Watts 1988; Srinivasan and Mason 1986). Our model fits the data quite well, as is indicated by low MAD and MSE.

All the parameters are significant. Parameter α provides an estimate of the maximum number of customers who are expected to try a company's product and services. Table 3 results show that the maximum number of "triers" is expected to be 67 million for Amazon.com, 2.48 million for Ameritrade, 171.2 million for Capital One, 81.95 million for eBay, and 4.72 million for E*Trade. The maximum number of actual customers will be less than this number as a result of defection.

From Equation 10, it is easy to show that the peak for customer acquisition occurs at $-\beta/\gamma$. Table 3 results suggest that this peak occurs approximately 10 to 21 quarters from the start of our data period (1997). In other words, for the companies in our data set, customer acquisition has already reached a peak.[5] After this time, companies will continue to acquire customers but at a slower rate. For example, Amazon added four million new customers in December 2000 but only three million customers in the subsequent two quarters.

Value of the customer base. The number of current customers and a forecast of customers to be acquired in the future enabled us to estimate the value of a firm's customer base (current and future). We used average acquisition costs, margins, and retention rates from Table 2 and parameter estimates from Table 3 as input to Equation 8. Table 4 presents estimates of customer value and market value for these firms as of March 31, 2002 (the end of our data period). Because stock prices change every day, firm value varies (sometimes dramatically) in a quarter. Therefore, in Table 4, we include the high and low market value for the January–March 2002 quarter. We also include P/E ratios for the companies because (1) they are commonly used in financial valuation methods, and (2) we wanted to emphasize that it is difficult to rely on this metric for fast-growing companies. For example, two of the companies (Amazon.com and E*Trade) have negative earnings, so P/E ratio is not defined. Furthermore, two other companies (Ameritrade and eBay) have only modest earnings, and thus their P/E ratios are extremely high and significantly outside the market average range of 20–30.

[5]To estimate an S-shaped curve, we need an inflection point in the data. The inflection point is the time of peak customer acquisition. For data sets in which the inflection point is not observed, there are two possible solutions: (1) provision of an external estimate of a parameter such as market size or (2) use of a Bayesian method to provide priors for the parameters.

Table 3

PARAMETER ESTIMATES FOR NUMBER OF CUSTOMERS (IN MILLIONS)

Parameters	*Amazon.com*	*Ameritrade*	*Capital One*	*eBay*	*E*Trade*
α	67.045 (3.615)	2.482 (.121)	171.200 (15.864)	81.945 (3.995)	4.719 (.064)
β	–4.114 (.139)	–3.345 (.114)	–3.052 (.079)	–6.009 (.145)	–3.441 (.086)
γ	.265 (.015)	.263 (.016)	.149 (.003)	.317 (.013)	.365 (.012)
Time to Peak of Customer Acquisition					
$-\beta/\gamma$	15.64	12.72	20.48	18.96	9.43
Calendar date	December 2000	September 2000	December 2001	June 2001	March 2000
Fit Statistics					
MAD	.556	.041	.393	.590	.049
MSE	.594	.004	.346	.763	.004

Notes: $-\beta/\gamma$ gives an estimate of the number of quarters from the start of the data for a company when customer acquisition is expected to reach its peak.

Table 4
VALUE OF CUSTOMERS, MARKET VALUE, AND P/E RATIOS

		Market Value ($ Billion)			
	Value of Customers ($ Billion)	*As of March 31, 2002*	*Quarterly High*	*Quarterly Low*	*P/E Ratio*
Amazon.com	.82	5.36	6.36	3.39	N.A.
Ameritrade	1.62	1.40	1.49	1.09	370.00
Capital One	11.00	14.08	14.31	9.48	9.08
eBay	1.89	15.85	19.45	13.67	112.02
E*Trade	2.69	3.35	4.49	2.71	N.A.

Notes: N.A. = not applicable.

As are the four Internet companies in our empirical analysis, Capital One is growing rapidly. However, unlike the Internet firms, Capital One has a long history of positive earnings and cash flow as well as a modest P/E ratio of 9.08. In other words, although conventional financial models of valuations may not work well for valuation of the other four companies, they should work well for Capital One. Therefore, our customer-based approach is partly validated if our model captures the market value of this firm. We estimated the value of current and future customers of Capital One to be $11 billion. Its market value as of March 2002 was $14 billion, with a low of $9.5 billion and a high of $14.3 billion for the first quarter of 2002. In other words, our customer value estimate is well within the range of the company's market value for the quarter. We also note that customer value estimates for Capital One increase to $14.1 billion if its retention rate is 90% instead of 85%.

For Amazon.com, we estimated the value of current and future customers to be approximately $.82 billion, far less than its market value of $5.36 billion. Even if Amazon's customer retention rate is 100%, its customer value is only approximately $3 billion. This suggests that either the market is still overvaluing Amazon or our model does not capture some components of its value.

We estimated the value of Ameritrade's customers to be $1.6 billion, which is quite close to its market value of $1.4 billion. Note that though we could not detect any significant time trend in Ameritrade's margins or acquisition costs from the data for the previous four years, recent turbulence in online trading may suggest lower margins, higher acquisition costs, and higher customer defection in the future. As we demonstrate in the sensitivity analysis, small changes in the expectations of input change the value of Ameritrade's customers within the range of its current market value.

Our analysis places the value of eBay customers at $1.89 billion, which is far less than its market value of $15.85 billion. Even if we assumed 100% retention, eBay's customer value would increase to only $5.3 billion. Given the good fit of the model to its customer growth and its remarkably consistent margins and acquisition costs, dramatic changes in customer value seem unlikely. Therefore, either the market is overvaluing eBay because it is one of the few dot-coms with positive earnings or our model does not capture some important option value. Some Wall Street analysts believe that eBay is significantly overvalued. For example, Faye Landes, an analyst at Sanford C. Bernstein who was anointed as an all-star analyst by *Fortune*, said, "[eBay is] trading at more than 30 times our 2005 estimates—that makes it one of the most expensive stock there is" (*Fortune* 2001a). Although it is possible that the market is overvaluing eBay, it is also possible that our model does not capture unique aspects of eBay's business. Specifically, eBay is an auction exchange, and thus there may be significant network externalities that are not captured by the traditional diffusion model. Furthermore, eBay's business includes both buyers and sellers, and the combination of both into "customers" may be an oversimplification. For example, eBay currently has a total of approximately 46 million customers. It is difficult to argue that if these customers are evenly split into buyers and sellers, it is the same as having 45 million sellers and 1 million buyers. In other words, it may be important to model buyers and sellers separately and then construct a model of interaction between them. We leave this for further research.

At its estimated retention rate of 95%, we estimated E*Trade's customer value to be $2.69 billion (a retention rate of 100% puts its customer value as $3.89 billion). As of March 2002, E*Trade's market value was $3.35 billion, with a low of $2.71 billion and a high of $4.49 billion for the quarter. This makes E*Trade's customer value a close proxy for its market value.

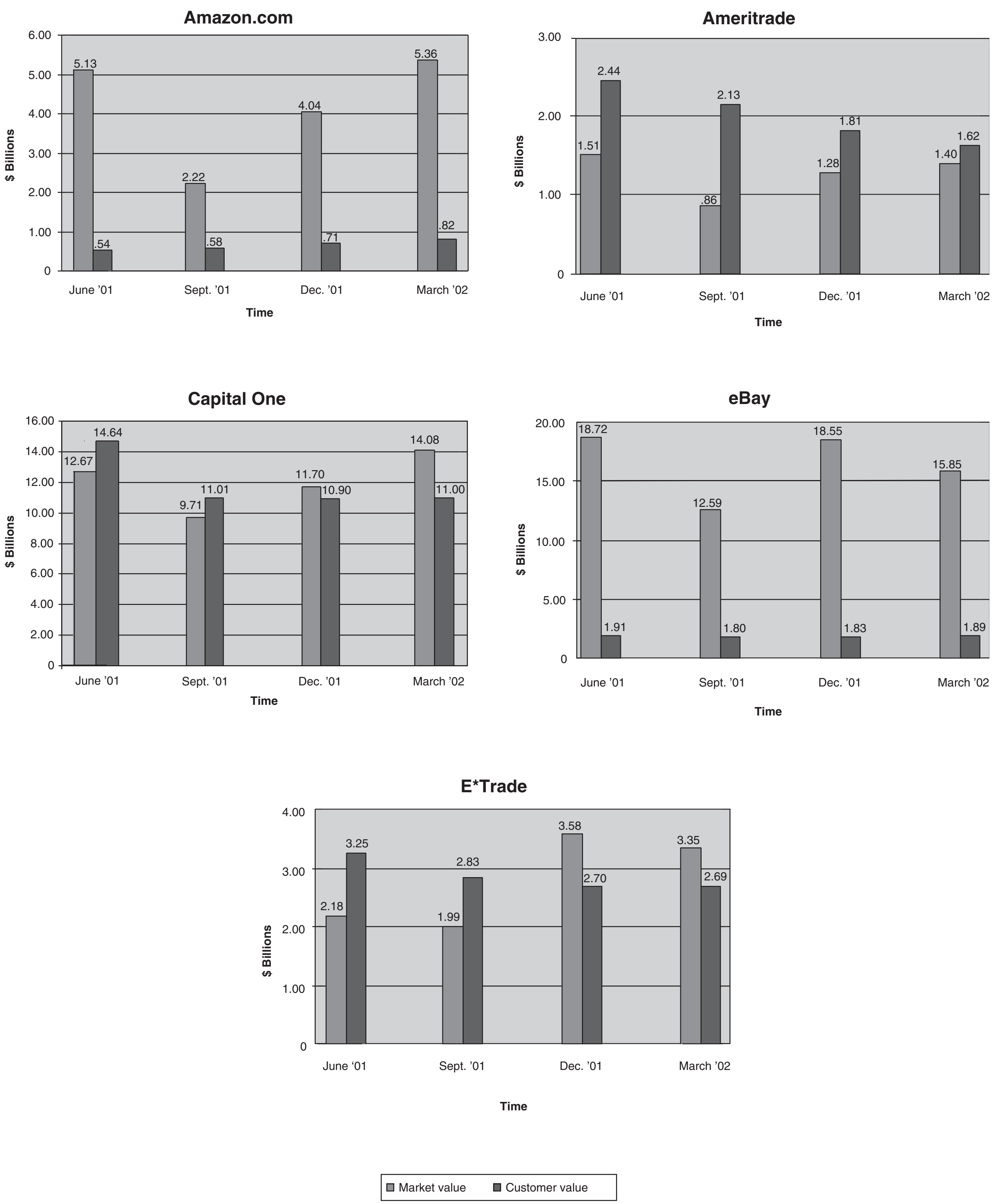
In summary, we found that for three of the five firms, customer value provides a close proxy for market value. Furthermore, we found that our method provides reasonable estimates when traditional financial methods may not work (e.g., for Ameritrade, which has a P/E ratio of 370; for E*trade, for which a P/E cannot be defined because of negative earnings). Equally important is that our method works well for a traditional firm (Capital One) for which standard financial valuation methods are robust.

Value over time. Thus far, our results show that for three of the five companies, customer value provides a good estimate of their market value at one point in time (i.e., March 2002). For any measure to be useful, it should be able to track firm value over time. To achieve this objective, we reanalyzed data for all five companies for the previous four quarters.[6] In other words, we used data up to June 2001 and estimated customer value for each of the five firms, and we compared these estimates with their market value as of June 2001. We repeated this analysis for each of the previous four quarters. In Figure 2, we present customer value estimates for each quarter and market value at the end of that quarter.

The results show that whereas customer value estimates for Amazon.com and eBay are consistently less than the

[6]It is possible to extend this analysis for more periods. However, for some firms that have not yet reached their inflection point in customer growth by the period of analysis, model parameters of customer growth tend to become unstable. It is possible to estimate these models either by assuming an external estimate of market size (e.g., Kim, Mahajan, and Srivastava 1995) or by using a Bayesian approach (Lenk and Rao 1990).

Figure 2
MARKET VALUE AND CUSTOMER VALUE OVER TIME



companies' market value, customer value estimates for Ameritrade, E*Trade, and Capital One are within reasonable range of their market values. We emphasize that, in general, market value shows significant fluctuations within a quarter, often without any new information about a company's operations. For example, at the end of the third quarter of 2001, market value for Capital One was $9.7 billion; however, during that quarter, the company's market value fluctuated between $7.7 billion and $14.2 billion.[7]

To confirm further the relationship between customer and market value, we ran a simple regression with market value of a company as the dependent variable and customer value as the independent variable. Having used data for four quarters for each of the five companies, the regression produced an R^2 of only .139. However, when we ran the regression without Amazon and eBay (two companies whose market values are significantly different from our estimate of their customer value), the R^2 was .927. Furthermore, the intercept in the regression was not significantly different from zero, and the parameter estimate of customer value (1.026) was not significantly different from one.

MANAGING CUSTOMER VALUE

Our analysis shows that customer value provides a good proxy for firm value. Because the estimation of customer value requires more detailed input than traditional valuation methods, its benefit is not only in terms of firm valuation. A good metric for customer value is the starting point for better management of customers as assets. In this section, we focus on two aspects: (1) how changes in acquisition costs, margins, and retention rates affect customer value of a firm and (2) the relative importance of customer retention, which is a key component of the marketing function, and the discount rate or cost of capital, which is a traditional focus of the finance function.

Impact of Acquisition Cost, Margin, and Retention Rate

Table 5 shows how customer value changes with changes in acquisition cost, margin, and retention rate. Our results show a consistent pattern: Improved customer retention has the largest impact on customer value, followed by improved margins, and reduced acquisition cost has the smallest impact.

[7]Sometimes market value fluctuations are significant across quarters as well (e.g., during the height of the dot-com fever). For example, in March 2000, market value for Amazon.com was $23.45 billion. A year later, in March 2001, its market value dropped to $3.67 billion, and as of March 2002, it had climbed back to $5.3 billion. Our estimates of Amazon's customer value for the entire two-year period are consistently less than $1 billion.

A 1% improvement in acquisition cost improves customer value by .02% to .32%. The greatest impact of reduced acquisition cost is for Capital One, which is consistent with Capital One's having passed its customer acquisition peak only recently (see Table 3): It is still acquiring a large number of customers. Therefore, any improvement in acquisition cost has a significant impact on the company's overall value. In contrast, Ameritrade and E*Trade passed their acquisition peaks several quarters previously and therefore have the least impact of improving acquisition cost.

A 1% improvement in margins, such as from cross-selling, improves customer value by approximately 1%. This result is consistent across all firms. A 1% improvement in customer retention improves customer value by 2.45% to 6.75%. The higher the current retention rate of a company (e.g., Ameritrade 95% versus Amazon.com 70%), the higher is the impact of improved retention.

In summary, we find that retention elasticity is 3–7 times margin elasticity and 10–100 times acquisition elasticity. These results are consistent with previous studies that emphasize the importance of retention (e.g., Reichheld 1996). Notably, after the dot-com bubble burst, Wall Street and many Internet firms began to focus on and reduce acquisition costs. Demers and Lev (2001) explain this by showing that before the market's correction for Internet stocks, the market treated expenditures on both marketing and product development as assets rather than current expenses. Demers and Lev further found that in the year 2000, after the shakeout, product development expenses but not marketing expenditures continued to be capitalized as assets. Consistent with our study and contrary to current market perception, Demers and Lev show that Web-traffic metrics (e.g., traffic, loyalty) continue to be value relevant.

We note two caveats for interpreting the results of Table 5. First, we did not include the cost of improving retention or margin. Therefore, even though improvement in retention has the largest impact on customer value, we cannot suggest that a firm should always improve its customer retention. Using a game theoretic model, Shaffer and Zhang (2002) show that it is not advisable for firms to eliminate either churn or customer defection completely. If a firm has 100% customer loyalty, it may be underpricing or "leaving money on the table." Second, our analysis ignores interactions among acquisition, retention, and margins. It is quite likely that certain acquisition programs (e.g., price promotions) attract customers with low retention rates, and studies (e.g., Thomas 2001) have provided methods to link customer acquisition and retention.

Table 5

IMPACT OF 1% IMPROVED RETENTION, ACQUISITION COST, MARGINS, AND DISCOUNT RATE ON CUSTOMER VALUE

	Customer Value ($ Billion)	*Percentage Increase in Customer Value (with a 1% Improvement)*			
	Base Case	*Retention*	*Acquisition Cost*	*Margin*	*Discount Rate*
Amazon.com	.82	2.45%	.07%	1.07%	.46%
Ameritrade	1.62	6.75	.03	1.03	1.17
Capital One	11.00	5.12	.32	1.32	1.11
eBay	1.89	3.42	.08	1.08	.63
E*Trade	2.69	6.67	.02	1.02	1.14

Impact of Retention Versus Discount Rate

Discount rate, or cost of capital, is a critical variable in the evaluation of the net present value of any cash flow stream and firm valuation, and thus the finance community spends considerable effort in measuring and managing a firm's cost of capital (see, e.g., Brealey and Myers 1996). In contrast, the marketing and business community has just begun to measure and manage customer retention, of which the importance to firm valuation is even less evident. To compare the relative importance of customer retention and discount rate, the right-hand column of Table 5 shows how changes in discount rates, in contrast to changes in marketing levers, affect customer value for the firms. The results show that a 1% improvement in customer retention enhances customer value (and, in turn, firm value) by approximately 2.45% to 6.75%, whereas a similar decrease in the discount rate increases customer value and thus firm value by only .5% to 1.2%. In other words, the retention *elasticity* is almost five times the discount rate elasticity.

Another way to examine the effects is to assess the value of customers for the typical range of retention and discount rates. The finance literature suggests a typical range of discount rates of 8% to 16% (Brealey and Myers 1996). On the basis of industry information (e.g., Reichheld 1996) and the retention rates for the five companies in our empirical analysis, we used a range of 70% to 90% for retention rate. Using these ranges, we reestimated customer value for the companies in our data set.

Table 6 reports our results. Several notable things emerge from this table. First, consistent with the Table 5 results, retention rate has a larger impact on customer value than does discount rate. For example, an improvement in customer retention from 70% to 90% increases customer value for Amazon.com by \$1.38 billion – \$.75 billion = \$.63 billion (for a 16% discount) to \$1.07 billion (for an 8% discount). In contrast, an improvement in discount rate from 16% to 8% increases Amazon's customer value by \$.15 million (for 70% retention) to \$.59 billion (for 90% retention). Second, there is a strong interaction between discount rate and retention rate. Specifically, the impact of retention on customer value is significantly higher at lower discount rates. This suggests that companies in mature and low-risk businesses should pay even more attention to customer retention. Third, the value of customers and, by implication, the value of a firm for the high retention–low discount scenario is 2.5 to 3.5 times its value under the low retention–high discount scenario. Although we do not consider the relative cost of improvement to the retention rate versus the discount rate, this analysis suggests the importance of marketing levers, rather than financial instruments, in improving customer and firm value.

CONCLUSION

Customer lifetime value is receiving increasing attention in marketing, especially in database marketing. In this article, we attempt to show that the concept not only is important for tactical decisions but also can provide a useful metric to assess the overall value of a firm. The underlying premise of our model is that customers are important intangible assets of a firm, and their value should be measured and managed as is any other asset. Our article builds on recent work in marketing in the area of customer lifetime value by extending it to the arena of financial valuation. We also build on recent work in accounting in which the approach has been to regress current market value of a firm against tangible and intangible assets. Implicitly, this approach assumes that the market is correctly valuing firms. The recent history of dot-com companies casts doubt on this assumption. In contrast, we estimate the value of a firm's current and future customer base from basic principles, which makes our analysis more stable than the typical accounting approach, which depends on the vagaries of the financial marketplace.

We use data from one traditional and four Internet firms in our empirical application. Our analysis reveals several notable results. First, we find that our estimates of customer value are reasonably close to the market valuation at the time of our study for three of the five firms. In contrast, traditional valuation methods do not work well for the valuation of many of the firms because most of them have negative earnings. The results show that customer-based metrics are still value relevant. Second, consistent with previous studies in marketing, we find that retention has a significant impact on customer value. Specifically, we find that retention elasticity is in the range of 3 to 7 (i.e., a 1% improvement in retention increases customer value by 3%–7%). In contrast, we find margin elasticity to be 1% and acquisition cost elasticity to be only .02% to .3%. Notably, the market appears to have treated marketing (and customer acquisition) expenditures as investment before the Internet crash but now treats them as expenses. Our results indicate that reducing acquisition costs may not be the most effective way for firms to improve value. Furthermore, to the extent that customers are assets, the market may be incorrect in treating customer acquisition costs as current expenses rather than investments. Third, we find that the retention rate has a significantly larger impact on customer and firm value than does the discount rate or cost of capital. Financial analysts and company managers spend considerable time and effort in measuring and managing discount rate because they understand its impact on firm value. However, our results show that it is perhaps more important not only for marketing managers but also for senior managers and financial ana-

Table 6

CUSTOMER VALUE AT TYPICAL RETENTION AND DISCOUNT RATES ($ BILLIONS)

Discount Rate	*Amazon.com: Retention Rate* 70%	80%	90%	*Ameritrade: Retention Rate* 70%	80%	90%	*Capital One: Retention Rate* 70%	80%	90%	*eBay: Retention Rate* 70%	80%	90%	*E*Trade: Retention Rate* 70%	80%	90%
8%	.90	1.25	1.97	.71	.97	1.52	7.33	10.95	18.94	1.56	2.18	3.47	1.07	1.52	2.46
12%	.82	1.10	1.62	.65	.85	1.25	6.21	8.88	14.14	1.39	1.89	2.82	.98	1.34	2.03
16%	.75	.98	1.38	.59	.76	1.06	5.35	7.39	11.04	1.29	1.70	2.41	.90	1.20	1.73

lysts to pay close attention to a firm's customer retention rate.

We acknowledge several limitations of our study. First, we had several quarters of data that enabled us to provide a good estimate of the number of future customers, which is an important input to our valuation model. The accuracy of the model would be hampered significantly in the early stages of a firm, when there is only limited information. This is similar to forecasting demand for an innovation with only a few data points. Advances in diffusion modeling suggest that in these cases, it may be desirable to use a Bayesian approach in which previous studies can provide informative priors (Lenk and Rao 1990; Sultan, Farley, and Lehmann 1990). Such an approach would be a useful extension in our case as well. A second limitation of our study is the assumption of a constant retention rate. This assumption implies that as a firm reaches maturity and its customer acquisition slows, it will eventually lose all its customers as a result of a constant defection rate. This aspect is likely to have a small impact on our valuation, because this effect occurs only in the distant long run and the future events have minimal impact on value as a result of discounting. Nonetheless, further research should examine this issue in greater detail. For example, two possible ways to alleviate the impact of this assumption is to have either dynamic retention rates or growth in market size. We also ignore links among acquisition costs, retention rates, margins, and number of customers. In reality, we would expect correlation among these factors, and a model that captures these links would be valuable.

In summary, our article provides a starting point for customer valuation and its relationship to the value of firms. We emphasize that we do not suggest replacing traditional financial models; indeed, our approach uses the well-established finance approach of DCF. However, by using DCF at a customer level, we are able to provide a useful method for forecasting the stream of future earnings, which is a key input to any valuation model. We hope that our work sparks more interest in this area and brings the fields of marketing and finance closer together.

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