Valuing Customers

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January 2002
Revised August 2002
Revised February 2003

Journal of Marketing Research, forthcoming

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Abstract

It is increasingly apparent that the financial value of a firm depends on intangible assets (e.g., brands, customers, employees, knowledge) that are not on the balance sheet. In this paper we focus on the most critical aspect of a firm – its customers. Specifically, we demonstrate how valuing customers makes it feasible to value firms, including high growth firms with negative earnings.

We begin by defining the value of a customer to a firm as the expected sum of discounted future earnings based on key assumptions concerning retention rate and profit margin. The value of all customers is determined by the acquisition rate and cost of acquiring new customers. We demonstrate this method by using publicly available data for five firms – one well-established firm (Capital One) where traditional financial valuation models work well, and four Internet firms (Amazon, Ameritrade, Ebay and E*Trade) where traditional financial models have difficulty.

Our results show a close relation between customer value and market value for Capital One, Ameritrade and E*Trade, as of March 31, 2002. Customer value also tracks market value of these firms over time. By contrast, we find that Amazon and Ebay are either overvalued or have high option value that is not captured in our model. We also compare the relative impact of improving retention (e.g., by better service), margins (e.g., by cross selling), and acquisition costs (e.g., by efficient marketing). Our results show that retention elasticity is in the range of 3-7. In other words, improving customer retention by 1% is likely to improve customer and firm value by 3-7%. In comparison, margin elasticity is about 1 and acquisition elasticity is only 0.02-0.3. We also find that 1% improvement in retention has almost five times greater impact on customer value compared to 1% improvement in discount rate or cost of capital. Our results suggest that the linking of marketing concepts to shareholder value is both possible and insightful.

Introduction

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

Traditional accounting has focused on measuring tangible assets and the resulting data reported in annual reports, 10Ks, etc. has formed the basis of firm valuation. However, intangible assets, among them brand, customer, and employee equity, are a 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 post-hoc attributed to the use of "too much marketing", i.e. big advertising budgets and reliance on questionable marketing metrics such as eyeballs and click-throughs, suggesting market-based measures may be in danger of being rejected *en mass*.

Here we merge the traditional financial valuation methods based on discounted earnings with the key marketing concept of the value of the customer to the firm. Specifically, we show how a disciplined analysis of value on the basis of customers and their expected future earnings (a) provides insights not possible at the traditional more aggregate level of analysis, (b) facilitates projections for new and growing businesses, and (c) provides an explanation for the now infamous dot.com bubble. The basis of this approach is customer lifetime value which is the discounted future income stream based on acquisition, retention and expansion projections and their associated costs. In essence this extends 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 & 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 companies, the cash flow stream is relatively easy to predict. Therefore financial models such as discounted cash flow (DCF) work reasonably well. In contrast, valuing high growth businesses is complex. These businesses have limited history to draw upon for future projections. They also typically invest heavily in the early periods, resulting in negative cash flows. Consequently, traditional financial methods have difficulty evaluating these businesses. It is hard to use a P/E (price to earning) ratio for a company that has no or negative E, or to use the DCF approach when a firm has negative cash flow. This was evident during the height of dot.com bubble when many innovative valuation methods emerged.

One popular measure to emerge in 1999-2000 was the number of customers or eyeballs. This metric was based on the assumption that growth companies need to acquire customers rapidly in order to gain first mover advantage and build strong network externalities, at times regardless of the cost involved (The Wall Street Journal, Nov 22, 1999). Academic research in accounting also provided validation for this belief. For example, Trueman, Wong and Zhang (2000) combined financial information from financial statements with the non-financial information from Media Metrix for 63 Internet firms for the period September 1998 to December 1999. A regression of market value on these components revealed that while bottom line net income had no relationship with stock price, both unique visitors as well as page views added significant explanatory power. A related study by Demers and Lev (2001) used similar data for 84 Internet companies for 1999-2000 to examine the relationship between market value and non-financial measures both during and after the Internet bubble. They found that non-financial measures such as reach (i.e., number of unique visitors) and stickiness (i.e., site's ability to hold its customers) explain share prices of Internet companies, both before and after the bursting of the bubble.

Note that these studies are correlational in nature and assume that the market value represents the true intrinsic value of the firm at any time – an efficient market argument. However, even if the markets are efficient in the long run, recent history suggests 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 about non-financial metrics, especially number of customers. For example, a recent article criticized a Wall Street icon, Mary Meeker, for relying too much on eyeballs and page views and even putting them ahead of financial measures (Fortune, May 14, 2001).

Our Approach

The current mood on Wall Street suggests that customer-based metrics are not only irrelevant for firm valuation but in fact can be misleading. We argue against this sentiment. 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 we can forecast the growth in number of customers, then it is easy to value the current and future customer base of a company. To the extent that this 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 where traditional financial methods work well. In addition, we use our approach to estimate the value of four Internet firms where traditional financial methods may have difficulty.

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

The closest parallel to our approach is that of Kim, Mahajan and Srivastava (1995) who use a discounted cash flow method to estimate the value of a business in the cellular communications industry. Our work differs from their approach in several important ways. First, our approach focuses on the company (versus industry) level and is applied to multiple firms. Second, we do not need to make any assumption about the time when growth ends. Growth in customers and firm value is explicitly modeled. Third, we incorporate customer retention which has a significant impact both substantively as well as methodologically. For example, current industry reports show that the annual churn rate in the telecommunication industry (the industry examined by Kim et al.) is over 20%. The industry estimates that this reduces firms' value by several billion dollars. Our analysis confirms that customer retention has a large impact on firm value. Including customer retention requires accounting for different customer cohorts that change the model conceptually and mathematically. Finally, including customer retention and acquisition in the model provides insights for managers about potential marketing levers available to them for improving customer and firm value.

In sum, the key contribution of our approach is to provide 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 where traditional financial methods have difficulty. Our main contributions lie in three areas: (a) in 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, (b) in providing insights about marketing levers (e.g., retention) that can help managers improve firm value, and (c) in 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 first build a model for the lifetime value of a cohort of customers, then aggregate this lifetime value across current and future cohorts, and finally construct models to forecast the key inputs to this model (e.g., the number of customers in future cohorts).

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

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

This is identical to the discounted cash flow approach of valuing perpetuity (Brealey and Myers 1996). When we account for the customer retention rate r, this formulation is modified as follows[2],

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

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 arbitrarily specify the number of years that a customer is going to stay with the company. Second, the retention rate accounts for the fact that over time the chances of a customer staying with the company go down significantly. Third, the typical method of converting retention rate into expected lifetime and then calculating present value over that finite time period overestimates lifetime value.[3] Fourth, both retention and discount rates ensure that earnings from 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 below. Here 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 his/her lifetime. In contrast, Reinartz and Kumar (2000) find that this pattern does not hold for non-contractual settings.

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[2] We recognize that retention rates may not be constant. However, we make this simplifying assumption for the ease of modeling and empirical application. Our data for Ameritrade supports this assumption.

[3] For example, consider a situation where annual margin from a customer is $100, retention rate is 80% and discount rate is 12%. Using equation (2) we estimate the lifetime value of this customer to be $250. An alternate approach would suggest that 80% retention rate implies that this customer is expected to stay with the company for 5 years. The present value of the $100 stream of income for five years is $360, an overestimate of about 44%.

Number of Customers and Margins for Each Cohort[4]

	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
.	.	.	.	.	.	.

Therefore the lifetime value of cohort 0 at current time 0 is given by,

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

Cohort 1 follows a pattern similar to 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,

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

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

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

In general, the lifetime value for the k-th cohort at current time 0 is given by

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

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

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

Although it is easier to conceptualize the model in discrete terms, in reality customer acquisition and defection is a continuous process. Schmittlein and Mahajan

[4] We have assumed that each customer cohort follows the same pattern of margins (m_0, m_1, m_2, …). While 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 datasets are insufficient to empirically validate a specific pattern.

(1982) show that estimating an inherently continuous process, such as Bass diffusion model, with a discrete version produces biases. Further, we model key inputs (e.g., n_k) as continuous functions. Therefore, we deal with a continuous version of customer value.

If the annual discount rate is i and we continuously compound m times a year, then 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 $e^{-\left(\frac{1+i-r}{r}\right)t}$. Therefore, the continuous version of equation (7) is,

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

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 etc. we turn to data in our empirical application to understand the nature of available information. The available data, its empirical pattern and theory guide us in our selection of appropriate models for these input variables.

Application

Data

We estimate our model using data from five companies – one traditional firm (Capital One) and four Internet companies (Amazon, Ameritrade, Ebay and E*Trade). We use a traditional firm to show that our approach is capable of providing good estimates of firm value – akin to standard financial models. Next, we use four Internet companies to show the usefulness of our approach when standard financial models may have difficulty because of low or negative cash flows. Our choice of companies was also directed by the availability of public data.

Based on annual reports, 10K and 10Q statements as well as other company reports we use quarterly data from 1996-97 to March 2002. The data for each quarter includes number of customers, margin and marketing costs. Using these data we estimate the acquisition cost and quarterly margin per customer. A summary of the data is given in Table-1.

Insert Table-1 Here

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 to estimate the number of customers in future periods is the Bass (1969) diffusion model. The continuous Bass model is based on the solution to a non-linear differential equation and the resulting sales or number of customers' equation is quite complex (Bass 1969, page 218). The discrete analog is simpler, but still poses challenges in our context because sales or number of new customers are a function of cumulative sales or customers. This recursive relationship makes the integration (or summation) more complex.

Insert Figure-1 Here

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

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

This S-shaped function asymptotes to α as time goes to infinity. The parameter γ captures the slope of the curve. The number of new customers acquired at any time is,

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

This model, also called the Technological Substitution Model, has been used by several researchers in modeling 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 very comparable to those from the Bass model.

Margin

Using financial statements it is relatively straightforward to get the quarterly revenues for a firm. However, assessing costs pose challenges since firms do not report direct costs in a consistent fashion. For example, although fulfillment cost (i.e., shipping and handling) is a large portion of Amazon's operating expense, it does not include it in calculating its margin. We include these costs in our estimate of the margin. Similarly, one of the largest expenses for the credit card company Capital One is the salary of its employees. We included salaries as direct cost in arriving at margins because of two reasons. First, Capital One explicitly states in its 2001 annual report, "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). This regression produced an R^2 of 0.974 with almost all of the cost allocated as variable. In other words, as a direct marketing company, increase in customers for Capital One is directly associated with the increase in employee expenses. We followed a similar process for the other firms.

After determining total margin for a quarter, we estimate 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. This 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 with a firm, the more s/he buys. He also suggests that the company has the potential of cross-selling its products to its customer base. In addition to increased revenue, Reichheld's research finds that the longer a customer stays with a company the lower is the cost of doing business with that customer. However, recently Reinartz and Kumar (2000) challenge these findings and show that duration of stay is not necessarily related to increased margin.

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 combines margins *across* several cohorts, each of them at different stage of their lifecycle. As a company expands its customer base it tends to draw more and more marginal customers who do not spend as much with the company as its original customers. Consequently average revenue per customer may decline over time. This is especially true if 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 a competitor N2K that further contributed to the decline in its revenue per customer from $18.15 in Q1 of 1999 to $14.42 in Q2 of 1999.

Given conflicting evidence in recent research and the lack of any systematic pattern in our data, we use the average of the last four quarters as the margin for future periods[5]. Later we perform sensitivity analysis to see how customer and firm value change with changes in margins.

Acquisition Cost

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

We operationalize 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 do 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 are in the growth stage of their life cycle where customer acquisition is 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 as $26.94 versus retention cost per customer of $2.15. Finally, our estimates of acquisition costs are quite close to estimates published in various industry reports.

[5] Four-quarter average, or trailing twelve month (TTM) as the financial community calls it, is also a common practice among financial analysts.

Similar to 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 Telecom industry where the acquisition cost per subscriber dramatically increased from $4,200 when AT&T bought TCI and Media One, to $12,400 when Vodafone acquired Mannesman. However, as a company grows its customer base and its reputation in the market, word of mouth as well as branding power make it easier to attract new customers. It is difficult to know how these two forces counterbalance each other. Since our data shows no significant patterns in the acquisition costs over time, we use last four quarters' average as the cost for future customer acquisitions.[6] We also assess 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, it is not made publicly available by most companies. Therefore we estimated retention rates from a variety of sources.

For Ameritrade, we obtained detailed account information from Salomon Smith Barney that shows Ameritrade's account retention rates to be 95.0% for the fiscal year 1999, 96.2% for 2000, 95.7% for 2001 and 94% (annualized) for the quarter ending March 2002. These numbers 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 could not get any specific information about E*Trade. Given its similarity with Ameritrade, we use 95% retention for E*Trade.

For Capital One, we obtained retention rate estimates from an industry expert. He suggested that retention rate for the North American Credit Cards is in the range of 85-88%. According to him, there are many factors that contribute to retention (e.g., credit quality, pricing, customer service). He further suggested that Capital One is slightly

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

worse than many other companies (e.g., MBNA) on some of these factors and its retention rate is in the range of 84-86%. Therefore we use the average of 85% as our best estimate for Capital One's customer retention rate.

In the recent past, Amazon changed the way it reports its number of customers in its financial statements. Previously Amazon reported cumulative customers (both active and inactive), but now it reports (retroactively from fourth quarter of 1999) only active customers. 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 about 70%. This estimate is similar to Amazon's self-stated retention rates and slightly lower 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 use 80% retention rate for Ebay, the average observed among US firms (Reichheld 1996). For all companies, we also conduct 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 as 12.56%. Finance texts generally suggest a range of 8% to 16% for this annual discount rate. Therefore, we use 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%, then it acquired 50,000 customers during the first time period. Therefore, cumulative number of customers who *ever tried* this 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* new (i.e. acquired minus defected) customers. Therefore, we model number of customers who *ever tried* firm's services, i.e. N_t. Once the parameters of this model are estimated, it is easy to obtain n_t as per equation (10). The model for forecasting number of customers was estimated using non-linear least squares as suggested by Srinivasan and Mason (1986). Parameters of this model along with estimates of acquisition cost, retention rate, margin and discount rate were then used as input to the valuation model in equation (8). This model was then evaluated using Mathematica.

Note that the procedure described above assumes that all customers (both active and inactive) potentially affect the future growth of customers. It is possible to modify this assumption and construct alternate, and potentially complex, models of diffusion. For example, one alternative model is to assume that while active and inactive customers define the remaining market potential, only currently active customers spread the positive word of mouth to affect future customer growth.[7] This model is similar in spirit to a diffusion model that incorporates replacement purchases (Kamakura and Balasubramanian 1987). We estimated this model for Amazon and found that its results are very similar to those obtained from our model. For example, this model projected the total market potential for Amazon as 71.8 million while our model estimated this number to be 67 million. Future research may wish to investigate alternative models of customer growth – for example a model that assumes negative word of mouth from defectors and positive word of mouth from currently active customers.

Results

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

[7] We thank the editor for suggesting this interesting formulation.

Insert Table-2 Here

All the parameters are significant. Parameter α provides an estimate of the maximum number of customers who are expected to ever try a company's product and services. Table-2 results show that the maximum number of triers are expected to be 67.0 million for Amazon, 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 due to defection.

From equation (10) it is easy to show that the peak for customer acquisition occurs at $-\beta/\gamma$. Table-2 results suggest that this peak occurs about 10-21 quarters from the start of our data period (around 1997). In other words, for the companies in our data set, customer acquisition has already reached a peak.[8] After this time companies will continue to acquire customers but at a slower rate. For example, Amazon added 4m new customers in December 2000, but added only 3m customers in the next two quarters.

Value of the Customer Base

The number of current customers and a forecast of customers to be acquired in the future enable us to estimate the value of a firm's customer base (current and future). We use average acquisition costs, margins and retention rates from Table-1, and parameter estimates from Table-2 as input to equation (8). Table-3 presents estimates of customer value and market value for these firms as of March 31, 2002 (end of our data period). Since stock prices change every day, firm value varies (sometimes dramatically) within a quarter. Therefore, we have included the high and low market value for the Jan-Mar 2002 quarter in this table. We have also included price-earnings or P/E ratios for these companies because (a) it is commonly used in financial valuation methods, and (b) to highlight that it is difficult to rely on this metric for fast growing companies. For example, two of the companies (Amazon and E*Trade) have negative earnings so P/E ratio is not defined. Further, two other companies (Ameritrade and Ebay) have only

[8] In order to estimate an S-shaped curve, we need an inflection point in the data. This inflection point is the time of peak customer acquisition. For datasets where this inflection point is not observed there are two possible solutions, either provide an external estimate of a parameter such as market size, or using a Bayesian method to provide priors for the parameters.

modest earnings, making their P/E ratio extremely high and significantly outside the market average range of 20-30.

Insert Table-3 Here

Capital One. Similar to 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 flows as well as a modest P/E ratio of 9.08. In other words, while conventional financial models of valuations may have difficulty in valuing 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 estimate 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 its 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%.

Amazon. Our estimate of the value of current and future customers of Amazon is about $0.82 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 about $3 billion. This suggests that either the market is still over-valuing Amazon or our model is not capturing some components of its value.

Ameritrade. We estimate 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 although we could not detect any significant time trend in Ameritrade's margins or acquisition costs from the past data of 4 years, recent turbulence in online trading may suggest lower margins, higher acquisition costs and higher customer defection in the future. As we show later in the sensitivity analysis, small changes in the expectations of these inputs change the value of Ameritrade's customers within the range of its current market value.

E-Bay. Our analysis puts the value of Ebay customers at $1.89 billion, far below its market value of $15.85 billion. Even if we assume 100% retention, its customer value increases 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 over valuing Ebay because it is one of the few dot.coms with positive earnings, or our model is not capturing some important option value. Some analysts on Wall Street do consider Ebay to be significantly over valued. For example, Faye Landes, an analyst at Sanford C. Bernstein, who was anointed as an all star analyst by Fortune magazine, said the following about Ebay, "It's trading at more than 30 times our 2005 estimates – that makes it one of the most expensive stock there is." (Fortune, June 11, 2001). While it is possible that market may be over valuing Ebay, it is also possible that our model does not capture unique aspects of Ebay's business. Specifically, Ebay is an auction exchange where there may be significant network externalities that are not captured by the traditional diffusion model. Further, Ebay's business entails both buyers and sellers and combining them both into "customers" may be an oversimplification. For example, Ebay currently has a total of about 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 among them. We leave this for future research.

*E*Trade.* At its estimated retention rate of 95%, we obtain 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 sum, we find that for 3 of the 5 firms customer value provides a close proxy for their market value. Further, we find that our method provides reasonable estimates when traditional financial methods may not work (e.g., for Ameritrade where P/E is 370, or for E*trade where P/E can not be defined because of negative earnings). Equally important is the fact that our method works well for a traditional firm (Capital One) where standard financial valuation methods are robust.

Value over Time

So far our results show that for 3 of the 5 companies, customer value provides a good estimate of their market value at one point in time, i.e. March 2002. Clearly, for any measure to be useful it should be able to track firm value over time. To achieve this objective we re-analyze data for all five companies for the last four quarters.[9] In other words, we use data up to June 2001 and estimate customer value for each of the five firms and compare these estimates with their market value as of June 2001. This analysis is repeated for each of the last four quarters. In Figure-2, we present customer value estimates for each quarter and market value at the end of that quarter.

Insert Figure-2 Here

Results show that while customer value estimates for Amazon and EBay are consistently below their market value, customer value estimates for Ameritrade, E*Trade and Capital One are within reasonable range of their market value. We should stress that market value generally 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 its market value fluctuated between a low of $7.7 billion to a high of $14.2 billion.[10]

To further confirm 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. Using data for four quarters for each of the five companies, this regression produced an R^2 of only 0.139. However, when this regression was run without Amazon and EBay (two companies whose market values are significantly different from our estimate of their customer value), the R^2 was 0.927.

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

[10] Sometimes market value fluctuations are very large across quarters as well (e.g., during the height of the dot-com fever). For example, in March 2000, market value for Amazon was $23.45 billion. A year later, in March 2001, it dropped to $3.67 billion; and as of March 2002 it climbed up to $5.3 billion. Our estimates of Amazon's customer value for this entire two-year time period are consistently below $1 billion.

Further, the intercept in this regression was not significantly different from zero while 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. Since estimating customer value requires more detailed inputs 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: (a) how changes in acquisition costs, margins, and retention rates affect customer value of a firm, and (b) the relative importance of customer retention, a key component of the marketing function, and the discount rate or cost of capital, traditionally a focus of the finance function.

Impact of Acquisition Cost, Margin and Retention Rate

Table-4 shows how customer value changes with changes in acquisition cost, margin and retention rate. Our results show a consistent pattern – improving customer retention has the largest impact on customer value, followed by improved margins, while reduction in acquisition cost has the smallest impact.

A 1% improvement in acquisition cost improves customer value by 0.02-0.32%. The biggest impact of reducing acquisition cost is for Capital One. This is consistent with the fact that Capital One has past its customer acquisition peak only recently (see Table 2) and it is still acquiring a large number of customers. Therefore any improvement in acquisition cost has a significant impact on its overall value. In contrast, Ameritrade and E*Trade have past their acquisition peak several quarters ago and therefore have the least impact of improving acquisition cost.

Insert Table-4 Here

Improving margins by 1%, for example by cross selling, improves customer value by about 1%. This result is consistent across all firms. Improving customer retention by

1% improves customer value by 2.45-6.75%. The higher the current retention rate of a company (e.g., Ameritrade 95% versus Amazon 70%), the higher the impact of improving retention.

In sum, 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 highlighted the importance of retention (e.g., Reichheld 1996). Interestingly, after the bursting of the dot.com bubble, Wall Street and many Internet firms started focusing on and cutting down acquisition costs. Demers and Lev (2001) explain this by showing that prior to the market's correction for Internet stocks, the market treated expenditures on both marketing and product development as assets rather than current expenses. They further found that in the year 2000 after the shake out, product development expenses continue to be capitalized as assets but not marketing expenditures. Consistent with our study, and contrary to current market perception, they show that web traffic metrics (e.g., traffic, loyalty) continue to be value-relevant.

We note two caveats for interpreting results of Table-4. First, we have not included 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. In fact, using a game theoretic model, Shaffer and Zhang (2002) show that it is not advisable for firms to completely eliminate churning or customer defection. If a firm has 100% customer loyalty it may be under pricing 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) may attract customers with low retention rates. Recent studies (e.g., Thomas 2001) have provided methods to link customer acquisition and retention.

Impact of Retention versus Discount Rate

Discount rate or cost of capital is a critical variable in evaluating net present value of any cash flow stream and firm valuation. Therefore, it is not surprising that the finance community spends considerable effort in measuring and managing a firm's cost of capital (e.g., see Brealey and Myers 1996). In contrast, marketing and business community has just begun to measure and manage customer retention. Its importance in firm valuation is even less evident. To compare the relative importance of customer retention and discount rate, the last column of Table-4 shows how changes in discount rates affect customer value for the firms, in contrast to changes in marketing levers. The results show that a 1% improvement in customer retention enhances customer value (and in turn firm value) by about 2.45-6.75%, while a similar decrease in the discount rate increases customer and therefore firm value by only 0.5-1.2%. In other words, the retention *elasticity* is almost five times the discount rate elasticity.

An alternative way to examine these 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 as 8% to 16% (Brealey and Myers 1996). Based on industry information (e.g., Reichheld 1996) as well as the retention rates for the five companies in our empirical analysis, we use a range of 70% to 90% for retention rate. Using these ranges, we re-estimate customer value for the companies in our data set.

Insert Table-5 Here

Table-5 reports our results. Several interesting things emerge from this table. First, consistent with our results of Table 4, retention rate has a larger impact on customer value compared to the impact of discount rate. For example, improving customer retention from 70% to 90% increases customer value for Amazon by \$1.38 - \$0.75 = \$0.63 billion (for 16% discount) to \$1.07 billion (for 8% discount). In contrast, improving discount rate from 16% to 8% increases Amazon's customer value by \$0.15 billion (for 70% retention) to \$0.59 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 high retention-low discount scenario is 2.5 to 3.5 times its value under low retention-high discount case. Although we have not considered the relative cost of improving the retention rate versus the discount rate, this analysis suggests the importance of marketing levers in improving customer and firm value as compared to the financial instruments.

Conclusion

Customer lifetime value is gaining increasing attention in marketing, especially database marketing. In this paper we attempt to show that this concept is not only important for tactical decisions, but can also 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, like any other asset, their value should be measured and managed. Our paper 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 the recent work in accounting where 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. Recent history for dot.com companies casts doubt on this assumption. In contrast, we estimate value of a firm's current and future customer base from basic principles. This makes our analysis more stable than the typical accounting approach, which is dependent on the vagaries of the financial market place.

We used data from one traditional and four Internet firms in our empirical application. Our analysis reveals several interesting results. First, we find that our estimates of customer value are reasonably close to current market valuation for 3 of the 5 firms. In contrast, traditional valuation methods have difficulty valuing many of these firms since most of them have negative earnings. These results show that customer-based metrics are still value relevant. Second, consistent with previous studies in marketing, we find that retention has a very large impact on customer value. Specifically we find that retention elasticity to be in the range of 3-7 (i.e., 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 0.02-0.3. Interestingly, the market appears to have treated marketing (and customer acquisition) expenditure as investment before the Internet crash but treats them as expenses now. Our results indicate that cutting acquisition costs may not be the most effective way to improve value. Further, to the extent that customers are assets, the market may be incorrect in treating customer acquisition costs as current expenses rather than as investments. Third, we find that the retention rate has a significantly larger impact on customer and firm value than the discount rate or firm's cost of capital. Financial analysts and company managers spend considerable time and effort to measure and manage discount rate because they understand its impact on firm value. However, our results show that it is perhaps more important for not only marketing managers but also for senior managers and financial analysts to pay close attention to a firm's customer retention rate.

We acknowledge several limitations of our study. We had several quarters of data that enabled us to provide a good estimate for the number of future customers – an important input to our valuation model. The accuracy of this 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 where previous studies can provide informative priors (Sultan, Farley and Lehmann 1990, Lenk and Rao 1990). Such an approach would be a useful extension in our case as well. A second limitation of our study is the assumption of constant retention rate. This assumption implies that as a firm reaches maturity and its customer acquisition slows down, it would eventually lose all its customers due to constant defection rate. This aspect is likely to have small impact on our valuation since this effect occurs only in the very long run and the events far away have minimal impact on value due to discounting. Nonetheless, future research should examine this issue in greater detail. For example, two possible ways to alleviate the impact of this assumption is to either have dynamic retention rates or growth in market size. We also ignored linkages between acquisition costs, retention rates, margins and number of customers. In reality we would expect correlation among these factors. A model that captures these relations would be very valuable.

In sum, our paper provides a starting point for valuing customers and its relationship to the value of firms. We emphasize that we are not suggesting replacing traditional financial models. In fact our approach uses the well-established finance approach of discounted cash flow. However by using it at a customer level we are able to provide a useful method for forecasting the stream of future earnings, a key input to any valuation model. We hope that our work sparks more interest in this area and also brings closer together the fields of marketing and finance.

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Table-1

Descriptive Data

Company	Data Period From	To	No. of Customers	Quarterly Margin	Acquisition Cost	Retention Rate
Amazon	Mar 1997	Mar 2002	33,800,000	$ 3.87	$ 7.70	70%
Ameritrade	Sep 1997	Mar 2002	1,877,000	$ 50.39	$ 203.44	95%
Capital One	Dec 1996	Mar 2002	46,600,000	$ 13.71	$ 75.49	85%
E-Bay	Dec 1996	Mar 2002	46,100,000	$ 4.31	$ 11.26	80%
E*Trade	Dec 1997	Mar 2002	4,117,370	$ 43.02	$ 391.00	95%

Number of customers is at the end of March 2002.

Quarterly margin is per customer based on the average of the last four quarters.

Acquisition cost is per customer based on the average of the last four quarters

Table 2

Parameter Estimates for Number of Customers (in millions)

		Amazon	Ameritrade	Capital One	Ebay	Etrade
Parameters	α	67.045 (3.615)	2.482 (0.121)	171.200 (15.864)	81.945 (3.995)	4.719 (0.064)
	β	-4.114 (0.139)	-3.345 (0.114)	-3.052 (0.079)	-6.009 (0.145)	-3.441 (0.086)
	γ	0.265 (0.015)	0.263 (0.016)	0.149 (0.003)	0.317 (0.013)	0.365 (0.012)
Time to Peak of Customer Acquisition	$-\beta/\gamma$	15.64	12.72	20.48	18.96	9.43
	Calender Date	Dec 2000	Sep 2000	Dec 2001	Jun 2001	Mar 2000
Fit Statistics	MAD	0.556	0.041	0.393	0.590	0.049
	MSE	0.594	0.004	0.346	0.763	0.004

$-\beta/\gamma$ 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.

MAD is mean absolute deviation and MSE is mean square error.

Table 3

Value of Customers, Market Value and Price-Earnings Ratio

	Value of Customers ($ billion)	Market Value ($ billion)			P/E Ratio
		As of Mar 31, 2002	High for the Quarter	Low for the Quarter	
Amazon	0.82	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

Table-4

Impact of Improving Retention, Acquisition Cost and Margins On Customer Value

	Customer Value ($b)	**% Increase in Customer Value for a 1% improvement in**			
	Base Case	**Retention**	**Acquisition Cost**	**Margin**	**Discount Rate**
Amazon	0.82	2.45%	0.07%	1.07%	0.46%
Ameritrade	1.62	6.75%	0.03%	1.03%	1.17%
Capital One	11.00	5.12%	0.32%	1.32%	1.11%
Ebay	1.89	3.42%	0.08%	1.08%	0.63%
E*Trade	2.69	6.67%	0.02%	1.02%	1.14%

Table-5

Customer Value at Typical Retention and Discount Rates

($ Billions)

Discount Rate	Amazon			Ameritrade			Capital One			Ebay			E*Trade		
	Retention Rate			Retention Rate			Retention Rate			Retention Rate			Retention Rate		
	70%	80%	90%	70%	80%	90%	70%	80%	90%	70%	80%	90%	70%	80%	90%
8%	0.90	1.25	1.97	0.71	0.97	1.52	7.33	10.95	18.94	1.56	2.18	3.47	1.07	1.52	2.46
12%	0.82	1.10	1.62	0.65	0.85	1.25	6.21	8.88	14.14	1.39	1.89	2.82	0.98	1.34	2.03
16%	0.75	0.98	1.38	0.59	0.76	1.06	5.35	7.39	11.04	1.29	1.70	2.41	0.90	1.20	1.73

Figure-1
Number of Customers

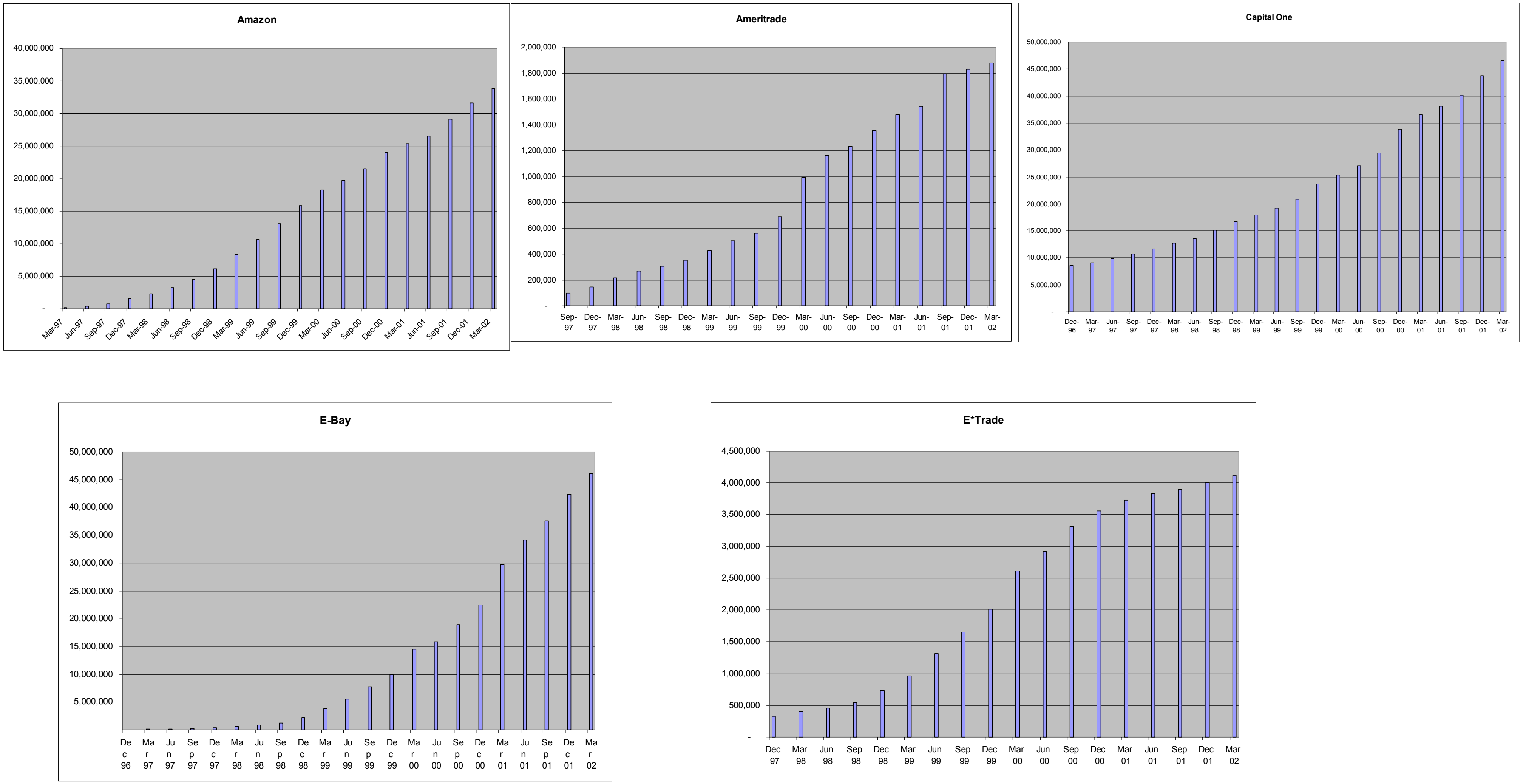

Figure-2
Market Value and Customer Value over Time