Valuing Customers

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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 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, which is 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 four Internet firms – Amazon, Ameritrade, Ebay and E*Trade. The results show a close relation between customer value and current market value for 3 companies. We find that Ebay is either overvalued or has a high option value that is not captured in our model. Our method also proves to be more stable over time than actual market capitalization. The results suggest that 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. In essence, 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 attempt to 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 and Deighton 1996, 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 predictable and relatively easy to project. 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. This was evident during the height of dot.com bubble when many innovative valuation methods emerged. In order to put our approach in context, we provide a brief glimpse of some of these valuation approaches.

The Wall Street Approach

Henry Blodget, the Internet guru on Wall Street, became famous in late 1998 for predicting that Amazon's share price would exceed $400. Blodget justified his valuation based on the following method. He first estimated Amazon's target market for books, music and videos to be around $100 billion. Next, he estimated that, similar to Wal-Mart, Amazon would become a leader in its category with a market share of 10%, giving it a revenue base of $10 billion. Although traditional retailers achieve a net margin of 1% to 4%, Blodget estimated that Amazon's leaner operation would fetch it a fatter margin of 7% or $700 million. Next, Blodget estimated a P/E ratio of anywhere between 10 (for a slow growth scenario) to 75 (for a fast growing scenario), thus giving Amazon a market cap as high as $53 billion or $332 per share (Fortune 1999).

In a variant of this approach Desmet et al. (2000) created various scenarios for Amazon with market share from 5% to 15% and operating margin of 7% to 14%. They assigned subjective probabilities for these scenarios and arrived at an expected valuation for Amazon at $23 billion. The approach of estimating market size, firm share in that market, its profit margin and P/E ratio is a well accepted approach in the financial community (e.g., Frank 2001). However, there is considerable subjectivity involved in estimating many of the input factors such as market share, profit margin etc.

Discounted Cash Flow (DCF) Approach

Several finance academics argue that traditional valuation methods such as DCF are valid for high growth companies as well. For example, in June 2000, Damodaran (2001) used this approach and estimated Amazon's share price value as $34.37. Damodaran's approach to arrive at a positive valuation using DCF for a company that so far has negative cash flows has five main inputs. First, revenue growth for the company is estimated. For Amazon, Damodaran estimated that the current annual revenue growth of 120% would go down to 5% by year 10, giving a compound annual growth of 40%. Second, you need to forecast operating margin. This is a challenging task given that the current operating margin for Amazon is –16.27%. Damodaran assumed that Amazon would reach the operating margin of 9.32%, the average for specialty retailing industry, by the end of the tenth year. Third, he estimated (based on industry average) that for every $3 in additional sales, Amazon would need to reinvest $1 in capital. Finally he estimates the beta for Amazon and its debt ratio. These assumptions helped him use the DCF approach to arrive at a $34.37 per share price for Amazon. Once again this approach is sound and intuitive but the assumptions needed to arrive at the valuation raise questions and demand more justification.

The Eyeball Approach

As mentioned before, the difficulty of valuing high growth companies, such as dot.coms, by traditional methods led to a series of new metrics and methods. One popular measure 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 (2001) 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 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 the conclusions about the value of eyeballs. Partly because of this reason 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

Current mood on Wall Street seems to suggest that customer-based metrics are not only irrelevant for firm valuation but in fact can be misleading. We argue against this prevailing sentiment. We suggest, and show, that value based on customers can be a strong and stable 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 by the lifetime value framework, 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 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 we use this approach using only published information from annual reports and other financial statements of several firms to estimate the value of their customer base.

Our approach is similar in spirit to Kim, Mahajan and Srivastava (1995) who estimate the market value of cellular communications industry by forecasting the number of customers, revenue per customer etc. However, Kim et al. focused on valuing the entire industry rather than a specific firm. Further, they did not include factors such as customer retention and customer acquisition cost, which are critical drivers of our model.

Model

Conceptually, the value of a firm's customer base is the sum of the lifetime value of its current and future customers. To build a mathematical and empirically estimable model, we first build a model for the lifetime value of a cohort of customers, then aggregate this lifetime value across all current and future cohorts, and finally construct models to forecast the key inputs to this model (e.g., 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 finance approach of valuing perpetuity (Brealey and Myers 1996). When we account for customer retention rate r, this formulation is modified as follows,

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

Note that we have used infinite horizon to estimate customer lifetime value. Many researchers have debated about the appropriate duration over which lifetime estimates should be based (Berger and Nasr 1998). We build our model for 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 automatically 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 produces significant overestimates of lifetime value.[2] Fourth, both retention and discount rates ensure that earnings from distant future contribute significantly less to lifetime value. Finally, models with infinite horizon 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 at each time period. Each cohort of customers goes through the defection and profit pattern as 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 at a constant rate 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.[3] 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.

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
.	.	.	.	.	.	.

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,

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[2] 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%.

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

(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 (1982) show that estimating an inherently continuous process, such as Bass diffusion model, with a discrete version produces biases. Further, we will construct models of key inputs (e.g., n_k) as continuous functions. Therefore, we deal with a continuous version of customer value. It is well known that if the annual discount rate is i and we continuously compound it m times a year, then the discount rate at the end of the year is $1/(1+i/m)^m$. In the limit 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,

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

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 four Internet companies. Although our model is not limited, nor specifically designed for such companies, we use data from these companies for two main reasons – the data are easily available, and valuation of these companies is especially hard using traditional financial metrics because of negative earnings.

Based on annual reports, 10K and 10Q statements as well as other company reports we use quarterly data for the period March 1997 to June 2001 for Amazon, Ameritrade, Ebay and E*Trade. The data for each quarter includes number of customers, gross margin and marketing costs. Using these data and some reasonable assumptions (discussed shortly), we estimate the acquisition cost and quarterly margin per customer. A summary of the data for the four companies is given in Table-1. We now focus on each input variable for our model, examine the empirical pattern in the data and use it along with theory to suggest an appropriate way to model these factors.

Number of Customers

One of the key inputs to our model is the number of customers in future cohorts. Figure-1 shows the growth in number of customers for each of the four firms. The data show a remarkable consistency with the classical diffusion theory. A natural candidate to estimate the number of customers in future periods is the Bass (1969) diffusion model. However, the Bass diffusion model (continuous version) 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 of the diffusion model is simpler, but it still poses some 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. Further, Schmittlein and Mahajan (1982) show that estimating an inherently continuous time model with a discrete approximation produces biased estimates.

Insert Figure-1 Here

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

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

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 then easily obtained by differentiating this function,

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

This model, also called the Technological Substitution Model, has been used by several researchers in modeling innovations and to project number of customers (e.g., Fisher and Pry 1971, Kim, Mahajan and Srivastava 1995).

Margin

For each firm we use publicly available data, such as financial statements, to obtain the gross operating margin for each quarter. We estimate quarterly margin per customer by dividing the total gross margin by the number of current customers in that quarter. Figure-2 shows the changes in quarterly margins over time for our sample of four companies. Unlike the number of customers, there is no systematic pattern in margins except for recent decline in the margins of Ameritrade and E*Trade due to significant slow down in online trading (we will discuss this more later).

Insert Figure-2 Here

This lack of systematic pattern echoes the debate among researchers in this area. For example, Reichheld (1996) finds that as a customer stays longer with a company and becomes more comfortable doing business with a firm, it buys more and at a higher frequency generating a larger revenue stream. 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. 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. Intuition and anecdotal evidence suggests that as a company expands its customer base, it tends to draw more and more marginal customers who do not spend as much money 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 very 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 this conflicting evidence in recent research and lack of any systematic pattern in our data, we assume margin to be constant over time. Specifically, we use the average of the last four quarters as the margin for future periods[4]. Clearly this is a simplifying assumption and we leave its detailed examination to future research.

Acquisition Cost

Although conceptually easy to define, it is somewhat 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. Here we operationalize it by dividing the marketing cost by the number of newly acquired customers for each time period, a reasonable assumption early on since these firms were

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

focused on acquiring new customers. Figure-3 shows the changes in acquisition costs over time for our four companies.

Insert Figure-3 Here

Similar to profit margins, there is no systematic pattern in acquisition costs. There are potentially two opposing forces that affect these 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, network externalities as well as branding power make it easier to attract new customers. For example, network externalities favor E-Bay in attracting new customers. It is difficult to know how these two forces counterbalance each other. Our empirical data shows no significant patterns in the acquisition costs over time. Therefore, for simplification purposes we once again assume constant acquisition cost and use last four quarters' average as the cost for future customer acquisitions.[5]

Retention

Customer retention is one of the most critical variables that affect customers' lifetime profit. Yet it is extremely hard to obtain precise estimates of customer retention, at least from publicly available data. Some studies suggest an average of 80% retention rate among established firms (Reichheld 1996). Given the ease of comparison shopping and the competitive intensity on the web, the retention rate is likely to be lower for many Internet firms. For example, a recent financial statement by Amazon indicates that only 60% of its customer accounts are currently active. While it is possible to estimate customer retention rates based on detailed customer databases (e.g., Schmittlein and

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

Peterson 1994), we estimate the value of customer base for the customer retention range of 60% to 80%.

Discount Rate

The discount rate is the weighted average cost of capital that accounts for the debt-equity ratio of a firm as well as its risk. Standard financial methods (e.g., Capital Asset Pricing Model) can be used to estimate these 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.[6] 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, and not the number of *actual* 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). We estimate our model under three different retention scenarios (60%, 70% and 80%). 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.

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[6] Since we use quarterly data for our empirical analysis, we convert the annual discount and retention rates to their quarterly equivalent. For example, a 12% annual discount rate is equivalent to a 2.87% quarterly rate, i.e., $(1+0.0287)^4 = (1+0.12)$

Results

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

Number of Customers

Table-2 provides parameter estimates as well as fit statistics for each of the four companies. We report mean absolute deviation (MAD) and mean squared errors (MSE) as measures of fit, since the 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.

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 if the retention rate is 60%, the maximum number of triers are expected to be 82.2 million for Amazon, 4.09 million for Ameritrade, 95.02 million for eBay and 8.51 million for E*Trade. The maximum number of actual customers will be less than this number due to defection. As the retention rate increases, estimates for the maximum number of triers go down systematically. For example, for Amazon these estimates are 82.2 million at 60% retention, 70.53 million at 70% retention and 60.21 at 80% retention. Thus regardless of our assumption of retention rate we get similar estimates for the maximum number of *actual* customers. In other words, the higher the retention rate, the fewer triers are needed to reach a given (projected) level of actual customers.

Although the α parameters are statistically significant for all four companies, the standard errors for Amazon and eBay are higher than those for E*Trade and Ameritrade. This is mainly due to the fact that growth in the number of customers has slowed down significantly for E*Trade and Ameritrade. This provides a clear inflection point in the S-shaped curve for these companies, allowing for better and more certain estimates. In contrast, eBay continues to grow rapidly. For example, it added 4.4 million new customers in the second quarter of 2001. Some of this growth is due to acquisition of new companies that is harder for the diffusion model to capture.

Small standard errors for parameters β and γ suggest that they are estimated with reasonable precision. 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 15-20 quarters from the start of our data period (around 1997). In other words, for the companies in our data set, acquisition is likely to slow down after 4 to 5 years or around the year 2001-2002. After this time companies will continue to acquire more customers but the actual number of customers acquired in each period is expected to be smaller than the previous period. For example, Amazon added 4m net new customers in December 2000, but added only 3m customers in the next two quarters.

Value of Customer Base

The actual 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 and margins from Table-1, and parameter estimates from Table-2 as input to equation (8). Results are presented in Table-3 for three different retention rates.

Insert Table-3 Here

Amazon. Our estimates of the value of current and future customers of Amazon range from \$2 billion to \$3.29 billion for retention rates of 60%-80%. Amazon indicates that its retention rate is over 70%. Some consultants have suggested that a reasonable assumption for Amazon's customer retention rate is 78% (Seybold 2000). With this retention rate, the value of Amazon's customers is about \$3 billion. In addition, like any other company Amazon has tangible assets. For example, at the end of June 2001, it reported cash and marketable securities worth \$609 million. These estimates indicate that the Amazon's current market value of about \$3.45 billion is in line with our expectations.

Ameritrade. We estimate the value of Ameritrade's customers to be in the range of $1.13 billion to $1.94 billion. The market value of Ameritrade at the end of August 2001 is $1.13 billion, which is our estimate of its customer value for a retention rate of 60%. Does it mean that the market is not valuing Ameritrade's tangible assets, or is Ameritrade's retention rate even lower than 60%? While it is difficult to answer this question precisely, we note that we assumed a constant margin in the future based on the average of the last four quarters. Recent turbulence in the market has slowed down online trading and had a significant negative impact on the margins of online traders like Ameritrade. For example, Ameritrade's average quarterly margin per customer was $124.24 in September 2000, $83.31 in December 2000, $67.47 in March 2001, and $60.14 in June 2001. In other words, using the average of $83.79 for future periods may be an overestimate. Assuming future margins to be $60, i.e. the same as in June 2001, the estimates for Ameritrade's customer value range from $0.76 billion to $1.34 billion. More than model fitting, projecting margin in the future requires a deep understanding of the industry and the company's competitive position in the market place. Our model requires these judgments as inputs. However, our approach also provides a means for researchers and analysts to assess the impact of their assumptions on the overall value of the firm.

E-Bay. Our analysis suggests that the value of Ebay customers range from $1.56 billion to $2.87 billion. Unlike Amazon or Ameritrade, these estimates are significantly lower than Ebay's current market value of $14.51 billion. Either the market is still 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 consider Ebay to be significantly over valued. For example, Faye Landes, an analyst at Sanford C. Bernstein, who was recently 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 oversimplification. For example, Ebay currently has a total of about 34 million customers. It is difficult to argue that if these customers are evenly split into buyers and sellers, it is the same as having 33 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.* E*Trade's current market value of $2.02 billion is within the range of our estimates of its customer value of $1.44 billion to $2.56 billion. Similar to Ameritrade, E*Trade is being affected by the recent slowdown in online trading among customers. Consequently, its quarterly margin per customer has gone down from $61.56 in September 2000 to $41.20 in June 2001. If we use the last quarter's margin as our estimate for the future instead of the four-quarter average, our customer value estimates range from $1.09 billion to $1.98 billion.

Changes in Value over Time

In the last few years we have witnessed significant volatility in the valuation of dot.com companies. In hindsight many of these valuations were misplaced. Therefore to further examine our model we go back in time to see if our approach provides more stable estimates of customer value than earlier market capitalization levels. This also attests the robustness of our model and the customer-based valuation approach.

To achieve this objective, we re-analyze data for all four companies for different time periods assuming an 80% retention rate. We start our analysis by using data up to March 2000 – the height of the Internet bubble. We then repeat this analysis by adding data for an additional quarter (i.e., Jun 2000, Sep 2000 and so on). Figure-4 shows customer value for the four companies based on this analysis. We also contrast these numbers with the market cap of the firms at that point in time.

Insert Figure-4 Here

Amazon. Customer value estimates for Amazon are fairly stable over time and range from $2.2 billion to $3.3 billion. In contrast, the market cap for Amazon during the same period varied from a high of $23.4 billion in March 2000 to a low of $5.1 billion in June 2001. It is also interesting to note that while Wall Street placed the highest market value on Amazon in March 2000, our customer value estimates are near the lowest at that time. This is largely due to high acquisition cost and low margins in March 2000. Over the next few quarters, Amazon has been more aggressive in trimming its acquisition cost and improving its margin. Therefore, while the changes in market value indicate a decline in Amazon's intrinsic worth, our analysis shows an actual improvement in Amazon's performance.

Ameritrade. Market value of Ameritrade has decreased sharply from March 2000 to June 2001. Significant slow down in online trading and declining margins are largely responsible for this trend. The drop in Ameritrade's value is also reflected in our estimates of its declining customer value that are driven largely by decreasing margins. For example, Ameritrade's quarterly margin per customer (based on trailing 4 quarter average) dropped from $106 in March 2000 to $84 in June 2001. However, Figure-4 shows that while both market value and customer value decline over time, market value is more volatile. Finally, we note that our model for forecasting number of customers did not converge for March, June and September 2000 because the data show no inflection point up to September 2000 (see Figure-1). This is a problem common to all forecasting models, such as Bass diffusion model. Traditional methods to overcome this problem include using Bayesian priors (e.g., Lenk and Rao 1990) or exogenous estimates of market size (e.g., Kim et al. 1995).

E-Bay. Ebay's market value fluctuates from a low of $8.9 billion in December 2000 to a high of $23 billion in March 2000. Unlike Ameritrade, Ebay's market value shows no particular trend, declining from March to December 2000 and then increasing after that time. Our estimates of customer value range from a low of $1.2 billion to a high of $2.9 billion. The change in our estimates of customer value over time is largely driven by the revised estimates of customers from the model as new data are added. As mentioned earlier, our estimates of customer value are consistently and significantly below Ebay's market value.

*E*Trade.* Both the market value and customer value of E*Trade decline consistently over time. Our estimates of customer value track changes in market value reasonably well. Changes in value are largely driven by declining margin. Once again, customer value is relatively less volatile than market value.

In sum, our analysis shows that customer value tracks changes in market value over time, and more importantly it provides a more stable estimate of value.

Managing Customer Value

Our analysis shows a strong link between customer value and firm value. 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 across all firms in our study. A 10% improvement in acquisition cost improves customer value by 1-2%. Improving margins, for example by cross selling, improves customer value by about 10-12%. In contrast, improving customer retention by 10% improves customer value by 28-32%. These results are consistent with previous studies (e.g., Reichheld 1996).

Insert Table-4 Here

Interestingly, after the bursting of the dot.com bubble, Wall Street and many Internet firms started focusing on and cutting down acquisition cost. 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 find 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 (2001) 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 inexpensive acquisition programs may attract customers with low retention rates. Recent studies (e.g., Thomas 2001) have provided methods to link customer acquisition and retention.

Retention Rate and Discount Rate

Discount rate or cost of capital is a critical variable in evaluating net present value of any cash flow stream and, hence, for 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, in Table-5 we show how changes in these variables affect customer value for the firms in our sample. Our results show that while a 10% improvement in customer retention enhances customer value (and in turn firm value) by about 30%, a similar decrease in the discount rate increases customer and therefore firm value by only 3-4%. In other words, the retention *elasticity* is almost ten times the discount rate elasticity.

Insert Table-5 Here

An alternative way to examine these effects is to assess the value of customers for typical range of retention and discount rates. Finance literature suggests a typical range of discount rates as 8% to 16% (Brealey and Myers 1996). The range for retention rates varies depending on the type of company and industry. For example, retention rate for Harley Davidson is reported to be in the upper 90%. However, for most Internet companies (similar to companies in our sample) a typical range is 60% to 80%. Using these ranges, we re-estimate customer value for the companies in our data set.

Insert Table-6 Here

Table-6 reports our results. Several interesting things emerge from these results. First, consistent with our results of Table 5, retention rate continues to have a larger impact on customer value compared to the impact of discount rate. For example, improving customer retention from 60% to 80% increases customer value for Amazon by \$2.93 - \$1.85 = \$1.08 billion (for 16% discount) to \$1.58 billion (for 8% discount). In contrast, improving discount rate from 16% to 8% increases Amazon's customer value by \$0.32 billion (for 60% retention) to \$0.82 billion (for 80% 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, can almost double when we move from low retention-high discount scenario to high retention-low discount scenario. For example, at 60% retention and 16% discount, Amazon's customer value is \$1.85 billion. This value almost doubles to \$3.75 billion if retention rate changes to 80% and discount rate shifts to 8%. More generally, the retention rate matters more than is currently acknowledged.

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 typical 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 and we use market value as a benchmark to compare our estimates. 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 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 of 3 of the 4 firms. In contrast, traditional valuation methods have difficulty valuing these firms since most of them have negative earnings. These results show that customer-based metrics are still value relevant and while Wall Street embraced these measures during the peak of the Internet bubble, it may be wrong in ignoring them after the crash. Second, unlike the wide fluctuations in market value of these firms over the last year, our estimates of customer value are quite stable over time since the patterns we estimate do not change radically with a new data point. This suggests that our approach may be tapping into intrinsic firm value. Third, consistent with previous studies in marketing, we find that retention has a very large impact on customer value. Specifically we find that 10% improvement in retention increases a firm's value of its customer base by about 30%. In contrast, a 10% improvement in acquisition cost improves value by only 1%, and a 10% improvement in margin increases value by about 11%. Interestingly, the market treated marketing (and customer acquisition) expenditure as investment before the Internet crash but treats these expenditures 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 treating them as investments. Fourth, 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 a 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. Such an approach would be a useful extension in our case as well. A second limitation of our study is the assumption of constant margins and acquisition costs in the future periods. We used this assumption because we did not find any discernable patterns in our data set. However, a detailed examination of this issue would be a useful next step. We also ignored linkages between acquisition costs, retention rates, margins and number of customers. In reality we would expect a strong 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 hope that our work sparks more interest in this area and also brings closer together the fields of marketing and finance.

Table-1

Descriptive Data

Company	Data Period From	Data Period To	No. of Customers	Quarterly Margin	Acquisition Cost
Amazon	Jun 1997	Jun 2001	35,100,000	$ 6.23	$ 8.41
Ameritrade	Dec 1997	Jun 2001	1,545,000	$ 83.79	$ 229.25
E-Bay	Mar 1997	Jun 2001	34,100,000	$ 4.30	$ 9.40
E*Trade	Mar 1998	Jun 2001	3,828,610	$ 52.91	$ 162.30

1. Quarterly margin is per customer based on the average of the last four quarters.
2. Acquisition cost is per customer based on the average of the last four quarters and 80% retention rate.

Table 2

Parameter Estimates for Number of Customers (in millions)

Company	Parameter	Retention = 60%		Retention = 70%		Retention = 80%	
		Estimate	Std Error	Estimate	Std Error	Estimate	Std Error
Amazon	α	82.20	3.59	70.53	2.94	60.21	2.36
	β	-4.77	0.08	-4.67	0.09	-4.57	0.09
	γ	0.31	0.01	0.31	0.01	0.32	0.01
	MAD	0.84		0.75		0.63	
	MSE	0.97		0.79		0.68	
Ameritrade	α	4.09	0.30	3.49	0.28	2.96	0.26
	β	-3.73	0.07	-3.63	0.09	-3.52	0.10
	γ	0.28	0.01	0.28	0.02	0.28	0.02
	MAD	0.04		0.04		0.04	
	MSE	0.003		0.003		0.003	
E-Bay	α	95.02	13.21	84.68	12.32	75.24	11.37
	β	-6.27	0.16	-6.17	0.17	-6.07	0.19
	γ	0.34	0.02	0.33	0.02	0.33	0.02
	MAD	0.98		0.71		0.62	
	MSE	1.77		0.79		0.73	
E*Trade	α	8.51	0.17	7.24	0.16	6.15	0.15
	β	-3.75	0.04	-3.66	0.05	-3.57	0.06
	γ	0.34	0.01	0.34	0.01	0.35	0.01
	MAD	0.29		0.24		0.28	
	MSE	0.09		0.06		0.08	

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

Table 3

Value of Customers and Market Cap

	Value of Customers ($ billion)			Market Cap ($ billion)	
	Retehtion Rate			As of June 30, 2001	As of August 29,2001
	r=60%	r=70%	r=80%		
Amazon	2.00	2.54	3.29	5.13	3.45
Ameritrade	1.13	1.45	1.94	1.51	1.13
Ebay	1.56	2.11	2.87	18.72	14.51
E*Trade	1.44	1.89	2.56	2.10	2.02

Table-4

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

	Customer Value ($b)	% Increase in Customer Value for a 10% improvement in		
	Base Case	Retention	Acquisition Cost	Margin
Amazon	2.54	28.34%	0.51%	10.51%
Ameritrade	1.45	30.18%	1.19%	11.19%
Ebay	2.11	30.80%	1.42%	11.42%
E*Trade	1.89	29.96%	1.11%	11.11%

Base Case: 70% customer retention

Table-5
Impact of Retention Rate and Discount Rate On Customer Value

	Customer Value ($b)	% Increase in Customer Value for a 10% improvement in	
	Base Case	Retention Rate	Discount Rate
Amazon	2.54	28.34%	2.91%
Ameritrade	1.45	30.18%	4.17%
Ebay	2.11	30.80%	2.91%
E*Trade	1.89	29.96%	3.12%

Base Case: 70% customer retention

Table-6

Customer Value at Typical Retention and Discount Rates

($ Billions)

Amazon

Discount Rate	Retention Rate 60%	70%	80%
8%	2.17	2.80	3.75
12%	2.00	2.54	3.29
16%	1.85	2.32	2.93

Ameritrade

Discount Rate	Retention Rate 60%	70%	80%
8%	1.24	1.61	2.23
12%	1.13	1.45	1.94
16%	1.05	1.31	1.72

E-Bay

Discount Rate	Retention Rate 60%	70%	80%
8%	1.71	2.37	3.32
12%	1.56	2.11	2.87
16%	1.44	1.91	2.53

E*Trade

Discount Rate	Retention Rate 60%	70%	80%
8%	1.56	2.08	2.92
12%	1.44	1.89	2.56
16%	1.33	1.72	2.29

Figure-1

Number of Customers

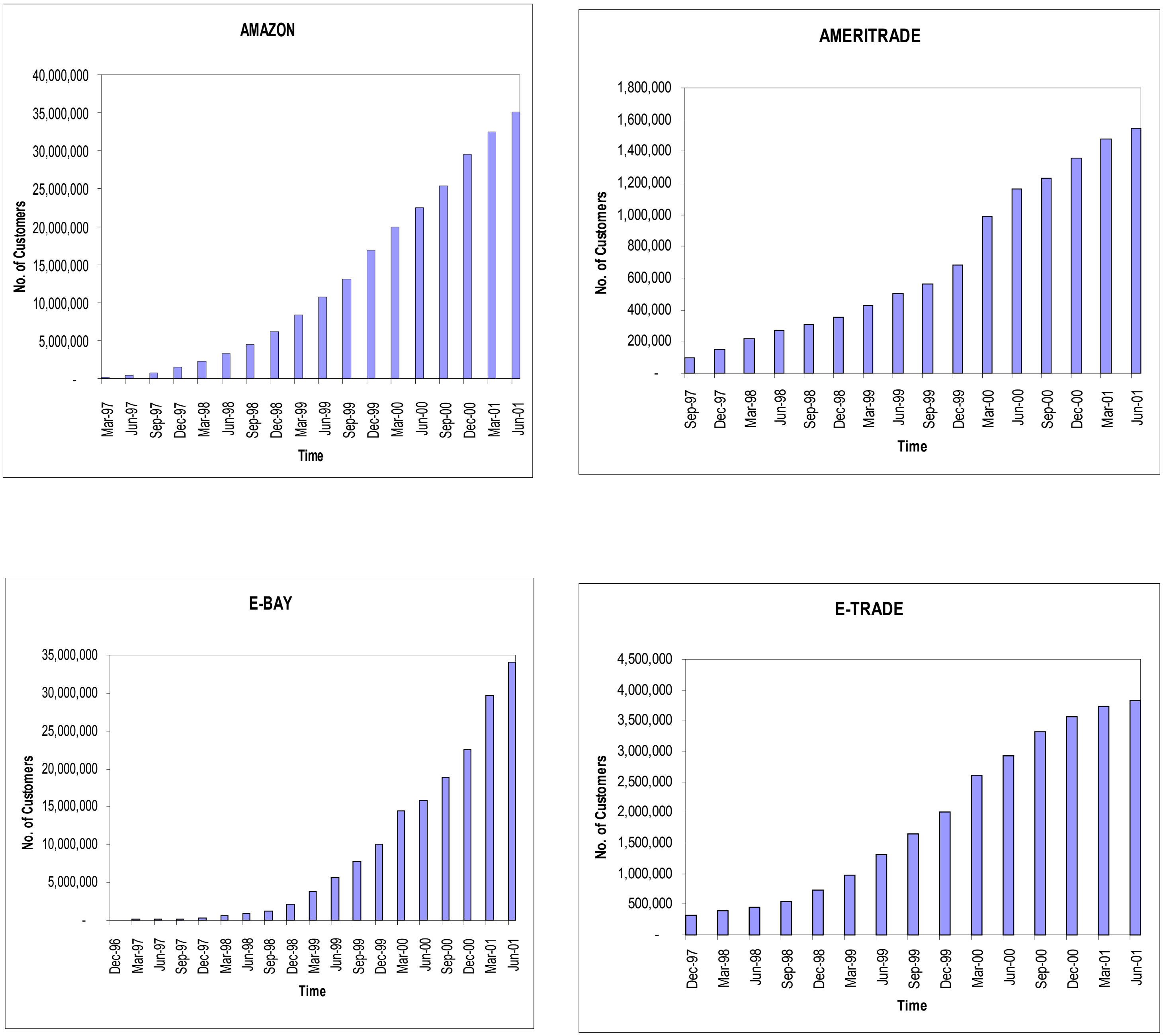


Figure-2

Quarterly Margin Per Customer

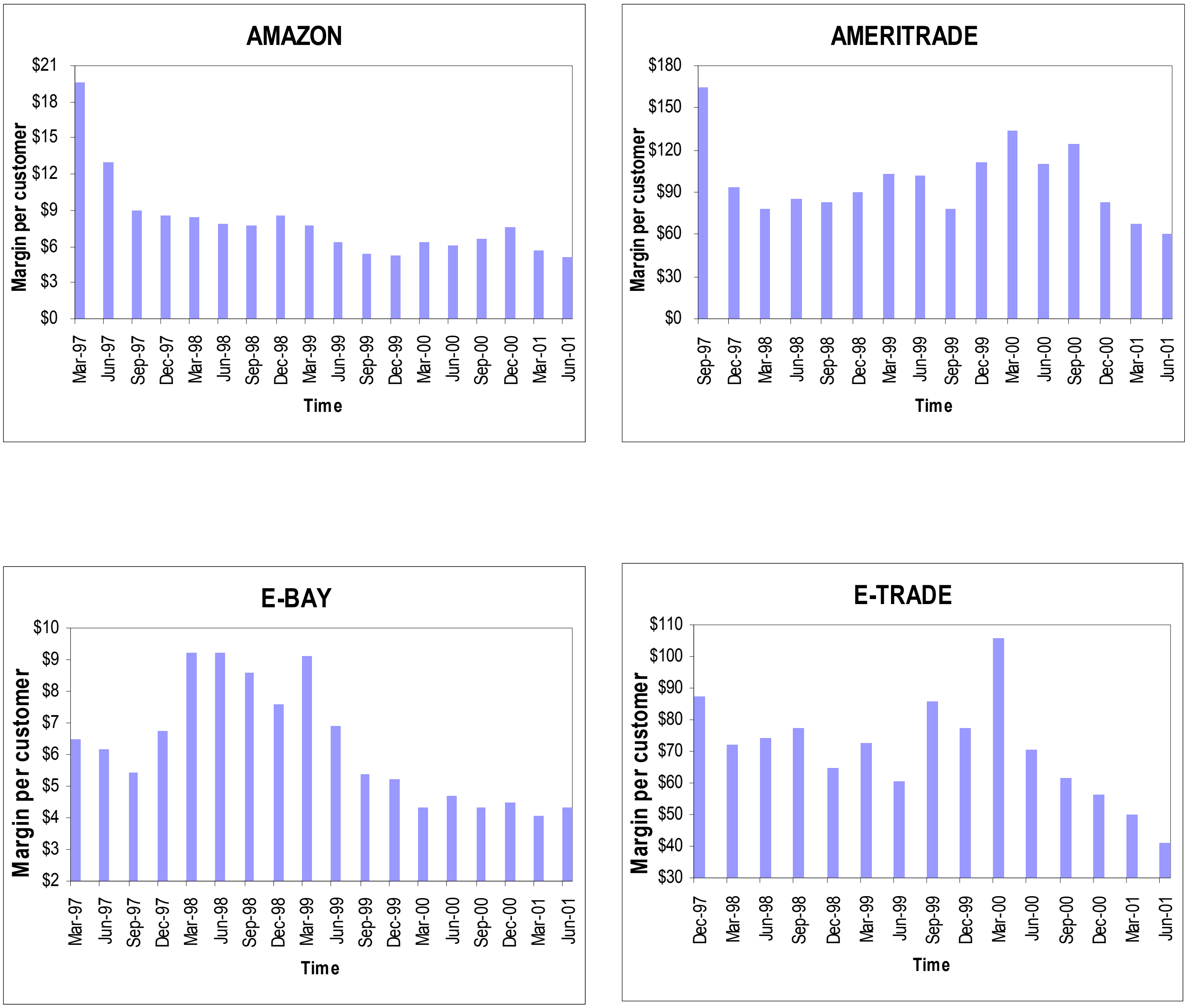


Figure-3

Acquisition Cost Per Customer

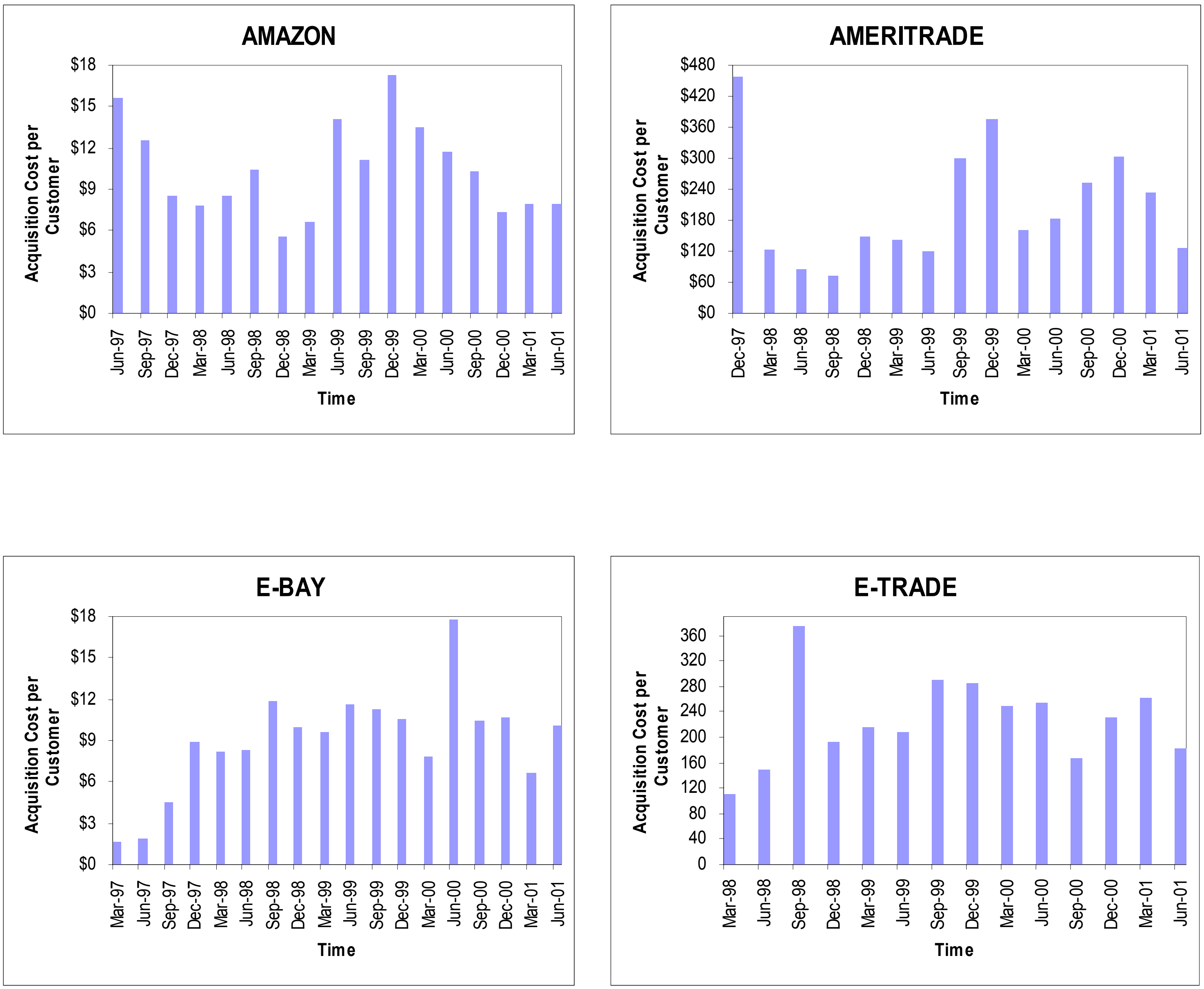
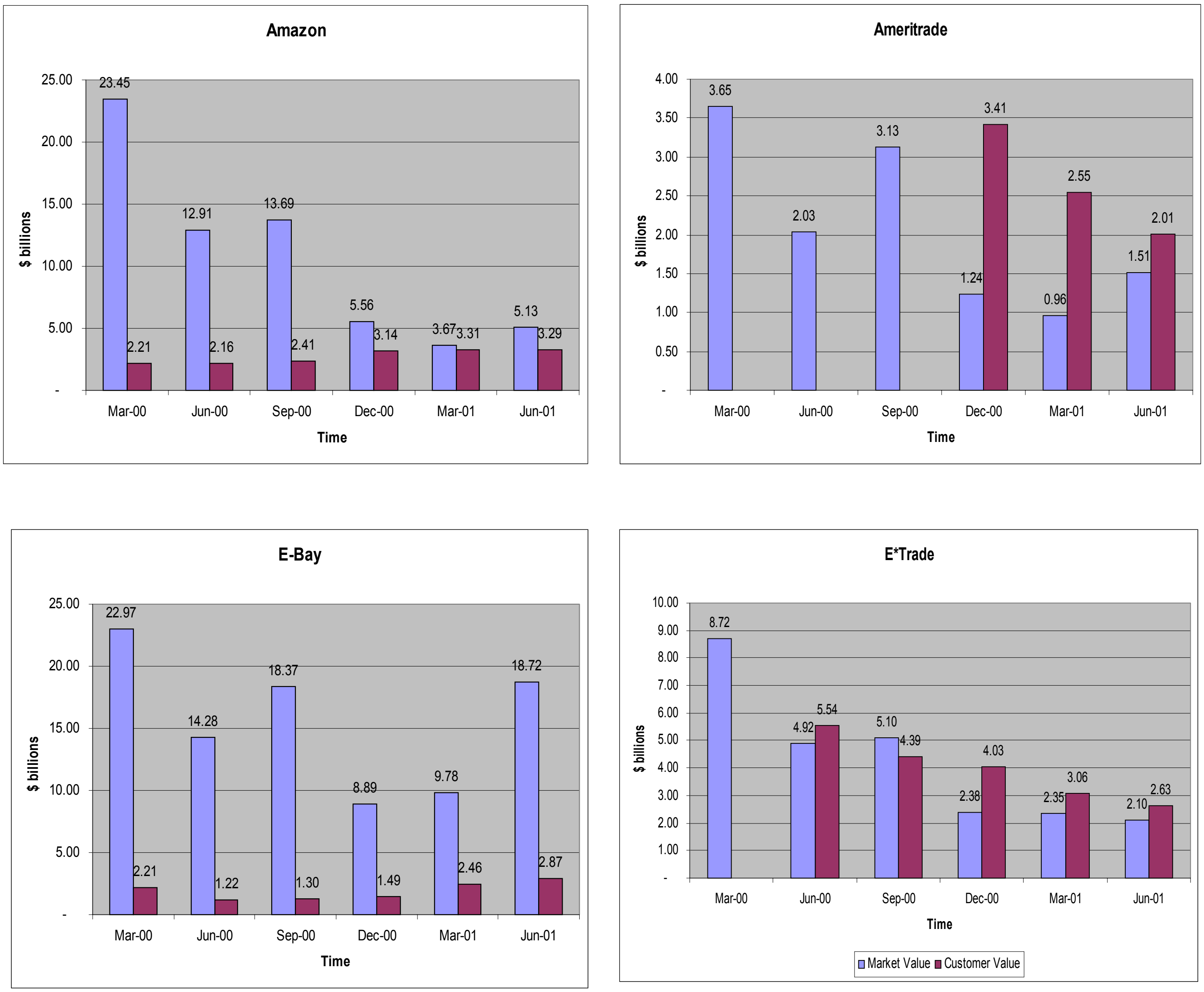


Figure-4

Over Time Changes in Customer and Market Value of Amazon



Due to non-convergence of our model, customer value could not be estimated for March-September 2000 for Ameritrade and for March 2000 for E*Trade.

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