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The Direct and Indirect Effects of Advertising Spending on Firm Value

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Marketing decision makers are increasingly aware of the importance of shareholder value maximization, which calls for an evaluation of the long-run effects of their actions on product-market response as well as investor response. However, the marketing literature to date has focused on the sales or profit response of marketing actions and the goals of marketing have traditionally been formulated from a customer perspective. Lately, there have been a few studies of the long-term investor response to marketing actions

Our research investigates one important aspect of this impact, the long-run relationship between advertising spending and market capitalization. We hypothesize that advertising can have a *direct* effect on valuation, i.e., an effect over and above its *indirect* effect via sales revenue and profit response. Our empirical results in two industries provide support for our hypothesis that advertising spending has a positive and long-run impact on own firms' market capitalization and may have a negative impact on the valuation of a competitor of comparable size. We quantify the magnitude of this investor response effect for and discuss its implications for future research.

Keywords: Advertising, stock-market valuation, marketing-finance interface, stock return modeling, optimal advertising spending, competitive response

The shareholder value principle advocates that a business should be run to maximize the return on shareholders' investment, and Shareholder Value Analysis (SVA) is fast becoming a new standard for judging managerial action. In this changing scenario, where short-term accounting profits are giving way to SVA, it is advisable that all investments made by managers be viewed in the context of shareholder returns. Thus, every investment, be it in the area of operations, human resources or marketing may now have to be justified from the SVA perspective. The common yardstick used by most investors in this context is the share price, or more generally, the wealth created by a firm is measured by its market capitalization.

This evolution presents a great opportunity for marketing. Indeed, traditional accounting, by focusing on short-term profits at the expense of intangible assets, may marginalize marketing. In contrast, SVA takes a long-term perspective and encourages managers to make profitable investments. In order to capitalize on this opportunity, marketing will have to justify its budgets in shareholder value terms. This is a difficult task, as the goals of marketing are traditionally formulated in customer attitude or sales performance terms. Furthermore, marketing may impact business performance in both tangible and intangible ways. Consequently, marketing budgets are vulnerable, especially advertising spending (Lodish and Mela 2007). While the effects of advertising on sales have been researched in depth (see e.g. Hanssens, Parsons and Schultz 2001 for a review), there has been little effort to study the direct impact of advertising on stock price (Figure 1). Thus the primary motivation of our paper is to investigate the impact of advertising spending on firm value above and beyond its effect on sales revenues and profits.

Insert Figure 1 about here

Tangible and Intangible Effects. Firm value has been classified as tangible and intangible value (Simon and Sullivan 1993). From a marketing perspective, tangible assets include sales and profits, and the impact of marketing instruments on these has been well documented for both the short run (e.g. Lodish et al. 1995) and the long run (e.g. Nijs et al 2001, Simester et al 2008). In modern economies, however, a large part of firm value may reflect its intangible assets, such as brand equity (Chan et al 2001). Since these intangible assets are not required to be reported in firms' financial statements under the generally accepted U.S. accounting principles, their valuation is complicated further. At the same time, research suggests that non-financial indicators of investments in "intangible" assets, such as customer satisfaction, may be better predictors of future financial performance than historical accounting measures, and should supplement financial measures in internal accounting systems (Ittner and Larcker 1998).

Intangible assets may be classified as: (i) market specific factors such as regulations that lead to imperfect competition, (ii) firm-specific factors, such as R&D expenditures and patents, and (iii) brand equity (Simon and Sullivan 1993). To date, the finance and policy literatures have established a relationship between firm value and factor (i) (e.g. Chhaochharia and Grinstein 2007, Lamdin 1999), which is beyond the scope of this paper.

Firm-specific factors (factor (ii)) have been shown to have a positive impact on firm value. Such factors include R&D expenditures (Chan et al 2001), discretionary expenditures such as R&D and advertising (Erickson and Jacobson 1992), and innovation (Pauwels et al 2004).

A few marketing papers deal with the link between brand-related intangible assets (iii) and firm value. These include studies on the stock-market reaction to the changing of a company's name (Horsky and Swyngedouw 1987), to new-product announcements (Chaney et al 1991), perceived quality (Aaker and Jacobson 1994), brand extensions (Lane and Jacobson 1995) and brand attitude (Aaker and Jacobson 2001). Research has also established that the impact of marketing variables on brand-related intangible assets may be moderated by the type of branding strategy adopted by a firm (Rao et al 2004, Joshi 2005). Recent work in marketing has also established a strong relationship between customer satisfaction and firm value (Fornell et al 2006). Based on the results in these studies, we may expect advertising to have an indirect impact on firm value (through an increase in sales and profits), as well as a direct effect (by building brand-related intangible assets). Our research thus relates factors (ii) and (iii) to firm value.

<u>Capital Market Efficiency</u>. Most of the studies listed above use the "Event Study" methodology, where stock prices / abnormal stock returns are tracked around a time window surrounding the focal event(s). As such, these studies address the long-run impact of the change on stock prices only if markets are (nearly) perfectly efficient, under the Efficient Capital Markets hypothesis (ECM hereafter). The ECM hypothesis (Fama 1970) states that the current stock price contains all available information about the future

expected profits of a firm. Future profit expectations are the only driver of stock price, and hence stock prices may be modeled as a random walk, in which changes in these expectations are incorporated immediately and fully. However, more recent work in finance, marketing and strategy suggests that the ECM hypothesis may not always hold (Merton 1987, Fornell et al 2006). In particular, researchers have questioned the appropriateness of the assumptions of *immediate* dissemination of all available information. Kothari (2001, pp. 208) acknowledges there is increasing evidence that "*markets may be informationally inefficient*" and "*prices might take years before they fully reflect available information*". In marketing, Pauwels et al. (2004) demonstrate that marketing activities such as new-product introductions contain information that takes several weeks to be fully incorporated in firm value. This finding motivates the use of long-run or persistence models instead of event windows to study the impact of intangible assets on firm value.

In conclusion, while there is some evidence of a possible relationship between marketing activities and financial performance, no studies have directly examined the long-run effects of advertising expenditures on firm value. Furthermore, to the best of our knowledge, only one study (Fosfuri and Giarratana 2009) has investigated the impact of competitive advertising on focal firm stock price. If the ECM hypothesis holds, we would find no long-run effects, since the impact of own and competitor advertising would be fully contained in next-period's stock price. The fact that some studies suggest otherwise indicates there can be an effect build-up beyond the short run. In this study, we use persistence or Vector Autoregressive (VAR) modeling (Dekimpe and Hanssens 1995a) to study the long-term effect of advertising expenditures on stock return. VAR models allow us to investigate long-run investor response to advertising or other firm actions, while recognizing the endogeneity of these discretionary expenditures (such as advertising and R&D) with profits, and hence firm value. We also model the impact of competitive advertising expenditures on firm value. The use of VAR modeling, though only recently introduced in the marketing-finance literature, has been shown to be successful in modeling stock return (e.g. Luo 2009). In addition, we will illustrate the economic impact of our results by simulating changes in market capitalization under different advertising spending scenarios, with and without competitive reaction. We begin with the development of our hypotheses.

Hypothesis Development

The central hypothesis tested in this research is:

H1: Advertising will have a positive long-run effect on stock return above and beyond its impact through sales revenues and profits.

The sources of advertising's impact on firm value are *spillover* and *signaling*, which we now discuss in detail.

Spillover. Advertising seeks to differentiate a firm's products from those of its competitors, thereby creating brand equity for its products (Aaker 1991). We hypothesize that this equity, which is created through marketing activity, and is ostensibly directed at customers and prospects, can *spill over* into investment behavior as well. For example, Frieder & Subrahmanyam (2001) find that investors favor stocks with strong brand names, even though these powerful brands did not generate superior short-run returns. The authors acknowledge that "*individual investors may believe, correctly or not, that they can expect greater appreciation potential in the stock of companies whose products are recognized brand names.*" Overall, their results indicate that brand awareness and perceived brand quality in consumer products may spill over to the demand for stocks of their companies.

Research in behavioral decision theory provides support for the spillover effect. Heath and Tversky (1990) find that individuals prefer to bet in areas where they feel confident and have knowledge about the uncertainties involved, compared to more ambiguous areas. Such a preference can carry over to investment decisions in that investors may prefer to hold branded stocks for which the flow of public information is higher. Further support is provided by Huberman (2001), who finds that investors often invest in the familiar, while ignoring principles of portfolio theory. Insofar as advertising generates familiarity, we would expect that heavily advertised stocks are more attractive investment options.

<u>Signaling</u>. In addition, advertising can also act as a signal of financial well-being or competitive viability of a firm. Numerous signaling mechanisms can influence investor behavior. Among the more recent research on this effect is Mathur and Mathur (2000) on the stock market's reaction to the announcement of "green" marketing strategies, and Mathur et al (1997) on the celebrity endorsement effect on firm valuation. The latter study finds that Michael Jordan's much publicized return to NBA basketball resulted in

an average increase in the market-adjusted values of his client firms of almost 2 percent, or over $1 billion in market capitalization. In the motion picture industry, pre-launch advertising has been shown to increase stock prices and possibly create unrealistic expectations about a movie's performance, leading to post-launch price corrections (Joshi and Hanssens 2009). Thus, advertising in various forms may serve as a signal of future earnings potential. In a study of the impact of environmental friendliness on firm value, Gifford (1997) found that merely establishing a pro-environment practice was insufficient, and that firms had to *advertise* this fact to the investment community before it translated into increased financial returns. In this case, advertising provides information that does not necessarily impact the *sales* of the firm, but has a direct effect on its stock price. Similarly, Mizik and Jacobson (2003) find that value creation (e.g. R&D) alone does not enhance firm value, and that it is necessary to have value appropriation (e.g. through advertising) for that to occur. Thus, while R&D can create value through innovation, the firm can only fully benefit once the innovations are commercialized. Evidence of this is provided by Pauwels et al (2004) who find that new-product introductions impact both the top and bottom line of firms, and by Sood and Tellis (2008) who find that even announcements indirectly related to innovation (such as funding, expansions and pre announcements of new product projects) impact firm value.

Further evidence in favor of signaling effects is provided by Chauvin and Hirschey (1993) who report that "*data on advertising and R&D spending appear to help investors form expectations concerning the size and variability of future cash flows*". Although their analysis is restricted to short-run effects, the results point in the direction of a positive impact of advertising on firm value. More recently, the signaling effect of advertising was examined in the accounting and auditing literature (Simpson 2008). The author finds an impact of advertising expenditures on both own and competitive firm market values, and also reports that firms voluntarily disclose their own advertising expenditures only if past disclosures lead to an increase in own firm value. This research is notable in that it demonstrates a competitive aspect of the advertising signaling effect, i.e. firms in the same space as the advertiser may suffer a decline in their valuation. We will incorporate this competitive aspect of advertising in our empirical analysis.

Direct and indirect effects. While not the primary focus of our research, our model will need to account for the effects of sales revenue and R&D, along with firm profitability, on valuation. Extensive prior research on the effects of advertising on sales provides an empirical generalization that the short-term elasticity on own brand sales is positive but low and that advertising will have a long-run effect only if the short run effect is significant (Lodish et al 1995). Thus, advertising can impact firm value indirectly through an increase in sales revenues. Furthermore, research in marketing and strategy has also demonstrated the positive impact of new- product introductions on sales (Nijs et al 2001). Since product innovation requires research and development, it has also been established that R&D expenditures have a positive impact on the *market value* of the firm (Cockburn and Griliches 1988).

While the studies above provide evidence that advertising may have a positive effect on valuation, we do not know its possible magnitude. In the short run, advertising will likely work through the indirect, tangible route, i.e., increasing valuation through lifting sales and profits, which are known to be incorporated immediately. The direct effect may or may not take longer to materialize, depending on how quickly investors update their perceptions of the firm's differentiation as a result of the advertising. Its magnitude is expected to be smaller, because cash-flow effects have already been accounted for. Overall, as both spillover and signaling are positive forces, we expect the net investor impact of advertising to be non-negative

Model

Model Specification

The relation between profits (P) and valuation has been examined extensively in the finance literature. On the other hand, the direct relationship between advertising (A) and valuation is more ambiguous. Only effective advertising can generate sales profitably, and not all advertising is effective. Furthermore, even effective advertising can reduce profit in the short run, since the advertising budget is a direct expenditure against current revenue. Lastly, per our hypothesis, there could be a *branding effect* of advertising by itself, over and above the additional cash flows generated by an ad campaign, which could impact the intangible assets of a firm. Thus we will need a systems model as opposed to a single-equation approach to study our hypothesis.

In addition, the workings of advertising need to be studied in the long run if its impact lasts well beyond the accounting period in which the advertising is spent. In so doing, we must recognize that firm value, sales, profits and advertising expenditures can all have feedback effects on one another. For example, a higher profit in one period may lead to increased advertising budgets, which in turn may boost sales and future profits. In order to disentangle these effects, we use a dynamic systems representation, in particular a vector-autoregressive (VAR) model in which the advertising and performance variables are jointly endogenous.

From a finance perspective, we use multiple measures of stock return to test our hypothesis (Jacobson and Mizik 2008). Specifically, we use market-to-book ratio, as well as matched firm returns as our dependent variable, and compare the results. While the market-to-book ratio is common in marketing-finance applications, the matched-firm approach has not received much attention. Hence, we discuss this metric in detail below.

The method of matching firms to adjust for the factors in the Fama-French 3-factor model (Fama and French 1992) was introduced by Barber and Lyon (1997) (BL henceforth). The basic principle is to use firm matching so that industry risk, firm size (large versus small) and equity (high versus low market-to-book ratio) effects are adjusted for in the calculation of the dependent variable itself. BL test this metric against several other stock return metrics from past finance literature, and conclude it is the superior metric under most circumstances.

The metric is calculated as follows.

1. Monthly returns, firm size, SIC and market-to-book value for the firms in our study are obtained using the CRSP database.
2. Firms within the same 4-digit SIC code are ordered by size and market-to-book ratio. We then match each firm for each month with a control firm in the same 4-digit Standard Industrial Classification (SIC). The firm that matches best with the focal firm is then selected as the matching firm.

3. In some cases, matched firms need to be identified from outside the 4-digit SIC of the focal firm for the following reasons:
    a. First, it is possible that there is no matching firm within + / - 30% of the size of the focal firm (which is the range recommended in BL).
    b. Second, it is possible that the matching firm is another focal firm. For example, HP could be a matching firm for IBM. However, this implies that IBM would also be the matching firm for HP, which would lead to pairs of values of equal magnitude but opposite sign[1].
    c. Finally, data could be missing from the CRSP database. In all of these cases, a matching firm is identified from a coarser SIC level (3-digit SIC or 2-digit SIC[2]). Once a matching firm is determined, the difference between the stock return for the focal firm and the matched firm is the matched firm return for the focal firm for that time period.
4. The difference between the returns of the focal firm and matched firm are the matched firm returns.

While the matched firms return (MFR henceforth) is a powerful metric, it is not without limitations. The results are dependent on finding the appropriate matching firm. Consequently, we will validate our results by using a market-to-book measure in addition to MFR.

[1] Note that collinear pairs are not a concern for firm-by-firm modeling as we do. However, it will affect the pooled model.
[2] Alternatively, it may also be beneficial / necessary to identify a matching firm from a completely different SIC classification, which may also be assigned to the focal firm as a secondary classification.

Apart from valuation, profits, sales and advertising expenditures, we also include an equation for R&D expenditures, as previous studies have concluded that stock prices react favorably to R&D spending, while R&D expenditures may themselves be dependent on firm performance.

In addition to the variables identified above, research has also identified innovation as a potential driver of stock prices. Therefore, we also include an innovation variable as an exogenous variable in our model. Recent research has indicated that investors react positively to firm innovation and even to announcements about possible future innovation (Sood and Tellis 2008). Innovation by competitors has been shown to affect a focal firm both directly as well as through the increased advertising that typically accompanies new-product launches (Fosfuri and Giarratana 2009). Indeed, Srinivasan et al (2009) have demonstrated that not only do firms spend more on advertising new products, but the effectiveness of that advertising is enhanced for truly path-breaking products. Following these studies, we treat the innovation variable as exogenous.

Since the variables Advertising (A), Sales Revenue (R), Profit (P) and R&D expenditures (RD) can all be jointly endogenous with stock return (MFR), a VAR model in differences with J lagged periods is[3]:

[3] For the sake of brevity we use MFR to represent both our stock return methods (MBR and MFR). In a time-series context, we know from the finance literature that MFR will have a random-walk component, so the VAR models will be specified in differences (Δ) or a mixture of levels and differences. In what follows we assume the former. For ease of exposition, exogenous variables are not shown.

$$\begin{bmatrix} \Delta MFR_t \\ \Delta R_t \\ \Delta P_t \\ \Delta A_t \\ \Delta RD_t \end{bmatrix} = \begin{bmatrix} \gamma_{MFR,t} \\ \gamma_{R,t} \\ \gamma_{P,t} \\ \gamma_{A,t} \\ \gamma_{RD,t} \end{bmatrix} + \sum_{j=1}^{J} \begin{bmatrix} \pi^j_{11} \pi^j_{12} \pi^j_{13} \pi^j_{14} \pi^j_{15} \\ \pi^j_{21} \pi^j_{22} \pi^j_{23} \pi^j_{24} \pi^j_{25} \\ \pi^j_{31} \pi^j_{32} \pi^j_{33} \pi^j_{34} \pi^j_{35} \\ \pi^j_{41} \pi^j_{42} \pi^j_{43} \pi^j_{44} \pi^j_{45} \\ \pi^j_{51} \pi^j_{52} \pi^j_{53} \pi^j_{54} \pi^j_{55} \end{bmatrix} \begin{bmatrix} \Delta MFR_{t-j} \\ \Delta R_{t-j} \\ \Delta P_{t-j} \\ \Delta A_{t-j} \\ \Delta RD_{t-j} \end{bmatrix} + \begin{bmatrix} u_{MFR,t} \\ u_{R,t} \\ u_{P,t} \\ u_{A,t} \\ u_{RD,t} \end{bmatrix} \qquad (1)$$

This representation combines market-response and decision-response effects. Consider the partitioned coefficient matrix for the first lag in this model:

$$\begin{array}{ccccc} \pi^1_{11} & \pi^1_{12} & \pi^1_{13} & \vdots & \pi^1_{14} & \pi^1_{15} \\ \pi^1_{21} & \pi^1_{22} & \pi^1_{23} & \vdots & \pi^1_{24} & \pi^1_{25} \\ \pi^1_{31} & \pi^1_{32} & \pi^1_{33} & \vdots & \pi^1_{34} & \pi^1_{35} \\ \cdots & \cdots & \cdots & \vdots & \cdots & \cdots \\ \pi^1_{41} & \pi^1_{42} & \pi^1_{43} & \vdots & \pi^1_{44} & \pi^1_{45} \\ \pi^1_{51} & \pi^1_{52} & \pi^1_{53} & \vdots & \pi^1_{54} & \pi^1_{55} \end{array}$$

In this matrix, the top-left partition represents the market-response coefficients for stock return (momentum), sales revenue and profit, respectively. The (3 x 2) matrix in the top-right corner shows the direct response effects of advertising and R&D on firm value, revenue and profit. The bottom-right partition captures firm-specific decision rules between advertising and R&D spending. Finally, the bottom-left matrix measures performance feedback effects. For example, an increase in next-period advertising spending due to higher sales revenue would be captured by the coefficient π^1_{42}. In the systems of equations (1), $[u_{MFR}, u_R, u_P, u_A, u_{RD}]' \sim N(0, \Sigma_u)$, and the order of the system, J, is determined by minimizing Schwartz' Bayes Information Criterion. A single equation in this system would look as follows (for MFR, assuming a lag length of one):

$$\Delta MFR_t = \gamma_{MFR,t} + \pi^1_{11}\, \Delta MFR_{t-1} + \pi^1_{11}\, \Delta R_{t-1} + \pi^1_{11}\, \Delta P_{t-1} + \pi^1_{11}\, \Delta A_{t-1} + \pi^1_{11}\, \Delta RD_{t-1} + \alpha_1 s + \alpha_2 t + \alpha_3 M + \alpha_4 I + u_{MFR,t}$$

(2)

, where the exogenous variables are as described in Table 1a. All variables, except MFR and firm profits, are taken in natural logarithms, so that the response effects may be interpreted as elasticities. However, some firms incur losses (negative profits) and negative MFR in certain time periods in the sample. Although logarithms could still be taken using an additive constant, this is an arbitrary data adjustment that biases the elasticity interpretation, and therefore these variables are measured in levels.

Insert Table 1 here

Our analysis comprises five parts. First, we test for evolution of all the variables in our study. A priori, we expect to find the performance variables to be evolving, following random-walk theory and extant marketing literature (Dekimpe and Hanssens 1995b). If evolution is found, we test for the presence of cointegration, or long-term co-evolution. For example, profits and advertising expenditures may both be evolving, but if advertising budgets are set in function of profits, we would expect a long-run relationship between the two variables. Depending on the outcome of these tests, suitable VAR models are estimated subsequently.

Next, impulse response functions (IRFs) are derived from the estimated models. The IRFs trace the over-time impact of a unit shock to any endogenous variable on the other endogenous variables. Following Dekimpe and Hanssens (1999), we use generalized IRFs (or simultaneous shocking) to ensure that the ordering of variables in the system does not affect the results and also to account for contemporaneous or same-period effects. Given a VAR model in differences, the total shock effect at lag k is obtained by accumulating the lower-order IRFs. Following Dekimpe et al (1999) and Nijs et al. (2001), we determine the duration of the shock (maximum lag k) as the last period in which the IRF value has a |*t*| statistic greater than 1.

Finally, we calculate the variance decomposition of the IRFs, i.e., the percentage of the forecast error variance of firm value that is attributable to advertising shocks, separate from the contributions of R&D, sales and profit shocks (Nijs et al 2007). This analysis separates the *direct* impact of advertising on firm value from its indirect impact via sales and profits.

Industry Setting and Data

Industry Setting

We choose two industries, personal computers and sporting goods, which were in different stages of the product life cycle, to help generalize our findings. The PC manufacturing industry experienced unprecedented growth in the 1990's (Figure 2), and was clearly in the growth phase of its life cycle. Dell, a relatively new participant, became the dominant PC manufacturer in the world, while more established competitors such as HP and IBM diversified their businesses (e.g. printers, services) to compensate for lost market share in the PC market. A survey of PC industry related articles in the Wall Street Journal (WSJ hereafter) from 1991 to 2000 reveals that capturing market share with aggressive advertising and pricing was the focus of most PC manufacturers. Advertising messages "moved from emphasizing superior technology across offerings to highlighting perceived flaws in competitors" (WSJ, Oct 21, 1992), while Dell highlighted its 1st place in the first J.D. Power customer satisfaction survey for the industry (WSJ, May 14, 1991). Apple unveiled a $100 million ad campaign in 1994 to launch its new iMac, partly with the intention of improving dealer morale (WSJ, Aug 14, 1998). Overall, the major competitors in the industry were using advertising campaigns to establish positions of superiority in a growing market and thus ensure long-run success.

In contrast, the sporting goods market was well established, with brands such as Nike and Reebok looking to gain market share at the expense of smaller competitors, through aggressive advertising and celebrity endorsements. A survey of articles in the WSJ reveals the highly competitive nature of the market ("New Reebok Ads Enrage Rival by Taunting Nike's Star Endorsers", WSJ, Feb 6, 1991; "Reebok Signs up Newest Star in Basketball for $15 million", WSJ, Jan 6, 1993).

Thus, despite their different stages in the product life cycle, t aggressive advertising was a key element in the strategies of firms in these two industries. For the PC industry, advertising aimed at establishing the brand, while in the sporting goods industry, it aimed at gaining market share over other established brands.

Data

We obtained 15 years (1991-2005) of monthly data on revenue, income, stock return, advertising, innovation announcements and R&D expenditures for the leading competitors in the PC manufacturing industry (Apple, Compaq, Dell, HP and IBM) and 10 years of data (1995-2004) for the sporting goods industry (Nike, Reebok, K-Swiss, Skechers). The stock-return data were converted to MFR data using the procedure outlined above. Table 1 in the web appendix provides descriptive statistics.

The five PC manufacturers accounted for 70% of the PC desktop market and almost 80% of the portable computer market at the end of 2005. Similarly, the leaders of the sporting goods market are represented in our sample, with the four firms accounting for $19 billion in sales revenue for 2004, which is about 28% of the industry. While the PC manufacturing industry was in a growth phase in the 1990's (Figure 1, web appendix), the sporting goods industry was in a mature phase (Figure 2, web appendix). Dell emerged as the leading contender in the PC industry, while firms like Apple struggled. In the sporting goods industry, however, Nike maintained its market leadership, despite the entrance of a new competitor (Skechers). This variability in performance and marketing efforts over time, both within each industry as well as across the two industries, provides a unique opportunity to study the long-term impact of advertising on stock return. Note also that, while we do not explicitly control for differences in the firms' branding strategy, all of the firms in our analysis employ *corporate* branding strategies, in which advertising has been shown to have a higher total impact on firm value (Rao et al 2004).

Data on income, stock return, sales and R&D expenditures were obtained from the CRSP and COMPUSTAT databases. Firm-specific information and accounting data are obtained from the COMPUSTAT database. Data on monthly advertising expenditures were provided by TNS Media Intelligence. The monthly Consumer Price Index was used to deflate all monetary variables. In addition we collected innovation data on all the firms in our dataset. Following Sood and Tellis (2008), we used FACTIVA and Lexis-Nexis databases to find innovation related announcements by these firms for the time period of our data. The innovation variable is a count variable of the total number of announcements related to innovation for a firm-period. Announcements include those related to *setup activities*, such as grants, funded contracts, *development activities*, such as patents and pre-announcements and *market activities*, which include actual launches and initial shipment. Since we are only interested in the total impact of innovation, we combine all these activities to form our innovation variable.

Results

We found that results from using either stock return metric were comparable, so our discussion will focus on the findings obtained from the matched firm return metric (MFR), the detailed results of which are available in the web appendix. Augmented Dickey-Fuller tests were used to verify the presence of unit roots in the data. MFR was found to be stationary, as predicted by the finance literature. Most sales revenues and advertising expenditures were found to be evolving, in line with the empirical generalizations described in Dekimpe and Hanssens (1995b)[4].

The estimated VAR models, with the appropriate lags determined by the SBIC, showed a good fit, with R^2 ranging from 0.155 to 0.202 in changes (0.936 to 0.990 in

[4] Detailed results available on request.

levels) for the PC industry and 0.183 to 0.310 in changes (0.908 to 0.975 in levels) for the sporting goods industry (see Table 1). Model adequacy was verified by performing two tests on the residuals. We test for the presence of serial correlation (LM test) as well as heteroskedasticity (White's test) and the results are shown in Table 2. The results indicate that the model residuals are white noise.

Insert Table 2 about here

The accumulated advertising and R&D elasticities (on sales) are given in columns 2 and 3 of Table 3. The advertising elasticities have the expected magnitude for all firms under study and are statistically significant for three of the five firms in the PC industry and two firms in the sporting goods industry.

Insert Table 3 about here

The positive sign and the small magnitude of R&D elasticities are attributable to the uncertainty and the long gestation period generally associated with R&D. Further, the R&D elasticities are persistent for Compaq, Dell and IBM. Hence, a shock to R&D expenditure has a long-term impact on firm sales revenue. We find that the R&D elasticities for all sporting-goods firms are insignificant, which may reflect the relatively low importance and variability of R&D spending in this industry (about 2 to 3% of sales). These results replicate previously established findings in the field, and thereby confirm their importance as covariates in our model.

Next, we examine the total effect of advertising on stock return. The last column in Table 3 shows the accumulated advertising elasticities on MFR. Note that these values combine the direct and the indirect advertising effects on firm value over time. The effect of an advertising shock accumulates over 8, 6, 7 and 7 periods for Apple, Compaq, Dell and HP respectively (or, the IRFs for these 4 firms are significant for 8, 6, 7 and 7 periods, respectively). Similarly, for Nike, Reebok and Skechers, the advertising shock accumulates over 6, 6 and 8 periods respectively. Since changes in advertising spending are typically not reported to investors, they are informed only through actual exposure. This explains why the effect of a change in advertising is not absorbed in stock price instantly. Instead, there is a long-run effect beyond the first period, consistent with our expectation, and hence we find partial support for our hypothesis.

Apple, Compaq, Dell and HP have positive and significant investor response elasticities, ranging from .007 to .01. The elasticity for IBM is positive but not significantly different from zero, which may be explained by the large size and scope of this company's operations. Indeed, the PC division of IBM accounted for only 11% of its revenue, in contrast with 78% for Apple and 63% for Compaq.

In the sporting-goods industry, three of the firms under study show positive and significant investor-response elasticities, ranging from .005 to .009. The highest elasticity is found for Skechers, which is also the youngest firm in this industry in our data[5].

An interesting finding is that there are several cases of significant investor response even when there is no consumer response[6] (Figure 4). Dell, HP, Nike and Reebok show an increase in firm value even in the absence of any impact on sales. Thus, advertising may have a positive impact even if it has no measurable effect on sales. In

[5] The elasticities obtained are aggregate elasticities across all products of the firms. While advertising expenditures and elasticities can vary across products, there is only one company stock price, which reflects overall performance, thus the need for aggregation.
[6] We thank an anonymous reviewer for this suggestion.

contrast, IBM and K-Swiss have a consumer effect, but no investor effect. This finding highlights the importance of focusing on a comprehensive long-run metric (such as firm value) when calculating the ROI of marketing instruments like advertising.

Insert Figure 4 about here

Overall, the investor-response elasticities are of an order of magnitude that is lower than the typical sales-response elasticities. This is to be expected, as the dependent variable is excess return, which is the (scaled) residual of the random-walk process that is known to underlie the behavior of stock prices. Even so, these low elasticities can generate a sizeable economic impact, as we will explore below[7].

Variance Decomposition

In order to measure the *direct* impact of advertising on stock return relative to other factors, we examine the forecast error variance decomposition (FEVD) of firm value. The FEVD calculates the contribution of the various covariates to the forecast variance of MFR. The results are presented in Tables 4a and 4b. This analysis is only meaningful for firms with significant investor-response elasticities from the IRF analysis.

Insert Tables 4a and 4b about here

Tables 4a and 4b show that advertising expenditures initially have a small impact on MFR. In the first few periods after the impulse, firm value is largely determined by past value, as predicted by the random-walk model. However, the impact of advertising increases over time (see Figure 3 in the web appendix for an example). Thus, for Apple,

[7] The investor-response elasticities for innovation and promotion in the automobile industry are even lower, yet still statistically significant (see Pauwels et al. 2004).

advertising explains only 0.569% of the forecast error variance in period 1, but 4.68% of the variance by period 8. Unlike the IRFs, the variance decomposition does not involve simultaneous shocking and hence the percentages represented here indicate the impact of advertising on firm value *over and above* its effect on sales and profits[8]. In conclusion, we find that advertising shocks often increase firm value in the long run, and beyond the impact that may be expected from their effect on revenues and profits.

Impact of Competitive Advertising

We verify how robust our results are to the inclusion of competitive advertising by re-estimating our model (1) for each firm after including a competition variable (ΔC_t). Since we lack sufficient degrees of freedom to simultaneously include advertising expenditures from all competing firms in one model, we estimate competition in pairs of firms[9]. Thus, for the PC industry, where we have 5 firms in our dataset, we estimate 20 separate models. The analysis reveals cointegration between the advertising expenditures of competing firms, prompting the use of vector error correction (VEC) models (Dekimpe and Hanssens 1999). After including the competitor advertising variable (ΔC_t), we estimate a system of the form:

[8] Cholesky Decomposition was used to estimate FEVD. The results are not sensitive to the ordering of the variables.
[9] This may bias our coefficients if the advertising expenditures are correlated. However, we find that all correlations among advertising variables are less than .04 in magnitude, which virtually eliminates the risk of bias .

$$\begin{bmatrix}\Delta MFR_t\\ \Delta R_t\\ \Delta P_t\\ \Delta A_t\\ \Delta RD_t\\ \Delta C_t\end{bmatrix}=\begin{pmatrix}\alpha_{MFR} & 0 & 0 & 0 & 0 & 0\\ 0 & \alpha_R & 0 & 0 & 0 & 0\\ 0 & 0 & \alpha_P & 0 & 0 & 0\\ 0 & 0 & 0 & \alpha_A & 0 & 0\\ 0 & 0 & 0 & 0 & \alpha_{RD} & 0\\ 0 & 0 & 0 & 0 & 0 & \alpha_C\end{pmatrix}\begin{bmatrix}e_{MFR,t-1}\\ e_{R,t-1}\\ e_{P,t-1}\\ e_{A,t-1}\\ e_{RD,t-1}\\ e_{C,t-1}\end{bmatrix}+\sum_{j=1}^{J}\begin{pmatrix}\pi_{11}^j & \pi_{12}^j & \pi_{13}^j & \pi_{14}^j & \pi_{15}^j & \pi_{16}^j\\ \pi_{21}^j & \pi_{22}^j & \pi_{23}^j & \pi_{24}^j & \pi_{25}^j & \pi_{26}^j\\ \pi_{31}^j & \pi_{32}^j & \pi_{33}^j & \pi_{34}^j & \pi_{35}^j & \pi_{36}^j\\ \pi_{41}^j & \pi_{42}^j & \pi_{43}^j & \pi_{44}^j & \pi_{45}^j & \pi_{46}^j\\ \pi_{51}^j & \pi_{52}^j & \pi_{53}^j & \pi_{54}^j & \pi_{55}^j & \pi_{56}^j\\ \pi_{61}^j & \pi_{62}^j & \pi_{63}^j & \pi_{64}^j & \pi_{65}^j & \pi_{66}^j\end{pmatrix}\begin{bmatrix}\Delta MFR_{t-j}\\ \Delta R_{t-j}\\ \Delta P_{t-j}\\ \Delta A_{t-j}\\ \Delta RD_{t-j}\\ \Delta C_{t-j}\end{bmatrix}+\begin{bmatrix}u_{MFR,t}\\ u_{R,t}\\ u_{P,t}\\ u_{A,t}\\ u_{RD,t}\\ u_{C,t}\end{bmatrix} \tag{3}$$

The addition of the extra vector of the error correction variables ($e_{., t-1}$) in the above system of equations results in additional coefficients to be estimated. To avoid overparameterization, we restrict insignificant coefficients from model (1) to be zero when estimating model (3). Variables are differenced if found to be non-stationary. The investor response elasticities obtained from this model are shown in Table 5.

Insert Table 5 about here

The competitive elasticities are predominantly negative for Apple, Compaq and Dell and insignificant for HP and IBM. The own-investor response elasticities (which are the average elasticities for the 4 paired models estimated for each firm), after accounting for competition, are shown as the diagonal values in Table 5. A comparison with the values in Table 3 reveals that the own elasticities retain their sign and significance, while their magnitudes are marginally different. Overall, the inclusion of competition does not alter the support for hypothesis H1.

The competitive elasticities can be better understood in the context of the relative market valuations (MV share henceforth) of these firms (Figure 4 in the web appendix). Competitive elasticities of small MV share firms are negative (and generally significant), while those of large MV share firms are not significant. A firm's advertising expenditure has a negative impact on the market valuation of competing firms if they are of comparable size, and no impact on firms much larger (in MV) than themselves. This result can be explained by the fact that the cross sales elasticities of the marketing expenditures are not significant[10].

The inclusion of competition thus provides the interesting insight that advertising not only impacts own firm valuation positively, but that it can also have a negative effect on competitors.

Empirical Validation

To check the validity of our model, we conducted three tests. The first checks for the presence of structural breaks in the data. Since these data span a period of fifteen years for the PC industry and ten years for the sporting goods industry, structural breaks in one or more of the series could occur. If a series in our sample were comprised of two stationary regimes separated by a structural break, it could appear to be evolving (Perron 1990). To guard against this, we carried out rolling-window unit-root tests (Pauwels and Hanssens 2007): a suitably long window of observations is selected (40 in this case), and the window is moved along the length of the series (180 observations for PCs and 120 for sporting goods). All the Dickey-Fuller (DF) statistics thus obtained are then compared to their unit-root critical values. These rolling-window unit-root tests indicated no evidence of structural breaks in the data. Second, we also test for the stability of the parameters obtained in our model. We obtain recursive estimates for the parameters in the stock

[10] Detailed results available upon request.

return equation from the VAR, using a rolling-window data sample as above. The results indicate that parameters are stable across.

Finally, we test for the possible effect of temporal aggregation in our series. While the MFR and advertising series were available at the monthly level, sales, R&D and profit series were only available quarterly. Using all series at the quarterly level causes a degrees of freedom problem, unless the data can be pooled across firms (Bass and Wittink 1975). Thus we re-estimated our VAR model in quarterly panel form for each industry. The poolability of the model was tested using the Chow F Test, extended to a system of equations (Chow, 1960):

$$\mathrm{F} = \frac{(RRSS - URSS)/r}{URSS/d},$$

where *RRSS* is the restricted (pooled model) sum of squared residuals, *URSS* is the sum of squared residuals in the unrestricted model (trace of the variance-covariance matrix), *r* is the number of linearly independent restrictions and *d* is the number of degrees of freedom for the unrestricted model. For a model with firm-specific intercepts and fixed response effects, this test yields F-values of 2.27 (PC) and 2.13 (sporting goods), which are below the critical value of 2.4 at the 95% confidence level. Hence, we conclude that the data are partially poolable, with firm-varying intercepts and common slopes:

$$\begin{bmatrix} \Delta MFR_{i,t} \\ \Delta R_{i,t} \\ \Delta A_{i,t} \\ \Delta P_{i,t} \\ \Delta RD_{i,t} \end{bmatrix} = \left[\tilde{\gamma} + \tilde{\beta}_{Compaq} + \tilde{\beta}_{Dell} + \tilde{\beta}_{HP} + \tilde{\beta}_{IBM} \right] + \sum_{j=1}^{J} \begin{bmatrix} \pi_{11}^{j} \pi_{12}^{j} \pi_{13}^{j} \pi_{14}^{j} \pi_{15}^{j} \\ \pi_{21}^{j} \pi_{22}^{j} \pi_{23}^{j} \pi_{24}^{j} \pi_{25}^{j} \\ \pi_{31}^{j} \pi_{32}^{j} \pi_{33}^{j} \pi_{34}^{j} \pi_{35}^{j} \\ \pi_{41}^{j} \pi_{42}^{j} \pi_{43}^{j} \pi_{44}^{j} \pi_{45}^{j} \\ \pi_{51}^{j} \pi_{52}^{j} \pi_{53}^{j} \pi_{54}^{j} \pi_{55}^{j} \end{bmatrix} \begin{bmatrix} \Delta MFR_{i,t-j} \\ \Delta R_{i,t-j} \\ \Delta A_{i,t-j} \\ \Delta P_{i,t-j} \\ \Delta RD_{i,t-j} \end{bmatrix} + \begin{bmatrix} u_{MFR,i,t} \\ u_{R,i,t} \\ u_{A,i,t} \\ u_{P,i,t} \\ u_{RD,i,t} \end{bmatrix}$$

(3)

In Equation (3), $\tilde{\gamma}$ is the common vector of intercepts. β_i is a (5 x 1) vector of company specific dummy variables. Thus, β_{Compaq} is 1 when variables correspond to Compaq and 0 otherwise.

The R^2 in changes for the panel VAR model is 0.237 (0.939 in levels) for the PC industry and 0.269 (0.966 in levels) for the sporting goods industry. The optimal number of lags, determined by the SBIC criterion, is 2, and the residual portmanteau test indicated that residuals are white noise. The most important confirmatory result is that the advertising elasticity of MFR is significant and positive for both industries (PC: 0.007, t-stat = 1.98 and sporting goods: 0.006, t-stat = 1.90). Thus our generalized estimate of the long-run advertising effect on firm valuation is between 0.006 and 0.007, and both the structural-break test and the temporal-aggregation test validate the results of our model.

Market Capitalization Projections of Increased Advertising Spending

The estimated investor response elasticities may be used to project the impact on market capitalization of various changes in the advertising level of firms with significant response effects. These forecasts quantify the economic impact of advertising spending on firm value. Indeed, even though the elasticities are small in magnitude, they can translate into a substantial impact on market capitalization.

Table 6a shows the change in market valuation for a 10% increase in advertising spending for the PC brands with significant customer as well as investor response to advertising, viz. Apple and Compaq. No competitive reaction takes place in these scenarios. In projecting the market valuation figures, we adjusted for the increased advertising spending, as well as the effects of a reduction in firm profits (and hence, stock returns). Compaq achieves gains in total market value that exceed the loss from the implied profit reduction in all four years of the simulation, while Apple gains in only one of the four years. These results derive from the opposing forces of cost increases (profit reduction), revenue and profit enhancement, and brand equity gains.

In contrast to the no-reaction scenario in Table 6a, Table 6b shows the change assuming that competition responds by increasing their advertising expenditures as well. We consider the competitor with the highest cross elasticity from Table 5 as being the responder. In all cases, the direct effect of advertising on valuation is insufficient to justify a sizeable increase in spending, i.e. a consumer response (indirect) effect is required as well. We therefore examine more closely the profit-maximizing advertising spending level as well.

Insert Tables 6a and 6b about here

Profit-maximizing spending. Using the well known Dorfman-Steiner (1954) conditions, optimal advertising for a profit maximizing firm is given by:

$$Adv_{opt,t} = (Sales_{b,t} * G_t * \varepsilon_A)^{1/(1-\varepsilon_A)} \quad (4)$$

, where $Adv_{opt,\,t}$ is the optimal advertising spend, $Sales_{b,\,t}$ is baseline sales (sales due to factors other than advertising), G_t is Gross Margin at time t and ε_A is the advertising elasticity. Baseline sales may be obtained as:

$$Sales_{b,t} = Sales_t \, / \, Adv_t^{\varepsilon_A} \quad (5)$$

Gross margins were obtained from annual financial reports for the respective firms. Using these data, we may derive the annual DS-optimal advertising budgets, and compare them with the actual expenditures. Table 7 provides these comparisons for the time period 1997-2000.

Insert Table 7 here

We conclude that that an increase in advertising spending would result in a gain in market capitalization only when the initial advertising expenditure is between 94% and 117% of the DS optimal level. Overall, our conclusion is that the market-capitalization effect of increased advertising spending can be sizeable, but is still subject to economic reasonableness: there must be a consumer-response impact to supplement the direct effect, and the spending must be in the vicinity of the profit-maximizing level.

Conclusions and Future Research

This study has provided conceptual and empirical evidence of a positive relationship between advertising expenditures and the market value of firms. The results show that there is an investor response effect of advertising *over and above* its expected effects through revenue and profit sales increases. The pooled estimate of the investor response elasticity in two industries is between .006 and .007.

Our findings have several important implications for managers. First, we show that advertising has a double impact on firm value – through direct and indirect routes, which provides a strong justification for investments in advertising. Second, we demonstrate that advertising may have an investor impact even if there is no tangible consumer impact. This implies that managers should be cognizant of the *total* impact of advertising spending, not only the near-term sales or profit impact. Third, we highlight the impact of competitive advertising on own firm valuation. Managers should be especially cognizant of aggressive advertising campaigns by firms of similar size, since they have the potential of negatively impacting own-firm stock price. Finally, we show the importance of keeping advertising expenditures reasonably close to the optimum. In our industries, we find that the market penalizes firms for significant deviations from optimal spending in both directions.

Several limitations help set an agenda for future research. First, we have only studied two industries, viz. PC manufacturers and sporting goods. A replication of the model in other industries and time periods will provide further cross-validation of the results. Second, this work may be extended to the differential impact of advertising media on market valuation. Third, it would be interesting to examine our hypothesis for firms that use either a house-of-brands or a mixed-branding strategy. Finally, our model could be extended to separate the *volume* effect of branding from the *price premium* effect (Ailawadi, Lehmann and Neslin 2003).

There are some limitations in our dataset as well. As in most valuation studies, revenue and profit data are *aggregated* to the firm level, i.e. they are not broken down by division. When applied to *tracking* stocks where there is a closer match between the product category and the corporate identity, our approach may reveal higher advertising-to-market value elasticities. Similarly, our advertising data did not include a breakdown of spending on product advertising vs. brand-image advertising. Partially as a result of this, some of our elasticities have relatively modest t-statistics.

Nevertheless, our results succeed in linking advertising directly to firm value, and thus underline the importance of building intangible assets. The direct relation between advertising and firm value provides managers with a new, more comprehensive metric of advertising effectiveness, viz., firm value. Even though the investor-response elasticity is small in magnitude, advertising can induce substantial changes to firm valuations.

Our findings open up several areas for further research. Among these, the presence of a long -run effect of advertising on the market value of a firm, possibly through the creation of brand equity, suggests that any action that grows brand equity may affect firm value. Thus, order of entry, distribution intensity or even choice of media may be hypothesized to affect the brand equity of a firm and thereby its market value. Another area of interest is the potential relationship between the quality of advertising execution and its impact on firm value. Anecdotally, Apple is highly regarded for its advertising campaigns. Its “1984” advertisement was rated the ‘Best Ever Super Bowl Ad’ by ESPN, and won a CLIO award (the world’s largest advertising competition). Between 1990 and 1998, various Apple Computers advertisements won 23 CLIO awards in different categories, compared to 1, 0, 7 and 11 awards for Compaq, Dell, HP and IBM respectively. Future research should examine to what extent such differences in perceived advertising quality have an influence on the investor community. Finally, since market value is affected by both the level and the volatility of sales revenue, further research needs to examine the effect of marketing variables on volatility.

TABLE 1: DATA DESCRIPTION AND SOURCES

VARIABLE	TYPE	DESCRIPTION	SOURCE
MFR	Endogenous	Matched Firm Return. Computed as described in text.	COMPUSTAT
MBR	Endogenous	Market-to-Book Ratio	COMPUSTAT
R	Endogenous	Sales Revenue in $ MM.	COMPUSTAT
P	Endogenous	Firm pre-tax profits in $ MM	COMPUSTAT
A	Endogenous	Advertising expenditures in $ '000	Purchased from TNS Media Intelligence
RD	Endogenous	Firm R&D expenditures in $ '000	COMPUSTAT
S	Exogenous	Seasonality	
T	Exogenous	Time trend	
M	Exogenous	Mergers and / or acquisitions	
I	Exogenous	New product announcements, as operationalized in Sood and Tellis (2008)	FACTIVA and Lexis-Nexis
SP	Exogenous	S&P 500 index	CRSP
SMB	Exogenous	Small minus Big; Fama-French factor	Kenneth French Data Library
HML	Exogenous	High minus Low; Fama-French factor	Kenneth French Data Library
RMF	Exogenous	Excess return on market (market return minus risk free return); Fama-French factor	Kenneth French Data Library

TABLE 2: MODEL FIT AND RESIDUAL ANALYSIS

	Fit Statistics		Residual Test Statistics	
	R^2 (In Changes)	R^2 (In Levels)	LM p-values	White p-values
Apple	.156	.941	.989	.965
Compaq	.193	.937	.913	.994
Dell	.202	.936	.895	.928
HP	.181	.979	.926	.973
IBM	.155	.990	.871	.905
Nike	.310	.975	.985	.966
Reebok	.271	.950	.963	.891
K-Swiss	.279	.954	.904	.952
Skechers	.183	.908	.933	.911

Note: The large p-values for residual statistics support the conclusion that there is no significant serial correlation and heteroskedasticity among residuals.

TABLE 3: CUSTOMER AND INVESTOR RESPONSE EFFECTS

	ADVERTISING+ ELASTICITY	R&D ELASTICITY	INVESTOR EFFECTS
Apple	.245***	-.005	.010***
Compaq	.108***	.313**	.006***
Dell	.015	.122**	.007**
HP	.013	.008	.008**
IBM	.152**	.080*	.009
Nike	.085	.386	.005**
Reebok	.110	.117	.007**
K-Swiss	.096**	-.028	.002
Skechers	.107*	-.076	.009*

+ Advertising and R&D elasticities are sales elasticities. Investor response effect is the elasticity of advertising on stock return.
* Significant at $p<.10$ for a one-tailed test. ** Significant at $p<.05$ for a one-tailed test. *** Significant at $p<.01$ for a one-tailed test.
NOTE: After adjusting for the outliers by using dummy variables, the R&D elasticity for Compaq falls to 0.131, which is comparable with that of other firms.

TABLE 4: FORECAST ERROR VARIANCE DECOMPOSITIONS*

4A: PC INDUSTRY

	Apple		Compaq		Dell		HP	
Period	MFR	Adv	MFR	Adv	MFR	Adv	MFR	Adv
1	87.48	.596^{+}	92.971	1.435^{+}	94.1	.943^{+}	97.77	.953^{+}
2	83.57	2.038	90.315	2.856^{+}	91.6	2.644^{+}	84.36	2.010
3	80.28	3.670	84.583	3.241	88.7	2.997	81.18	3.134
4	78.73	4.587	83.875	4.542	84.9	4.201	80.90	3.124
5	78.48	4.651	83.489	5.338	84.1	5.184	80.84	3.248
6	78.44	4.679	83.433	5.452	82.8	5.523	80.84	3.266
7	78.44	4.679	83.330	5.676	80.7	5.715	80.83	3.285
8	78.43	4.681	83.327	5.677	79.8	5.692	80.82	3.288
9	78.43	4.681	83.308	5.716	79.8	5.726	80.82	3.289
10	78.43	4.681	83.307	5.717	79.8	5.727	80.82	3.290

+Not significant. All other figures are significant at p<.05.

4B: SPORTING GOODS INDUSTRY

	Nike		Reebok		Skechers	
Period	MFR	Adv	MFR	Adv	MFR	Adv
1	98.268	.077^{+}	99.116	.183^{+}	98.433	.095^{+}
2	96.580	.878^{+}	96.734	.639^{+}	92.737	1.452^{+}
3	91.414	2.787^{+}	91.092	.822^{+}	89.831	1.954^{+}
4	89.126	4.003	90.313	1.464^{+}	88.669	2.822
5	88.960	4.108	89.881	1.894^{+}	88.420	3.223
6	88.696	4.118	89.821	1.951^{+}	88.402	3.523
7	88.600	4.185	89.710	2.065	88.395	3.528
8	88.588	4.189	89.707	2.065	88.392	3.529
9	88.574	4.198	89.687	2.085	88.391	3.529
10	88.564	4.208	89.685	2.086	88.391	3.529

* Read: if Matched Firm Return (MFR) for Apple is projected 1 to 10 periods into the future, only 0.596% of the forecast error variance in the first forecast period is explained by shocks to advertising expenditures. This percentage grows to 4.681% of the variance by the tenth forecast period. In contrast, 87.481% of the forecast error variance in period 1 is explained by momentum (variance in past values of MFR). This percentage declines to 78.438% of the variance by period 10.

TABLE 5: INVESTOR RESPONSE EFFECTS WITH COMPETITIVE ADVERTISING

		Impact On				
		Apple	Compaq	Dell	HP	IBM
Impact Of	Apple	*.0082***	-.0019*	.0000	.0000	.0000
	Compaq	-.0010*	*.0076***	-.0010	.0000	.0000
	Dell	-.0022*	-.0016	*.0072**	-.0010	-.0014
	HP	.0000	-.0021	.0019	*.0069*	.0011
	IBM	.0000	.0000	.0016	.0018	*.0053*

* Significant at $p<.10$ for a two-tailed test.
** Significant at $p<.05$ for a two-tailed test.
Coefficients smaller than 10^{-4} displayed as 0.0000

* The impact of Dell advertising on Apple can be read as: A percent increase in Dell advertising will result in a .0022 unit reduction in the stock return of Apple.

TABLE 6A: MARKET VALUATION IMPACT OF A 10% ADVERTISING INCREASE

Apple

Year	Current MV*	Increase due to Revenue	Increase due to Direct Effect	Reduction due to Cost	New MV	Net Gain
1997	$1,500	$1.42	$.08	$2.72	$1,499	**No**
1998	$3,700	$3.51	$.19	$4.53	$3,699	**No**
1999	$12,700	$12.06	$.64	$5.36	$12,707	**Yes**
2000	$3,700	$3.51	$.19	$8.06	$3,696	**No**

Compaq

Year	Current MV	Increase due to Revenue	Increase due to Direct Effect	Reduction due to Cost	New MV	Net Gain
1997	$35,600	$23.52	$1.40	$4.15	$35,621	**Yes**
1998	$57,800	$38.18	$2.28	$5.42	$57,835	**Yes**
1999	$36,600	$24.18	$1.44	$6.04	$36,620	**Yes**
2000	$19,800	$13.08	$0.78	$5.23	$19,809	**Yes**

All figures in millions of dollars

* Market Valuation

TABLE 6B: MARKET VALUATION IMPACT OF 10% INCREASE IN OWN AND COMPETITIVE ADVERTISING

Apple

Year	Current MV*	Increase due to Revenue	Increase due to Direct Effect	Reduction due to Cost	Reduction due to Competition	New MV	Net Gain
1997	$1,500	$1.42	$0.08	$2.72	$0.42	$1,498	**No**
1998	$3,700	$3.51	$0.19	$4.53	$1.04	$3,698	**No**
1999	$12,700	$12.06	$0.64	$5.36	$3.56	$12,704	**Yes**
2000	$3,700	$3.51	$0.19	$8.06	$1.04	$3,695	**No**

Compaq

Year	Current MV	Increase due to Revenue	Increase due to Direct Effect	Reduction due to Cost	Reduction due to Competiti on	New MV	Net Gain
1997	$35,600	$23.52	1.40	$4.15	$6.41	$35,614	**Yes**
1998	$57,800	$38.18	2.28	$5.42	$10.40	$57,825	**Yes**
1999	$36,600	$24.18	1.44	$6.04	$6.59	$36,613	**Yes**
2000	$19,800	$13.08	0.78	$5.23	$3.56	$19,805	**Yes**

All figures in millions of dollars

* Market Valuation

TABLE 7: COMPARISON OF ACTUAL ADVERTISING EXPENDITURES WITH OPTIMAL

Apple

	DS Optimal Advertising Expenditure	Actual Expenditure	Deviation from Optimal
1997	$319,134	$406,760	27%
1998	$299,814	$676,570	126%
1999	$426,437	$400,530	-6%
2000	$411,020	$1,203,630	193%

Compaq

	DS Optimal Advertising Expenditure	Actual Expenditure	Deviation from Optimal
1997	$797,084	$923,330	16%
1998	$885,658	$720,582	-19%
1999	$1,029,938	$1,204,020	17%
2000	$1,199,531	$1,163,920	-3%

* All figures are in hundreds of dollars

FIGURE 1

ADVERTISING AND FIRM VALUE

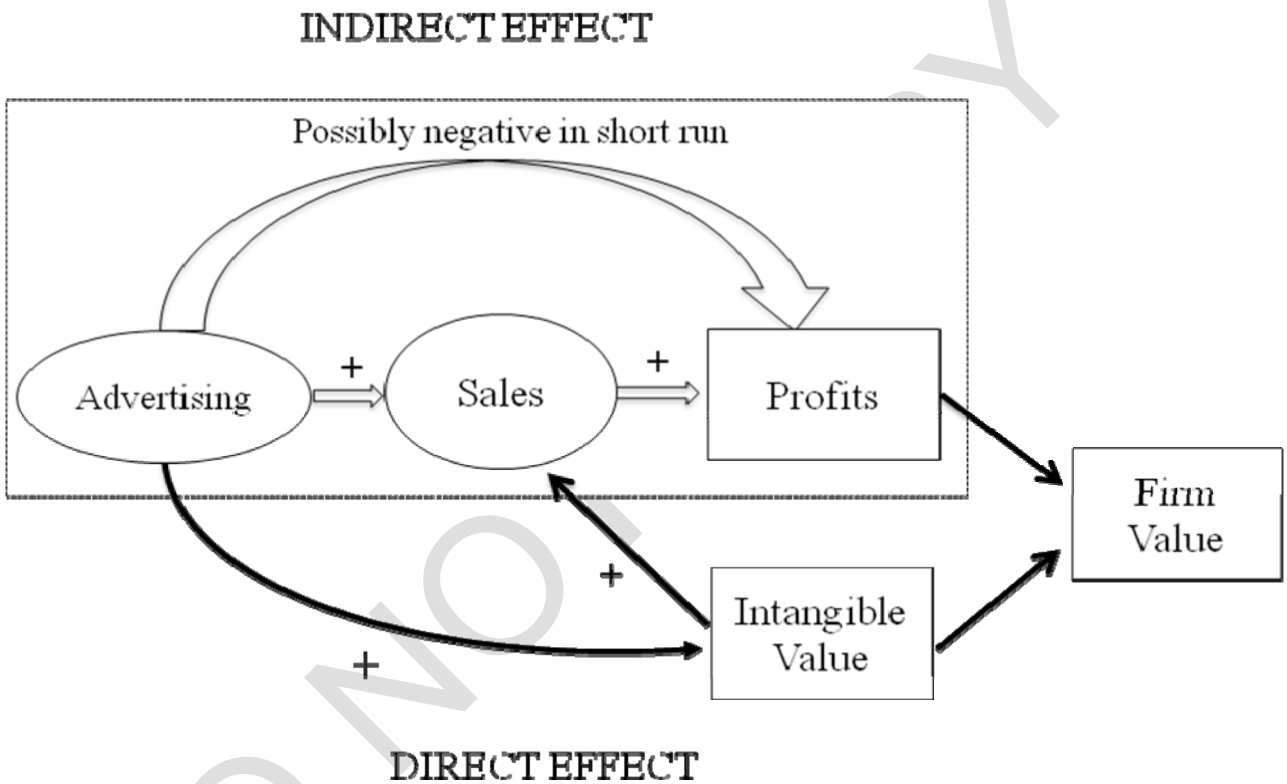

FIGURE 2

CONSUMER AND INVESTOR RESPONSES

Consumer Response (Indirect Effect)	Insignificant	Significant
Significant	IBM K-Swiss	Apple Compaq Skechers
Insignificant	N/A	Dell HP Nike Reebok

Investor Response (Direct Effect)

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The Direct and Indirect Effects of Advertising Spending on Firm Value

Amit Joshi*

Dominique M. Hanssens

Web Appendix

Table 1: MONTHLY DATA DESCRIPTIVE STATISTICS

APPLE					
	ADVERTISING ($000)	MV ($MM)	PROFIT ($MM)	R&D ($000)	SALES ($MM)
Mean	5994.44	5182.03	8.60	37.76	572.43
Median	4859.95	4386.12	28.53	41.90	561.51
Std. Dev	4476.36	3153.20	58.36	11.85	147.61

COMPAQ					
	ADVERTISING ($000)	MV ($MM)	PROFIT ($MM)	R&D ($000)	SALES ($MM)
Mean	7256.21	18891.17	29.89	50.53	1371.17
Median	5456.80	11826.89	62.28	39.86	1295.98
Std. Dev	5959.21	15723.93	177.90	38.65	899.29

DELL					
	ADVERTISING ($000)	MV ($MM)	PROFIT ($MM)	R&D ($000)	SALES ($MM)

Mean	4874.66	25419.59	52.01	13.17	778.36
Median	1613.30	3416.57	23.80	7.29	475.41
Std. Dev	6383.941	34551.82	52.234	14.11719	678.9532

HP					
	ADVERTISING ($000)	MV ($MM)	PROFIT ($MM)	R&D ($000)	SALES ($MM)
Mean	7366.96	40101.65	156.64	164.54	2342.60
Median	5753.90	38042.69	170.86	163.92	2575.32
Std. Dev	5899.29	25622.29	66.71	30.81	707.79

IBM					
	ADVERTISING ($000)	MV ($MM)	PROFIT ($MM)	R&D ($000)	SALES ($MM)
Mean	18957.61	75022.15	159.67	402.32	5369.06
Median	18576.10	56481.47	364.04	361.28	5196.40
Std. Dev	12282.14	46541.15	610.61	117.64	769.52

NIKE					
	ADVERTISING ($000)	MV ($MM)	PROFIT ($MM)	R&D ($000)	SALES ($MM)
Mean	14057.33	4787.89	56.28	28.05	825.44
Median	14455.90	4723.41	54.23	32.20	795.81
Std. Dev	5611.37	3988.30	74.67	24.27	518.65

REEBOK					
	ADVERTISING ($000)	MV ($MM)	PROFIT ($MM)	R&D ($000)	SALES ($MM)
Mean	3312.62	597.40	9.49	16.49	274.87
Median	2691.90	605.51	8.36	16.73	266.81
Std. Dev	2003.75	689.60	23.78	5.41	117.15

K-SWISS					
	ADVERTISING ($000)	MV ($MM)	PROFIT ($MM)	R&D ($000)	SALES ($MM)
Mean	1319.07	100.60	2.10	3.82	15.43
Median	1188.30	77.06	1.56	2.96	13.88
Std. Dev	1253.70	255.39	6.05	2.08	22.84

SKECHERS					
	ADVERTISING ($000)	MV ($MM)	PROFIT ($MM)	R&D ($000)	SALES ($MM)
Mean	2448.60	155.77	2.41	1.41	61.10
Median	2347.70	166.57	2.78	1.53	68.58
Std. Dev	1270.81	230.32	8.77	1.79	62.64

Table 2: Results from Market-to-Book Model

	Advertising Elasticity	R&D Elasticity	Investor Response Effects
Apple	.291***	.003	.016***
Compaq	.154***	.296*	.008***
Dell	.011*	.127**	.008**
HP	.020	.004	.007**
IBM	.129*	.096*	.012
Nike	.109*	.253	.007***
Reebok	.096	.131	.010**
K-Swiss	.082**	-.010	.005
Skechers	.131*	.033	.010*

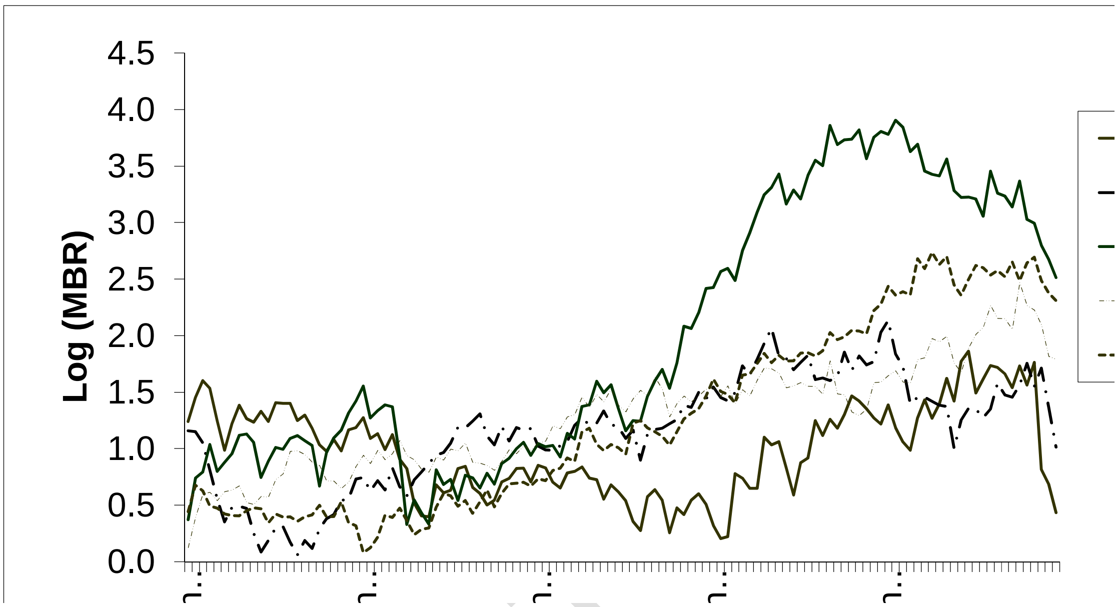
* Significant at p<.10 for a one-tailed test. ** Significant at p<.05 for a one-tailed test. *** Significant at p<.01 for a one-tailed test.

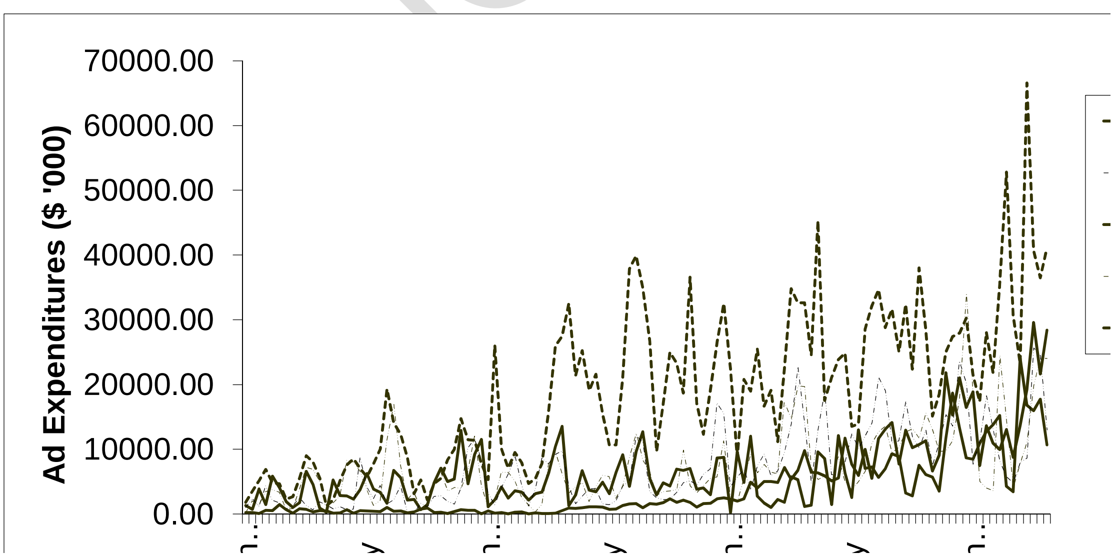
Table 3: List of Matching Firms Used to Calculate MFR

Firm	Matching Firms
Apple	NCR, DEC, Xeros Corp, Pitney Bowes Inc, EMC Corp, Silicon Graphics, Micron Technologies, Seagate Technology, Gateway Inc, Diebold Systems, Sun Microsystems
Compaq	NCR, Pitney Bowes, Sun Microsystems, Amdahl Corp, DEC, Xeros Corp, Creative Technologies, Sprint Corp, Micron Technologies, Iomega Corp
Dell	Measures, Diebold, Stratus Computers, Seagate Technology, Amdahl Corp, Creative Technologies, Micron Technologies, EMC Corp, Verifone Inc.
HP	DEC, Sprint, Bay Networks, Gateway 2000, Maxtor, NCR, EMC, Sun Microsystems, Palm Inc, Pitney Bowes
IBM	NCR, Amdahl, Sun Microsystems, Silicon Graphics, DEC, Micron Technologies, Pitney Bowes, EMC, Sprint Corp
Nike	Gap, TJX Companies, Weyco Group, Timberland Co, Nine West Inc., Stride Rite Corp
Reebok	Tommy Hilfiger, Warnaco Grp, Stage Stores, Russell Corp, Lands End, Abercrombie & Fitch,
K-Swiss	Vans, Wolverine World Wide, Lacrosse Footwear, LA Gear, Florsheim Shoe Co, Puma, Deckers Corp
Skechers	Florsheim Shoe Co, Saucony, Rocky Shoes and Boots, Deckers, Brown Shoe Corp, Madden Steven Ltd, Candies Inc

Figure 1

Market-to-Book ratio and Advertising in the PC industry*

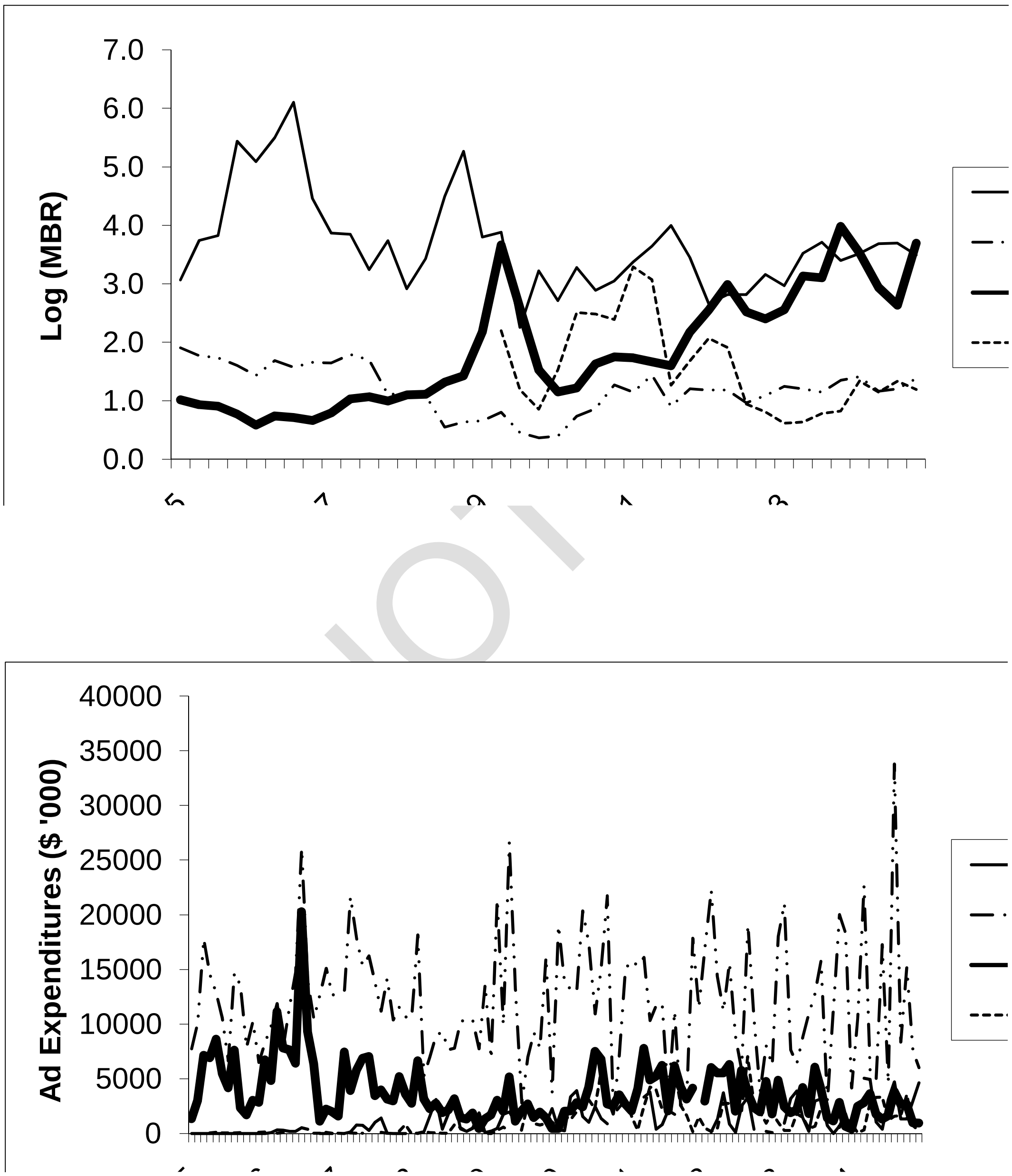




*For ease of exposition, Market-to-Book ratio has been expressed in logs and advertising in levels

Figure 2

Market-to-Book ratio and Advertising in the Sporting Goods Industry*

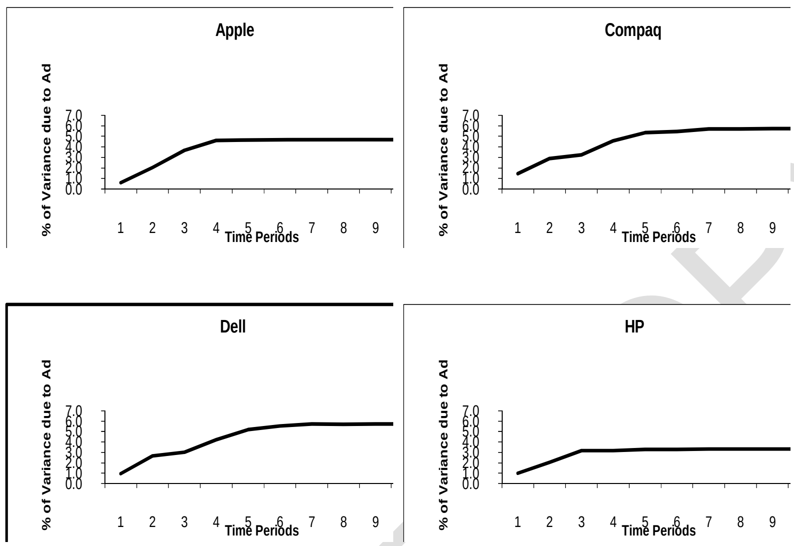


*For ease of exposition, Market-to-Book ratio has been expressed in logs and advertising in levels

Figure 3

Forecast Error Variance Decomposition*:

An Illustration in the PC Industry

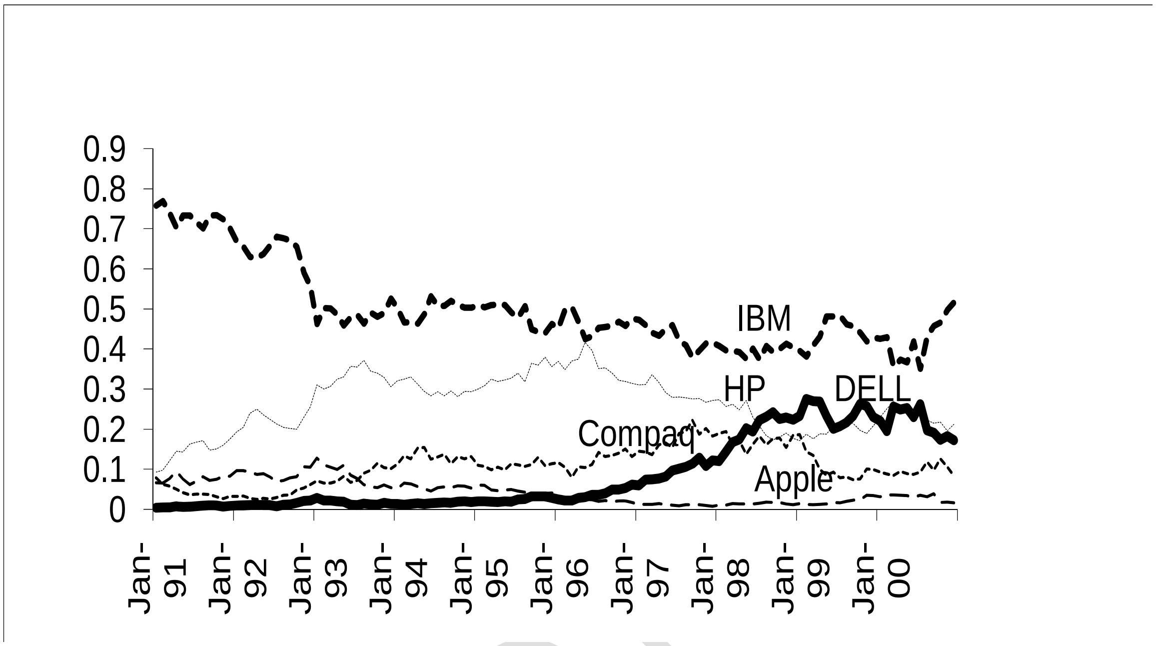


*Read as mentioned for Table 3

Figure 4

Market Valuation Shares for the PC

Competitors



* Share only reflects firms in our database.