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Essays on Advertising's Impact on Firm Risk, Firm Value, and Analysts' Forecasts

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Essays on Advertising's Impact on Firm Risk, Firm Value, and Analysts' Forecasts

by

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DEDICATION

I dedicate this dissertation to my parents, Yong-Dae Kim and Hee-Ok Kim.

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Essays on Advertising's Impact on Firm Risk, Firm Value, and Analysts' Forecasts

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Marketing managers are often challenged to show, in the language of finance, that marketing expenditures enhance financial performances. Responding to this call, the first essay examines the impact of a firm's advertising and research and development (R&D) on the systematic risk of its stock, a key finance metric for publicly listed firms. Integrating developments in the accounting, finance, and marketing literatures, we propose that both a firm's advertising and R&D will create market-based assets that will insulate the firm from changes in the stock market, thereby lowering its systematic risk. After controlling for factors that accounting and finance researchers have shown to be associated with the systematic risk, we find that a firm's advertising and R&D lower its systematic risk. For theory, the findings extend prior research that has focused on the effect of marketing initiatives on performance metrics without consideration of the impact of those initiatives on the firm's systematic risk. For practice, the ability of advertising and R&D to reduce systematic risk highlights the multi-faceted financial

implications of marketing programs. This study's findings may also surprise senior management and finance executives who are skeptical of the financial accountability of marketing programs.

In the second essay, we extend the existing literature to identify a fundamental signal from advertising (S_{ADV}) which the stock market and financial analysts might recognize as value-relevant information. We find that increases in the proposed advertising signal increase the cumulative abnormal stock returns (CAR) after controlling for the accounting and finance variables known to affect CAR. However, surprisingly, we find that the value-relevant advertising signal (S_{ADV}) is not related to financial analysts' expectation of firm value and their earnings forecasts, and that S_{ADV} increases the errors in analysts' earnings forecasts. We thus provide empirical evidence that analysts under-react to the fundamental advertising signal, S_{ADV}, despite the fact that the measure is impounded in firms' stock prices. With the findings, this study joins a growing literature that demonstrates a link between marketing and financial value of a firm, and furthermore encourages finance professionals' better understanding of marketing accountability.

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CHAPTER 1: INTRODUCTION

There is a growing consensus that senior management and finance executives focus on maximizing shareholder value and do not value marketing performance metrics (e.g., awareness, sales growth, loyalty, customer satisfaction, repeat purchase), because they do not understand how or even whether these metrics are of interest to the firm's shareholders (Ambler 2003). Consequently, marketing executives are urged to "speak in the language of finance" with their finance colleagues and senior management (Srivastava and Reibstein 2004) because financial return is the dialogue required to access funds from the financial purse strings that are crucial for the implementation of marketing programs. To address this gap, in this essay, we examine whether a firm's advertising and research-and-development (R&D) expenditures affect a metric of interest to both finance executives and senior management: the firm's "systematic risk," or β.[1] We first provide the motivation for the study.

Portfolio theory (Lintner 1965; Sharpe 1964), a key development in finance, posits that investors can diversify away a portion of the risk associated with a firm's stock by constructing a portfolio of stocks whose returns correlate imperfectly with one another. In equilibrium, the risk that is priced in the stock market is the stock's

[1] As we subsequently discuss, to eliminate potentially confounding effects of firm size on systematic risk, in the empirical estimation, we scale the firm's advertising and R&D by its sales.

systematic risk, which is a function of the extent to which the stock's return changes when the overall market changes.[2] This market-driven variation in a firm's stock returns, which cannot be diversified away, is its "systematic risk," or β.[3] By construction, the stock market, as a whole, has a β of 1.0. A stock whose return, in response to a change in the market, falls (or rises) more than does the market's return falls (or rises) has a β above 1.0. If, in response to a change in the market, a stock's return falls (or rises) less than the market's return falls (or rises), its β is less than 1.0. Thus, β, a measure of the stock's sensitivity to market changes, is an important metric for publicly listed firms.

In this essay, we examine the relationship between a firm's advertising and R&D and its systematic risk. Recent developments in the market-based assets theory (Srivastava, Shervani, and Fahey 1998) suggest that a firm's advertising creates intangible market-based assets (e.g., brand equity) and that those assets strengthen performance including sales growth, market share, and profitability (Boulding and Staelin 1995; Erickson and Jacobson 1992) and shareholder value (Joshi and Hanssens 2004; Rao, Agarwal, and Dahloff 2004). We suggest that the consumer loyalty and the bargaining power over distribution channel partners inherent in those intangible market-based assets help insulate the firm from the impact of stock-market downturns, thus lowering the firm's systematic risk. On the basis of developments in the finance literature, we propose another way that advertising-created market-based assets might affect a firm's systematic risk. Frieder and Subrahmanyam (2005; p. 57) note that

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[2] Thus, beta is measured as (covariance (stock and market))/(variance (market)).

[3] We use the terms 'systematic risk', 'beta', or β to denote the systematic risk of the firm's stock.

because of increased firm awareness due to advertising, all else being equal, "investors prefer holding stocks with high recognition and consequently, greater information precision." Grullon, Kanatas, and Weston (2004) find that a firm's advertising results in broader ownership of the stock. We anticipate that this broader ownership may insulate the stock's return from market downturns.

Consistent with these theoretical developments, two recent studies (Madden, Fehle, and Fournier 2006; Singh, Faircloth, and Nejadmalayeri 2005) have explored the relationship between a firm's advertising and its systematic risk. Singh et al. (2005) report a significant, negative relationship between a firm's advertising and its systematic risk. Using a sample of "best-performing firms" from the Stern-Stewart database for the period between 1998 and 2001, Singh et al. (2005) find that higher advertising expenditure (operationalized as advertising dollars) is associated with lower systematic risk. Madden et al. (2006) compare the performance of three stock portfolios—a portfolio of firms with strong brands (using Interbrand's measure of brand strength), a portfolio of firms excluding firms with strong brands, and a portfolio of all firms—and find that the portfolio of firms with strong brands, relative to the other two portfolios, has higher returns and lower systematic risk.

Singh et al. (2005) and Madden et al. (2006) studies raise intriguing research questions: Will the negative relationship between advertising (or brand strength) and systematic risk hold under other conditions including a more general sample that includes poorly performing firms, or with measures of advertising scaled for firm size (to remove the confounding effect of firm size)? Will the negative relationship between advertising and systematic risk hold controlling for other accounting characteristics that have been shown to link to a firm's systematic risk which may vary across portfolios (but not controlled for in the Madden et al.'s study)? In addition, we perceive a research opportunity for us to incorporate unobserved firm heterogeneity (to rule out endogeneity caused by omitted variables) and to use lagged predictor variables (to rule out reverse causality), issues that have not examined in prior research. There is also evidence in the literature linking a firm's R&D expenditure to its financial performance (Boulding and Staelin 1995; Capon, Farley, and Hoenig 1990; Erickson and Jacobson 1992) and shareholder value (Jaffe 1986). We hypothesize that as in the case of advertising, R&D creates intangible market-based assets that insulate the firm from the negative impact of stock market downturns, thus lowering the firm's systematic risk.

Accordingly, we examine the impact of a firm's advertising and R&D on its systematic risk, proposing that a firm's advertising and R&D lower its systematic risk. We test the hypotheses using data on publicly listed firms obtained from the COMPUSTAT and Center for Research on Stock Prices (CRSP) databases for the period between 1979 and 2001, which resulted in the creation of a panel data set of 19 five-year moving windows with 3198 observations for 644 firms. Following precedent in the finance literature (Damodaran 2001), we estimate the firm's systematic risk, β, using 60 months of stock returns in a five-year moving window using equal-weighted stock market returns. To eliminate the potentially confounding effects of firm size on systematic risk, we scale the firm's advertising and R&D expenditures by its sales.

We control for the firm's growth, leverage, liquidity, asset size, earnings variability, and dividend payout, factors that finance and accounting scholars have shown to be associated with its systematic risk. The model includes two additional control variables that may affect a firm's systematic risk: firm age and competitive intensity in the industry. We estimate the effect of a firm's advertising/sales and R&D/sales on its systematic risk using a fixed-effects model formulation that accounts for unobserved firm heterogeneity and serial correlation of errors.

The results strongly support the hypotheses that higher advertising/sales and higher R&D/sales lower a firm's systematic risk after controlling for factors that prior research has shown to be associated with systematic risk. These two effects are robust to alternative estimates of systematic risk (we estimate β using value-weighted, as opposed to equal-weighted, market returns and relax the restriction that all 60 months of stock returns must be present to estimate β) and to alternative measures of advertising and R&D (we scale them by assets rather than by sales), and the results are not driven by multicollinearity. Our findings are novel and important and hold implications for both marketing theory and practice.

We organize this article as follows: In the next section, we provide a brief overview of systematic risk. Following that, we develop hypotheses that relate a firm's advertising and R&D to its systematic risk. We then describe the proposed estimation approach, the data, the measures, and the results. We conclude with a discussion of the paper's contributions, its limitations, and opportunities for further research.

CHAPTER 2: AN OVERVIEW OF SYSTEMATIC RISK

A central issue in portfolio theory in finance is the maximization of returns for individuals who invest in assets, that is, in firms' stocks (Lintner 1965; Mossin 1966; Sharpe 1964). The key idea of portfolio theory is that investors can construct a portfolio of stocks with imperfectly correlated returns and thus eliminate non-systematic (i.e., individualistic) risk associated with those stocks. The remaining variability, the firm's systematic risk, reflects the extent to which its stock's return responds to movement of the average return on all stocks in the market. That is, a firm's systematic risk measures its stock's sensitivity to market-wide events and is, referred to as, its β.

In 1970, Beaver, Kettler, and Scholes (hereinafter, BKS) related systematic risk to variables that describe the financial position of a firm. Specifically, they suggested that higher systematic risk will be related to:

- Higher growth because, in a competitive economy, the excessive earnings opportunities may erode when new firms enter the industry.

- Higher leverage because the earnings stream of common shareholders becomes more volatile as debt increases.

- Lower liquidity because liquid or current assets result in less volatile returns than do fixed assets.

- Smaller asset size because smaller firms have higher default risk.

- Lower dividend payout because the need to offer steady dividends will cause firms with greater volatility to pay out a lower percentage of earnings.

- Higher levels of earnings variability because this will result in a lower payout to stockholders.

- Higher earnings co-variability with the market because this will result in higher earnings volatility again lowering the return on the stocks.

Considering two periods (1947-1956 and 1957-1965), BKS (1) regressed the aforementioned firm characteristics on systematic risk in the first time period and (2) examined whether a model of systematic risk from time period 1 predicted systematic risk in time period 2 better than did systematic risk in time period 1.

Two diverse streams of empirical research have emerged from the BKS study. The first stream of research, not related to this paper's research objectives, focuses on the prediction of the firm's systematic risk, β, in a future period (Elgers 1980; Eskew 1979; Ismail and Kim 1989). The second stream of research, more pertinent to this paper, augments the predictor variables in the BKS study with additional firm characteristics that may explain systematic risk. While there are several studies in this stream, our review indicated a lack of cumulative knowledge building in this area. Rather, each study added some new variables to a subset of the variables in the BKS study. Variables considered in past research include dividend policy (Bildersee 1975), financial structure (Hill and Stone 1980), operating leverage (Mandelker and Rhee 1984), earnings funds flow and cash flow (Ismail and Kim 1989), international diversification (Goldberg and Heflin 1995), and strategic profiles (Veliyath and Ferris 1997).

Similarly, two studies (Bharadwaj and Menon 1993; Kroll, Wright, and Heiens 1999) explore the relationship between aspects of a firm's marketing strategy and its risk. Using service strategic business units (SBU's) from the Profit Impact of Marketing

Strategy (PIMS) database, Bharadwaj and Menon (1993) find that some aspects of marketing (i.e., promotional expenditure, sales force expenditure, relative price) are associated with lower variability in return on investment while other aspects of marketing (i.e., advertising, customization) are associated with higher variability in return on investment. Although variability in return on investment, a surrogate for total risk, confounds systematic risk with non-systematic risk, these results suggest a relationship between firms' marketing activities and their systematic risk. Kroll et al. (1999) consider a surrogate for systematic risk, the covariance of firms' cash flows relative to a market portfolio of equities, and find that the superior product quality of SBU's (again using the PIMS database) decreases that surrogate measure of risk. As noted earlier, Singh et al. (2005) and Madden et al. (2006) find that higher levels of advertising expenditure are associated with lower systematic risk.

Note that there is a vigorous, ongoing debate about the usefulness of systematic risk for predicting future firm value in the finance literature (Fama and French 1992).[4] However, our focus is on β as a measure of risk, not on β as a predictor of future firm value. Reiterating its central role in investment practice, systematic risk, β, is an important metric for publicly listed firms measuring their stocks' vulnerability to market downturns. Indeed, as testimony of its importance, a review of current investment practices indicated that leading investment firms (e.g., Fidelity Inc., Merrill Lynch, Value Line) use β extensively in the construction of investment portfolios. Thus, shareholders

[4] Specifically, Fama and French (1992), using historical data, examine whether expected returns are better predicted by the firm's past beta's than by other variables. Using realized average returns, they find a stronger empirical correlation of future firm value with a firm's book-to-price and with size but not with the measure of its historic beta.

and senior management of publicly traded firms are very interested in β and, consequently, in the impact of advertising and R&D on β.

In sum, while there is much work relating a firm's accounting characteristics (e.g., dividend payout, growth, leverage, liquidity, asset size, and earnings variability) to its systematic risk, we know much less about the relationship between important indicators of marketing strategy (e.g., advertising and R&D expenditures) and systematic risk. Singh et al. (2005) and Madden et al. (2006) are two exceptions. Addressing this research gap, we examine the effects of a firm's advertising and R&D, two important manifestations of the firm's marketing strategy, on its systematic risk.

CHAPTER 3: THEORY

We next develop hypotheses relating a firm's advertising and R&D to its systematic risk. Note that, to eliminate the potentially confounding effects of firm size on systematic risk in the empirical estimation, we scale the firm's advertising and R&D by its sales. We first discuss the effects of the firm's advertising on its systematic risk, followed by the effects of R&D on systematic risk.

Advertising

To start with, a large body of work indicates that advertising has a direct effect on various firm performance metrics including sales (Leone 1995), profit (Erickson and Jacobson 1992), and firm value (Joshi and Hanssens 2004). Reinforcing these performance rewards to advertising, developments in brand equity (Aaker 1996; Keller 1998) suggest that firms' advertising efforts create consumer and distributor brand equity, an intangible market-based asset with important strategic and performance implications. For example, increased advertising and the resultant brand equity increase the differentiation of a firm's products (Kirmani and Zeithaml 1993) and make them less easily substitutable (Mela, Gupta, and Lehmann 1997). Increased brand equity also increases price premiums (Ailawadi, Neslin, and Lehmann 2003) and lowers price sensitivities (Kaul and Wittink 1995; Sethuraman and Tellis 1991). Furthermore, increased advertising and resultant higher brand equity produce an asymmetric sales response to sales promotions (Blattberg, Briesch, and Fox 1995), such that highly advertised brands are affected less (than less advertised brands) by competitors' sales promotions.

In addition to the benefits of advertising and brand equity in current product markets, advertising and the resultant brand equity also strengthen and stabilize the firm's performance in new product markets. For example, the brand equity of current flagship brands generate greater receptiveness of consumers and distribution channel partners to new product introductions (Kaufman, Jayachandran and Rose 2006) and will enable the firm to migrate customers to more profitable products and/or to cross-sell products to existing customers (Kamakura et al. 2003). Thus, as suggested by Srivastava et al. (1998), brand equity may function as financial hedging contracts when firms enter new markets with new technologies. In addition, brand equity also creates both consumer and distributor loyalty, acts as a barrier to competition, and provides bargaining power over distributors; these are all benefits that insulate a firm's stock from market downturns and thus lower its systematic risk (Veliyath and Ferris 1997).

Finally, a firm's brand equity may also lower its systematic risk by serving as a capital market information channel to the firm's stockholders (Frieder and Subrahmanyam 2005; Grullon et al. 2004). Grullon et al. (2004) report that firms with higher advertising have higher liquidity and greater breadth of stock ownership. Frieder and Subrahmanyam (2005) report that a firm's increased brand perceptions (consistent with higher brand equity discussed above), a direct outcome of its increased advertising, increases ownership of the firm's stock by individual investors (relative to institutional investors) because of individual investors' preferences for stocks with higher-quality information (advertising plays an information role for a firm's stockholders). This higher liquidity and increased breadth of ownership may help insulate the firm's stock returns from market downturns, thus lowering its systematic risk. Thus, we propose:

H1: The higher a firm's advertising, the lower its systematic risk.

Research and Development (R&D)

There is a large body of finance, management, and marketing research relating the intangible assets created by R&D to the firm's financial performance. Although there is a debate about the sizes of the effects of R&D investments on different performance metrics (Boulding and Staelin 1995; Erickson and Jacobson 1992), it is well-established that firms' R&D investments generate persistent profits (Roberts 2001), high stock returns (Chan et al. 2001; Mizik and Jacobson 2003; Pakes 1985), and superior market value (Jaffe 1986). In a meta-analysis of 210 profitability studies, Capon, Farley and Hoenig (1990, p. 1157) conclude, "Dollars spent on R&D have an especially strong relationship to increased profitability."

As with advertising-created market-based assets, R&D-created market-based assets may also insulate a firm's stock from market downturns. Veliyath and Ferris (1997) report a relationship between the strategic profile of a firm, including its advertising- and R&D-driven differentiation, and its systematic risk. Similarly, the number of a firm's new product introductions lowers its systematic risk (Chaney et al. 1991). This relationship between R&D and systematic risk occurs because a firm which invests in R&D exhibits greater dynamic efficiency and greater flexibility than its competitors (who invest less in R&D) enabling it to adapt to environmental changes including in input prices, technologies, and customers (Miller and Bromiley 1990). This efficiency and flexibility help insulate the firm from market downturns, thus lowering its systematic risk.

We focus on the effects of a firm's R&D, an activity with uncertain returns, on its systematic risk. If the focus is on total risk (non-systematic risk and systematic risk), R&D may increase total risk because R&D may decrease the predictability of a firm's future income streams (Kothari et al. 2002). Analysts exhibited greater disagreement about year-ahead earnings for R&D intensive firms than for other firms (Barth et al. 2001). Another study notes that post-investment reported earnings are more highly variable for firms with higher R&D levels than for firms with lower R&D levels (Chambers et al. 2002). To the extent that these kinds of volatility are specific to a firm or an industry, they are non-systematic and can be diversified away (Lubatkin and O'Neill 1987).

In summary, while extant empirical research suggests that R&D may increase a firm's non-systematic risk, this literature also suggests that R&D creates strategic differentiation, efficiency, and flexibility, which insulate the firm from market downturns, thus lowering its systematic risk. Thus, we propose:

H2: The higher a firm's R&D, the lower its systematic risk.

CHAPTER 4: METHOD

Data

The data for this study included all firms listed on the New York Stock Exchange (NYSE) during the period between 1979 and 2001. We obtained accounting, financial, advertising, and R&D data on firms from COMPUSTAT, and we obtained their stock prices for the computation of systematic risk from CRSP.

Measures

The dependent variable, systematic risk, is an inherently long-term construct capturing the extent to which a firm's stock return co-varies with market return (Beaver, Kettler and Scholes 1970). A firm's systematic risk changes slowly over time. We follow the precedent in prior finance research (Damodaran 2001) and estimate the firm's systematic risk, β, using a five-year moving window.

Accordingly, we estimate the firm's systematic risk, β, for a five-year moving window using stock returns for the previous 60 months, relative to the equal-weighted return for the stock market for that period. We subsequently test the robustness of the results to β estimates relative to the value-weighted returns and for β estimates when monthly stock returns were available for at least 50 of the 60 months of the moving window (which allows us to increase the number of firms in the data set). In addition, to avoid problems associated with very low-priced stocks, we excluded a stock from the five-year moving window if the average of its monthly closing stock prices was less than $2 (Ball et al. 1995; Hertzel et al. 2002). Finally, we included a firm in the moving window only if it reported information on its advertising and R&D in COMPUSTAT for all years in the five-year moving window.

Systematic Risk. Similar to BKS's (1970) approach, we use monthly stock data to compute firm *i*'s systematic risk measure $\hat{\beta}_i$, *ex post*, for a period by using a least squares regression of the form:

$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$, *t= Start,…, End* where

$$R_{it} = \ln\left[\frac{D_{it} + P_{it}}{P'_{it-1}}\right] \text{ and } R_{mt} = \ln\frac{L_t}{L_{t-1}}$$

where R_{it} is the *ex post* rate of return for stock *i* during period *t*, R_{mt} is an index of the *ex post* return for all NYSE firms during month *t* (i.e., the market rate of return), and α_i is the intercept of the fitted line of R_{it} using R_{mt}. D_{it} is cash dividend payable on common stock *i* in month *t*, P_{it} is closing price of common stock *i* at end of month *t*, P'_{it-1} is closing price at end of month *t-1* adjusted for capital changes (e.g., stock splits, and stock dividends), and L_t and L_{t-1} are the Fisher's link relative, a market price index of all firms on the NYSE at months *t* and *t-1* respectively, adjusted for dividends and all capital changes. The slope of the regression equation $\hat{\beta}_i$ is the empirical estimate of systematic risk β_i of firm *i*.

We obtained $\hat{\beta}_i$ by estimating a separate regression using the monthly stock returns for each firm *i* for each five-year moving window resulting in up to 19 observations per firm. For the first moving window, we used the monthly stock returns for all firms on CRSP for 1979, 1980, 1981, 1982 and 1983 to compute the firm's systematic risk, β. For the second moving window, we used the monthly stock returns for firms for 1980, 1981, 1982, 1983, and 1984. For the last and 19th moving window, we used the monthly stock returns for all firms for 1997, 1998, 1999, 2000, and 2001. To ease interpretation of the results, we eliminated 52 observations where the firm's estimated systematic risk was negative.

Advertising and R&D. We measured advertising by the mean of the firm's advertising expenditure as reported in DATA45 scaled by its sales reported in DATA12 for the five-year period from the annual data reported in COMPUSTAT. DATA45 in COMPUSTAT includes the cost of advertising media (radio, television, newspapers, and periodicals) and promotional expenses.[5] We measured *R&D* by the mean of the firm's R&D expenditure as reported in DATA46 scaled by its sales reported in DATA12 for the five-year period from the annual data reported in COMPUSTAT. Scaling the firm's

[5] Past research has shown that sales promotion activities negatively affect brand loyalty (Mela, Gupta, Lehmann and 1997) and have a nil effect on stock returns (Pauwels et. al. 2004). We are cognizant that some firms may report sales promotion expenditure as a part of their advertising expenditure. However, because firms do not indicate, the split between advertising and sales promotions, we assume that most advertising expenditures reported in DATA45 in COMPUSTAT relate to communication of product benefits to customers. Thus, differences in the percent of such mis-reported advertising expenditure that pertains to sales promotion adds error to our estimates, making our tests of hypotheses conservative.

advertising and R&D expenditures by its sales rules out the alternative explanation that the negative effect of advertising and R&D on systematic risk may be because larger firms may have lower systematic risk. We subsequently test and report that the model estimation results are robust to scaling of the advertising and R&D by the firm's assets DATA6 (instead of its sales).

Given the theoretical processes discussed in the hypotheses development, we anticipate a lagged effect of a firm's advertising and R&D on its systematic risk. Thus, we used lagged measures of advertising/sales and R&D/sales, which preclude a potential reverse causality explanation of the effects (Boulding and Staelin 1995).

Accounting Variables. Given this paper's objective of exploring the effects of a firm's advertising and R&D on its systematic risk, as accounting researchers have done, we use accounting variables that BKS (1970) use as control variables in our model. Accordingly, we included six accounting characteristics of the firm in the model: asset growth rate, leverage, liquidity, asset size (log), earnings variability, and dividend payout (see BKS (p. 666) for the logic for the operationalization of these variables). The inclusion of the firm's asset size serves as a further control for the effects of the firm's size on its systematic risk. We are unable to include covariability of earnings, which was included in the BKS model, because its calculation requires ten years of data. We provide the definitions of these measures and the data fields from COMPUSTAT used for BKS's computation in the Appendix A and in the Appendix B.

Additional Control Variables. We also include two additional control variables in the model. First, we include the firm's age measured by the number of years since its listing on the stock market as older firms may have lower systematic risk. Second, to control for industry-specific effects, following the suggestion of an anonymous reviewer, we include the industry's competitive intensity, measured by the Herfindahl's four-firm concentration ratio as the proportion of market shares of the largest four firms to the industry's sales at the 2-digit standard industry classification (SIC) level. *A priori*, we do not hypothesize the directional effect of competitive intensity. The fixed-effects formulation we employ to estimate the model precludes the inclusion of time-invariant industry dummies in the model.

The number of observations for which we had complete data on systematic risk, lagged advertising/sales, lagged R&D/sales, and the control variables is 3198 (for 644 firms). The number of firms in the sample by each moving window suggests that, over time, the number of firms in each moving window increases at first, reaches a maximum (N = 371 in moving window 10 (years = 1989—1993)), and then declines to N = 162 in the last moving window (years = 1997—2001). This drop in the number of firms in the moving windows over time occurs because of missing data for advertising and R&D. The average value for systematic risk for all firms in a given window varies across the years ranging from 0.856 (window 14) to 1.140 (window 18), whereas average asset size (log) ranges from \$6.243 million (window 14) to \$4.951 million (window 6). Lagged advertising/sales and lagged R&D/sales vary as follows: average lagged advertising: highest = 0.055 in window 15 to lowest = 0.033 in window 1; average lagged R&D: highest = 0.088 in window 15 to lowest = 0.036 in window 1. 3% of observations reported zero advertising expenditure and 3.9 % of observations reported zero R&D

expenditure. Table 1 contains the descriptive statistics and correlation matrix of the measures, and Figure 1A and Figure 1B contain the frequency distribution of asset size (log) and systematic risk respectively of observations in the study.

A perusal of Table 1 and Table 2 (which we discuss in detail subsequently and contains the results of the model estimation) suggests that the pattern of bivariate correlation matrix in Table 1 is different from the pattern of regression results in Table 2. For example, the model estimation results in Table 2 indicate that advertising/sales and R&D/sales have coefficients that are negative and significant at $p < 0.01$. However, in the bivariate correlation matrix in Table 1, the correlation between R&D/sales and β is positive and significant at $p < 0.01$, and the correlation between advertising/sales and β is negative, but is only significant at $p < 0.10$. This "disconnect" occurs because the bivariate correlation matrix does not account for the fixed effects, serial correlation, or window dummies in our model structure. To explore this issue further, we created an "adjusted" bivariate correlation matrix, wherein we remove the effects of fixed effects, serial correlation, and window dummies from the predictor variables by regressing fixed effects, serial correlation, and window dummies on each of the predictor variables and systematic risk. We used the residuals from each of these regressions to create an adjusted correlation matrix (this and all other results not reported in the paper are available, on request, from the authors). The pattern of correlations in the adjusted correlation matrix corresponds closely to the regression results in Table 2.[6] Thus, multicollinearity does not appear to be driving the results of the model.

[6] We also performed stepwise regression analyses, adding one predictor variable at a time to the model, and found consistent results for the effects of lagged advertising and lagged R&D (the directionality, significance, and the sizes of the coefficients) across these stepwise regressions showing that there are no harmful effects of multicollinearity.

CHAPTER 5: RESULTS

Model Estimation Procedure

As the panel data set of moving windows consists of repeated observations of firms, we estimated a fixed-effects, cross-sectional, time series regression model with a correction for serial correlation of errors (Baltagi and Wu 1999; Bhargava et al. 1982; Woolridge 2002). Specifically, the model has the following structure:

$Y_{it} = \alpha + X_{it}\beta + \nu_i + \varepsilon_{it}$ i = 1,…., N; t = 1,…., T_i and where

$\varepsilon_{it} = \rho\varepsilon_{i,t-1} + \eta_{it}$ in addition, where $|\rho| < 1$ and η_{it} is independent and identically distributed (i.i.d) with mean 0 and variance $\sigma^2{}_{\eta}$ and ν_i are assumed to be fixed parameters that may be correlated with the covariates X_{it}. These X_{it} includes the accounting variables of growth, leverage, liquidity, asset size, earnings variability, dividend payout, age, competitive intensity, and advertising and R&D. The failure to correct for serial correlation of errors, if present, can result in inflated standard errors of parameter estimates and incorrect tests of hypotheses. See Bhargava, Franzini, and Narendranathan (1982) for the detailed statistics of the fixed-effects panel data model with correction for first order serial correlation of errors.[7]

[7] The most frequently analyzed process in the empirical econometrics literature is the first order autoregression or AR(1) process where the errors across time *t* and *t-1* are correlated. Higher order processes involving several periods are both intractable and place a high burden on the researchers to justify more complex time series processes. Thus, as noted by Greene (2003; p. 257), "the first-order

We estimate the model using the *xtregar* procedure in STATA 9.0. In addition to the predictor variables of lagged advertising/sales and lagged R&D/sales, we also include the BKS control variables and the two additional control variables of age and competitive intensity. As discussed earlier, we used lagged measures of advertising/sales and R&D/sales. Because this structure precludes a potential reverse causality explanation, we can explore a causal relationship between advertising/sales, and systematic risk and R&D/sales and systematic risk (Boulding and Staelin 1995). We include dummies for each moving window to account for any differences across windows.

We checked for first-order serial correlation in errors, as Woolridge (2002) proposes. This test rejected the hypothesis that there is no first-order serial correlation ($p < 0.01$), in support of the inclusion of an autoregressive (AR1) disturbance term. We report the results of the estimation of the proposed model in Column 1 of Table 2.

The proposed model is statistically significant ($F(671, 2527) = 17.90$, $p < 0.01$), and the R-square (within) for the proposed model is 0.161. The rejection of the hypothesis of null fixed effects (F-value significant at $p < 0.01$) reinforces the need for fixed-effects correction. The estimated autocorrelation coefficient, ρ is large at 0.668, and the Durbin-Watson statistic (Baltagi and Wu 1999) is not significant ($t = 1.200$, n.s.), reconfirming the need to adjust for serial correlation in errors.

We first compare the coefficients of the accounting variables in this study with the results obtained by BKS (1970). We note that BKS report significant effects for

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autoregression has withstood the test of time and experimentation as a reasonable model for underlying processes that probably, in truth, are impenetrably complex."

dividend payout ($b = -0.58$, $p < 0.01$), growth ($b = 0.84$, $p < 0.05$), and earnings variability ($b = 3.03$, $p < 0.01$). In our results, significant coefficients indicated that growth ($b = 0.359$, $p < 0.01$) and leverage ($b = 0.515$, $p < 0.01$) are positively associated with a firm's systematic risk, whereas asset size ($b= -0.091$, $p < 0.01$) is negatively associated with systematic risk. Given the changes in stock market regimes over time and the refinements in the estimation procedure we use in this paper (i.e. we use a panel data model, incorporating fixed effects and serial correlation in errors), the differences in this study's coefficients relative to those that BKS (1970) report are not surprising.[8] We infer that differences among our findings, those in the BKS, and those of BKS's model approach using the 1980-1999 data reported in footnote 8 arise because of differences (1) in stock market regimes across the years arising from changes in the range of predictor variables, and (2) in econometric estimation procedure across our study and the BKS

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[8] We also estimated the model estimated by BKS for the twenty years in this study by constructing two data sets: one for period 1980-1989 and another data set for the period 1990-1999 by averaging the various accounting variables for the ten years following the procedure in the BKS paper.

The results of the ordinary least squares regression for the model with accounting variables were significant in both ten year periods: period 1: $F(6, 338)=22.501$, $p < 0.01$; period 2: $F(6, 231)=17.742$, $p < 0.01$; with the following R-squares: period 1: R-sq: 0.285; period 2: R-sq: 0.315). The following accounting variables were significant: period 1: growth (+ and $p < 0.01$), leverage (+ and $p < 0.05$), earnings variability (+ and $p < 0.01$) and asset size (- and $p < 0.01$); period 2: growth (+ and $p < 0.10$), leverage (+ and $p < 0.05$), earnings variability (+ and $p < 0.01$), and asset size (- and $p < 0.01$).

From the above we can see the impact of methodology. BKS, with their data and methodology, found growth, earnings variability, and dividend payout significantly associated with beta but asset size and leverage were not associated with beta. Considering the question of why BKS did not identify asset size and leverage as predictors of beta, recall that BKS eliminated leverage and asset size in a stepwise regression of data averaged over ten years. We conjecture that panel-structure-adjusted correlations may have shown that leverage and asset size were then (as they are now) good predictors of systematic risk. The raw correlation structure in our panel data is consistent with this conjecture. Correlations of liquidity, in the panel data set, with both asset size ($\rho = .34$) and leverage ($\rho = -.37$) are high. In summary, we suggest that the difference between our results and BKS's results are, in large part, driven by an up-to-date econometric estimation approach in this paper. After correcting for methodology, the remaining differences in our findings might be due to change in the marketplace—or they might be due to the fact that BKS's use of stepwise regression artificially eliminated leverage and asset size that our proposed model (with its panel structure) identifies as important predictors of beta.

study—we incorporate information on the panel data structure in the estimation, whereas the BKS study do not.

With respect to the other control variables, the firm's age ($b = -0.022$, $p < 0.01$) and competitive intensity ($b = -0.885$, $p < 0.01$) are significantly associated with lower systematic risk. The accounting variables of liquidity ($b = 0.001$, n.s.), earnings variability ($b = -0.018$, n.s.), and dividend payout ($b = 0.000$, n.s.) are not related to systematic risk.

We next discuss the two hypothesized effects. The results indicate that, as expected in H1 and H2 respectively, higher lagged advertising/sales ($b = -3.187$, $p < 0.01$) and higher lagged R&D/sales ($b = -0.501$, $p < 0.01$) lower the firm's systematic risk. Following the suggestion of an anonymous reviewer, we re-estimated the proposed model including the square of lagged advertising/sales and the square of lagged R&D/sales to explore non-linear effects. The results were similar to those reported in Column 1 of Table 2 with no significant effect for the squared terms. We discuss this finding in detail in the discussion section. We also re-estimated the model using the interaction effect of lagged advertising and lagged R&D, but find no support for this interaction effect.

Thus, the estimation results strongly support H1 and H2, indicating that after controlling for factors that accounting researchers have shown to affect the firm's systematic risk, increases in both advertising/sales and R&D/sales lower a firm's systematic risk. We next report the results of additional analyses that examine the robustness of the results.

Additional Analyses

Explanatory Power of Proposed Model. We compared the performance of the proposed model, which includes lagged advertising/sales and lagged R&D/sales, with a baseline model that only includes the accounting measures of growth, leverage, liquidity, asset size, dividend payout, and earnings variability, and the two additional control variables of age and competitive intensity (results not reported here). The model with lagged advertising/sales and lagged R&D/sales outperforms the baseline model based on the Schwarz Bayesian Information Criterion (SBC) (lower number indicates superior fit): SBC (proposed model) = 3705.873 versus SBC (baseline model) = 3741.607. The direction and significance level of the coefficients of the BKS variables in this baseline model without lagged advertising/sales and lagged R&D/sales are unchanged confirming that there is no evidence of multicollinearity of lagged advertising/sales and lagged R&D/sales with the control variables.

Alternative Estimates of Systematic Risk. The proposed model reported in Column 1 of Table 2 uses equal-weighted market returns to estimate the firm's systematic risk, β. To examine the robustness of the proposed model's results to alternative specifications for systematic risk, we also estimated beta for the five-year moving window using the value-weighted market returns and obtain generally consistent results for the effects of advertising/sales and R&D/sales on the firm's systematic risk with value-weighted beta estimates (Column 2 of Table 2).

To examine the robustness of the negative effects of advertising/sales and R&D/sales on beta, we expanded the data to include firms for which only 50 of the 60 months of stock returns in a moving window were available for estimating beta. Columns 3 and 4 of Table 2 contain the results of model estimation using equal-weighted and value-weighted measures of market return in the estimation of beta for the expanded sample that includes observations with 50 or more months of stock returns for the 60-month moving window. The effects of advertising/sales and R&D/sales on systematic risk using the larger data set of firms with as few as 50 months of stock returns are similar to those obtained using the smaller data set which includes firms for which all 60 months of stock returns are available to estimate beta.

Changes Regression. Following the suggestion of an anonymous reviewer, we explored the robustness of the results using a changes regression (Boulding and Staelin 1995). We first created the difference value for a variable, as the difference between the variable at time t and at time t-1. The correlation matrix of the differenced variables suggested potential multicollinearity problems, especially between "change in advertising scaled by sales" and "change in R&D scaled to sales," which perhaps is not surprising because increases in R&D are likely to be associated with increases in advertising. To reduce the impact of this multicollinearity, we orthogonalized predictor variables using factor analysis. Varimax rotation ensured that each factor had one and only one predictor variable loading heavily on that factor (variables' loadings on their respective factors exceeded 0.98). We report the results of the changes regression models using difference scores for beta, which we estimated with 60 months of equal-weighted returns using both raw predictor variables and factor-score predictor variables in Column 5 and 6 of Table 2. The results of this estimation indicate that a reasonable model fit and that increases in a firm's lagged advertising/sales and increases in lagged R&D/sales reduce the firm's systematic risk, in support of H1 and H2.[9]

Reverse Causality. As we have noted, the model we estimated considered the impact of the firm's advertising/sales in period t-1 and R&D/sales in period t-1 on systematic risk, β in period t to rule out reverse causation. However, it is possible that either because of inertia (i.e., advertising budgets and R&D budgets are set as a percentage of sales) or because managers are forward looking, advertising and R&D budgets in period t-1 may be related to period t's firm characteristics, particularly, systematic risk.

To rule out reverse causality, we performed the Granger-Causality Wald Tests (Dekimpe and Hanssens 2000; Granger 1969). Specifically, we performed Granger-causality Wald tests for each time series in the data set using a bivariate approach (Leeflang and Wittink 1992) between 1) the firm's systematic risk and its advertising/sales and 2) the firm's systematic risk and its R&D/sales. The results of the Wald tests indicated that a firm's systematic risk did not "Granger cause" either advertising or R&D, empirically ruling out the reverse causality explanation.

In addition, we performed two regressions to rule out potential reverse causality explanations. First, we regressed advertising/sales in time period t as a function of all

[9] We obtain generally similar results for the models using beta computed using value-weighted market returns.

predictor variables in the proposed model *and* beta in time period t-1. Second, we regressed R&D/sales in time period t, as a function of all predictor variables in the proposed model *and* beta in time period t-1. Both models included fixed effects, an auto correlation error term, and window dummies. The results of the regressions (not reported here) indicated that, consistent with the lack of reverse causality established above, beta in time period t-1 does not affect either advertising/sales or R&D/sales in time period t.

Potential Endogeneity of Advertising and R&D. Following the explanation that a firm's managers may be forward looking, we also seek to rule out potential endogeneity explanations of the firm's advertising/sales and R&D/sales. First, we note that our fixed-effects formulation already rules out endogeneity that might be caused by omitted variables. Second, following Boulding and Staelin (1995), we check for endogeneity of lagged advertising/sales and lagged R&D/sales using an instrumental variable estimation procedure.

We use the firm's advertising/sales and R&D/sales in time period t-2 as the instrument for the firm's advertising/sales and R&D/sales in time period t-1 and re-estimate the model relating a firm's 2-period-lagged advertising/sales and R&D/sales to its systematic risk. The results of this instrumental variable estimation procedure (not reported here) are consistent with those obtained with the one-period-lagged predictor variables of advertising/sales and R&D/sales reported for the proposed model in Column 1 of Table 2. Following the instrumental variable estimation, we also performed the Davidson-MacKinnon test (Woolridge 2002; pp. 118-122) of endogeneity for lagged advertising and lagged R&D and find no support for endogeneity of either advertising or R&D.

Alternative Measures of Advertising and R&D. In the results discussed thus far, we scaled both the firm's advertising and R&D expenditures by its sales. Following the suggestion of an anonymous reviewer, we re-estimated the model with measures of the firm's advertising and R&D scaled by its assets. The results (not reported here) using a model identical to the model reported in Column 1 of Table 2 with advertising/sales and R&D/sales replaced by the advertising/assets and R&D/assets respectively indicate a reasonable model fit (F significant at $p < 0.01$). The directionality of the parameter estimates of the predictor variables are consistent with those reported in Column 1 of Table 2 although the significance level changes to $p < 0.05$; advertising/assets ($b = -0.737$, $p < 0.05$) and R&D/assets ($b = -1.024$, $p < 0.05$) lower the firm's systematic risk.

Alternative Measure of Earnings Variability. In addition, following the suggestion of an anonymous reviewer, we re-estimated the model using cash flow variability as a control variable instead of earnings variability used by BKS. Again, the results (not reported here) indicated a reasonable model fit (F significant at $p < 0.01$) with consistent results for the effects of both advertising/sales ($b = -3.509$, $p < 0.01$) and R&D/sales ($b = -0.443$, $p < 0.05$) on systematic risk.

Thus, the results are robust to alternative model specifications, including the regression of differenced variables; alternative measures of systematic risk, including equal-weighted or value-weighted market returns and 60 months or 50 months of returns; alternative measures of advertising and R&D scaled by firm's sales or assets; and earnings variability or cash flow variability. We also empirically rule out reverse causality (i.e., systematic risk lowers advertising and R&D) and endogeneity of both advertising and R&D expenditures. In summary, the additional analyses strengthen our confidence in our key findings that both lagged advertising/sales and lagged R&D/sales lower a firm's systematic risk.

CHAPTER 6: DISCUSSION

The accountability of marketing initiatives, especially as measured by metrics of interest to a firm's shareholders, is under increasing scrutiny from senior management and finance executives who control marketing budgets. Not surprisingly, marketing scholars have turned their attention to relationships between various aspects of a firm's marketing strategy and shareholder value producing a wealth of insights that indicate an important role for marketing in shareholder wealth creation. However, there are few insights relating a firm's marketing initiatives to its systematic risk, an important metric of risk for publicly listed firms. In this paper, we examine the impact of a firm's advertising and R&D, two important manifestations of a firm's marketing strategy on its systematic risk. We conclude with a discussion of the paper's findings, theoretical contributions, managerial implications, limitations, and opportunities for further research.

Theoretical Implications

To our knowledge, this is the first empirical study covering a broad multi-industry sample of firms over a 22-year period to demonstrate that, after controlling for those accounting and finance factors related to systematic risk, increases in advertising/sales and R&D/sales lower a firm's systematic risk. The negative relationship between a firm's advertising expenditure and its systematic risk (shown by Singh et al. (2005) in a limited empirical context and by Madden et al. (2006) without controlling for accounting and finance factors and firms specific effects) holds up for all firms across a long time that extends from 1979 to 2001. By focusing on the firm's systematic risk, an important metric of considerable interest to senior executives of publicly listed firms, we address the several calls for marketing scholars and practitioners to speak in the language of finance (Rust et al. 2004; Srivastava et al. 1998).

The finding of a non-significant effect of the quadratic term for a firm's advertising/sales and R&D/sales on its systematic risk is interesting and merits discussion. We offer two possible explanations for this phenomenon. First, perhaps there are diminishing returns to increased advertising/sales (and R&D/sales) for some range of advertising/sales (and R&D/sales) values, but that advertising/sales (and R&D/sales) values have been constrained well below that optimum, in a range for which that relationship is linear. Such a situation may occur, if firms are wise enough to set advertising/sales (and R&D/sales) for optimal financial returns, and if that optimal financial return level is lower than that required to deliver the lowest beta. Alternatively, the linear effect of advertising/sales may occur because a firm's senior management and finance executives lack the tools to evaluate the potential impact and thus set advertising/sales below levels that yield the lowest systematic risk. A second possible explanation for our inability to detect a quadratic effect when there are diminishing returns to increases in advertising/sales is heterogeneity across firms, industries, and/or time in the relationship between advertising/sales and beta. As finance and accounting researchers have done previously, in interest of generality, we estimate our model with the broadest possible cross-section of firms and industries and for an extended period, which lends confidence to the study's findings. Future research, which explores firm, industry, and/or time specific effects that moderate the effects of advertising on its systematic risk may uncover firms, industries, or periods for which such diminishing returns may be identifiable.

In a departure from most prior studies on systematic risk, β, which have used a silo-based approach (i.e., using only accounting and financial measures), we include accounting, financial, and marketing variables (in this case, advertising and R&D) in our model of systematic risk. The negative impact of advertising/sales and R&D/sales on systematic risk in our model that also includes financial variables suggests potential interchangeability between the firm's marketing and financial choice variables in managing its systematic risk. Future research that examines other such interchangeable effects of other aspects of firms' marketing and financial strategies on metrics of interest to capital markets (e.g. cost of capital, intangible value, stock returns) would be valuable to senior marketing executives who are often under pressure from their senior management teams to justify investments in their advertising and R&D programs.

This study's finding that a firm's advertising/sales and R&D/sales lowers its systematic risk, combined with results from other studies (Mizik and Jacobson 2003; Madden et al. 2006) that show that a firm's advertising increases its stock return, leads to an interesting conjecture. Consistent with the notion that advertising and R&D increase a firm's stock returns, a post hoc analysis indicated that lagged advertising/sales and lagged R&D/sales were highly correlated with the firm's intangible value (ρ(advertising/sales, Tobin's Q)= 0.013, $p < 0.01$); ρ (R&D/sales, Tobin's Q) = 0.283, $p < 0.01$). Specifically, we conjecture that the risk-lowering and return-enhancing effects of advertising and R&D may contribute to the anomaly that Fama and French (1992) identify. Although the capital asset pricing model assumes that firms with higher systematic risk can expect higher future returns, Fama and French find that there is no relationship between a firm's risk in one period and its return in the future. If it is the case that those firms who invest in advertising and R&D have been able to raise their returns while lowering their risk, then one might expect no empirical evidence of the "high risk leads to high return" link. Such an effect would be consistent with the finding in the finance literature that investors prefer highly advertised firms (Grullon et al. 2004) and the finding in the marketing literature that advertising has a direct impact on stock price beyond its indirect effect through increased sales (Joshi and Hanssens 2004). Empirical research that explores this issue further would be valuable and would contribute to both the marketing and the finance literature.

Managerial Implications

The study's findings also generate useful implications for managerial practice. Given the increasing calls for accountability of marketing initiatives, this paper's findings that a firm's higher advertising/sales and R&D/sales lower its systematic risk are novel and useful. Marketing executives can use these findings to stress the multi-faceted role of strong advertising and R&D programs, beyond their effects on market (e.g., sales, market shares) and financial (e.g. return on assets, cash flow) performance outcomes.

Given the dual benefits of advertising and R&D for firm value through effects on both stock returns (Mizik and Jacobson 2003) and systematic risk, firms must be cautious in cutting back on their advertising and R&D programs. A reduction in a firm's advertising or R&D can have a double negative effect, not only reducing its financial performance, attendant cash flows, and stock returns, but also increasing its systematic risk, cost of capital, and discount rate.

We believe the study's findings may surprise senior management and finance executives, some of whom may view their firm's advertising programs and R&D programs as discretionary activities. Indeed, we believe that marketing executives can raise potentially provocative questions about whether extant allocation norms for advertising and R&D (e.g., as a fixed percentage of sales) still apply. Could marketing executives rightfully argue that some proportion of the firm's advertising and R&D budgets be considered a financial expenditure aimed at lowering its interest burden?

Although we are mindful about this paper's limited influence in changing established finance managers' mind-sets about the uncertain returns to their firms' advertising and R&D investments, we hope that this paper serves as an impetus for an ongoing dialog among senior management, finance executives, and marketing executives about the important 'financial' role of their firms' advertising and R&D expenditures (Rust et al. 2004).

Indeed, the study's specific findings can guide marketing executives to initiate a dialogue with their finance counterparts. For example, what are their firm's historical levels of advertising/sales, R&D/sales, and systematic risk, both independently and compared to those of other firms in the industry? What are the implications of advertising and R&D budgets going forward, not only on the firm's marketing objectives (e.g., sales, and market share) and financial objectives, (e.g., cash flows, return on assets) but also on its systematic risk? We anticipate that the answers to these and related questions could guide the development of benchmarks to assess the returns to advertising and R&D programs. Such ongoing dialogues may be very instructive to senior management and finance executives who control advertising and R&D budgets but are skeptical about the financial accountability of returns to these investments.

Limitations and Future Research

Given data availability constraints for publicly listed firms, in this study, we focused on the relationship between a firm's systematic risk and advertising and R&D, two important indicators of the firm's emphasis on differentiation and, therefore, of its marketing strategy. Theoretical research using complementary methods (e.g., in-depth interviews, surveys, field studies) to develop a conceptual model and propositional inventories relating other elements of marketing strategy (e.g., marketing channels) to systematic risk will be useful in setting a research agenda for further empirical research.

Furtheremore, we measured the firm's advertising and R&D using their aggregated, annual dollar amounts scaled by the firm's sales. Although advertising and R&D expenditures are important, especially from the perspective of senior management and finance executives, they represent consolidated input measures, which do not account for differences in implementation of advertising (e.g., creativity of advertising campaigns, efficiency of media planning) and new product development programs (e.g., intellectual property rights, new product success rates, entry timing). Disaggregated measures of a firm's advertising and R&D programs for all publicly listed firms are not available. Further research that focuses on a few industry contexts and uses disaggregated measures of the various elements of advertising programs and new product development programs, including aspects of the programs' effectiveness, could provide a useful extension to generate actionable managerial implications regarding the effects of various elements of a firm's advertising and new product development program on its systematic risk.

In summary, we view this study as an important first step in establishing that advertising and R&D lower systematic risk of the firm's stock. We hope that the study's findings stimulate further work in this area.

ESSAY 2: A FUNDAMENTAL SIGNAL FROM ADVERTISING: ANALYST UNDER-REACTION

CHAPTER 7: INTRODUCTION

The market-based assets theory indicates that marketing expenditures and resulting marketing intangibles (e.g., brand equity) enhance firm value by increasing future cash flows and reducing the financial risk of a firm (Srivastava et al. 1998, 1999). Previous empirical studies have revealed significant links between marketing expenditure, brand equity, and stock returns (Hirschey and Weygandt 1985; Chauvin and Hirschey 1993; Barth et al. 1998; Graham and Frankenberger 2000; Aaker and Jacobson 2001; Mizik and Jacobson 2003; Pauwels et al. 2004; Srinivasan et al. 2006, working paper; Joshi and Hanssens 2005, working paper; McAlister et al. 2007). An important motivation behind those studies comes from the observation that senior management does not pay enough attention to marketing numbers, and it may even be the case that financial experts ignore the impact of marketing on firm value (Ambler 2000, 2003). While the fact that marketing impacts firm value has been empirically shown, the notion that marketing is ignored by top management and financial experts comes from ad hoc surveys and anecdotal evidence (Ambler 2003; IPA report 2005; Quelch and McGovern 2006). There has been no empirical study of the impact of marketing numbers that considers both the reaction of the financial experts and the reaction of capital markets. In this paper we do just that.

We propose a "fundamental signal from advertising," an accounting-based advertising signal that stock market participants might perceive as a driver of firm value. We structure the advertising signal in a way that is consistent with the structure of measures that financial analysts are reported to use and that investors are advised to use in the analysis of financial statements (Lev and Thiagarajan 1993). We examine the market's and financial analysts' responses to the proposed advertising signal to determine whether the market reacts to this advertising signal and whether financial analysts appreciate and incorporate this signal in their earnings[10] forecasts. Based on this empirical test, we offer the proposed advertising signal as a marketing metric, which should be of interest to senior management and to financial analysts.

This paper proceeds as follows. In the next section, we propose a fundamental signal from advertising and introduce our measures of "market reaction" and "financial analysts' reaction" typically used in the finance and accounting literature. We develop hypotheses regarding the impact, or lack thereof, of the proposed signal on "market reaction" and "analysts' reactions." We describe the method used to test the hypotheses and provide the empirical results. We conclude with a discussion of the implications of this work for managers and for researchers.

[10] Throughout the paper, 'earnings' means earnings per share, which is net income (after tax) minus dividends paid, divided by the number of shares outstanding.

A Fundamental Signal from Advertising (S_{ADV})

Fundamental analysis is a method of security valuation that involves examining a firm's sales, earnings, growth potential, assets, expenses, etc. (investorwords.com). Fundamental analysis is an important and basic tool that investors use to assess a firm's financial health as they look for under- and over- valued stocks. After reviewing analysts' reports and commentaries on financial statements in the context of such analysis, Lev and Thiagarajan (1993) constructed a set of measures to reflect those financial situations that seemed to cause analysts to change their forecasts of a firm's future earnings. They called the constructed predictor variables "fundamental signals" and tested whether the impact of these fundamental signals were associated with stock returns. In other words, they examined whether these signals were *value-relevant*, that is, whether the accounting numbers have a significant impact on stock market values (Holthausen and Watts 2001).

Specifically, Lev and Thiagarajan (1993) proposed that an accounting predictor variable, X, be included in a form related to ΔX, where ΔX is defined as $(X - \overline{X})/\overline{X}$, where $\overline{X}$ is the average of the previous two years' observations of X. The precise form for the fundamental signal based on accounting number X is ΔX - ΔSales. A positive value for one of Lev and Thiagarajan's (1993) fundamental signals (i.e., fundamental signals related to inventory, accounts receivable, gross margin, or SG&A) suggests potential problems at the firm, lowering expected firm value and hence lowering analysts' forecasts for future earnings.[11] Several accounting studies have demonstrated that these fundamental signals are significantly related to firm value (Abarbanell and Bushee 1997, 1998; Amir, Lev, and Sougiannis 2003; Covrig and Low 2005) after accounting for reported earnings. The findings have been interpreted to indicate that, in establishing firm value, the stock market goes beyond consideration of reported earnings to use these fundamental signals to assess the "quality of the earnings."

Perhaps surprisingly, none of these studies included a fundamental signal related to "advertising."[12] The closest these models typically come to including advertising as a force that shapes firm value is to include SG&A (which includes advertising) as a shaping force.

In this study, we introduce a fundamental signal related to advertising (S_{ADV}), which is measured as ΔSales - ΔAdvertising. When this quantity is positive, sales are increasing faster than advertising; when negative, sales are increasing slower than advertising. We suggest S_{ADV} as a signal which the stock market recognizes as an important value driver while financial analysts might depreciate in their earnings forecasts. We discuss why the two parties' amount of attention to S_{ADV} can be different in the 'hypotheses' section.

Structure of Fundamental Signals. Lev and Thiagarajan (1993) give the fundamental signals their specific functional form because they need the signals to represent the *unexpected* change in the underlying variables. The need to use unexpected

[11] The structure for the fundamental signal of gross margin (GM) is ΔSales - ΔGM.
[12] In this paper, we define "advertising" as publicly reported "Advertising Expense," DATA45 in COMPUSTAT, which includes the cost of advertising media (radio, television, newspapers, and periodicals) and promotion expenses, but excludes selling and other marketing expenses. (COMPUSTAT User's Guide)

change arises from the efficient market hypothesis, which underlies virtually all capital market research in finance and accounting (Kothari 2001; Lee 2001). That hypothesis holds that a firm's current stock price reflects the market's expectations about all future cash flows for that firm. Given this hypothesis, revelation of any information that is consistent with the market's current expectations will have no impact on a firm's stock price. It is only the revelation of information that is inconsistent with current expectations that will change a firm's stock price.

Thus, the efficient market hypothesis holds that a firm's current stock price reflects the market's beliefs about the values that accounting variables will take in all future periods. When one of those accounting variables takes on an *unexpected* value, stock price changes. The written pronouncements of analysts (e.g., *Quality of Earnings Report* on Harris Corporation 1989) referenced by Lev and Thiagarajan (1993) reveal that analysts expect several accounting variables (inventory, accounts receivable, gross margin, and SG&A) to change at the same rate as sales (i.e., analysts expect the percent change in an accounting predictor variable, ΔX, to be equal to the percentage change in sales, $\Delta Sales$). Only a disproportionate (to sales) percentage change in X will surprise analysts and, consequently, change those analysts' forecasts. Hence, Lev and Thiagarajan (1993) define ΔX - $\Delta Sales$ to be a fundamental signal. In this paper, we use this structure identified by Lev and Thiagarajan (1993) for the fundamental signals of accounting predictor variables (i.e., fundamental signals of inventory, accounts receivable, gross margin, and SG&A) and for the proposed fundamental signal from advertising, S_{ADV}.

Firm Value and Analysts' Expectation of Firm Value. Following the tradition in accounting and finance, we represent firm value by CAR (cumulative abnormal stock returns) calculated with monthly stock returns reported by CRSP (Center for Research in Security Prices), we represent analysts' forecasts of firm value by PVE, the present value of consensus analysts' forecasts of earnings for five years into the future from I/B/E/S (Institutional Brokers' Estimate System).

CHAPTER 8: HYPOTHESES

Is S_{ADV} Value-Relevant?

For the construct of S_{ADV}, we use advertising expenditures and sales aggregated over a year and across markets that the firm has served. Implicit in accountants' model of fundamental signals is our assumption that accounting variables (like inventory, accounts receivable, etc.) scale with sales. That is, an accounting variable is assumed to change at the same rate that sales change. Translating this logic to the accounting measure "advertising," the percentage change of sales (ΔSales) is the *expected* percentage change of advertising (ΔAdvertising).

In particular, given that ΔAdvertising is positive, a positive S_{ADV} (ΔSales > ΔAdvertising > 0) may occur *either* (1) when the firm managed their firm-level advertising expenditures effectively *or* (2) when growth potential for a market tapped by the firm looms larger than expected, *or both*. When ΔAdvertising is negative, a positive S_{ADV} (ΔSales > ΔAdvertising, and ΔAdvertising < 0) occurs when sales fall at a slower rate than advertising. In that case, a positive S_{ADV} is consistent with the firm's accumulated brand equity causing sales to fall at a slower rate than advertising. Presumably stock investors interpret a positive S_{ADV} in these ways. With the two possible presumptions, we hypothesize that a positive S_{ADV} is related to stock returns positively.

First, a temporal improvement of advertising effectiveness, as the underlying cause of a positive S_{ADV}, has been shown to be associated with stock prices theoretically and empirically. The resource-based view of the firm posits that improvement in a firm's capability to translate marketing inputs (such as advertising) into outputs will lead to higher firm value (Wernerfelt 1984; Dutta et al. 1999). Empirically, prior marketing studies have shown that a firm's marketing capabilities are associated with firm value (Dutta et al. 1999; Mittal et al. 2005; Luo and Donthu 2006). Dutta et al. (1999) measured marketing, R&D, and operational capabilities of a firm using stochastic frontier estimation model (SFE) and found that their measure of marketing capability was significantly associated with firms' profits and Tobin's Qs. Mittal et al. (2005) measured a firm's marketing inefficiency in creating consumer satisfaction using data envelope analysis (DEA) and found that a dual emphasis on marketing efficiency and the level of marketing expenditure led to higher firm value. Luo and Donthu (2006) measured marketing communication productivity (MCP) by applying DEA and found that MCP had an inverted-U relationship with Tobin's Q and stock return.

These findings, which link measures of marketing effectiveness (or marketing communication effectiveness) and firm value, are intriguing. Unfortunately, measures estimated with SFE and DEA are not easily accessible to most investors, suggesting the importance of finding a signal of advertising effectiveness that *is* readily available. Since S_{ADV} has been structured to be easily accessible to market participants, we expect that S_{ADV}, as a measure of advertising effectiveness, is positively associated with firm value.

Second, another potential cause of a positive S_{ADV} is a strong upward spike in aggregated sales at the year when S_{ADV} is measured. In this case, the stock market might construe a positive S_{ADV} as a signal for either the firm's successful entry into untouched markets or sales takeoff of the firm's innovative products. In both scenarios, the stock market is likely to consider a positive S_{ADV} as the value relevant information.

Therefore, although more information is required to figure out the main determinant of a firm's S_{ADV}, based on the aforementioned presumptions about stock market's interpretations of a positive S_{ADV}, we hypothesize that a positive S_{ADV} is positively related to CAR.

H1: Higher levels of S_{ADV} are associated with higher levels of the annual cumulative abnormal stock returns (CAR).

Analysts' Earnings Forecasts and their Inefficiency

It is generally accepted that analysts' earnings forecasts provide an important input to stock market participants (Loh and Mian 2003; Cheng 2005). This link between analysts' earnings forecasts and market reactions has been well-established (e.g., Abdel-khalik 1982; Brown, Foster, and Noreen 1985). Accordingly, models of stock return include analysts' earnings forecasts as a predictor variable (Cheng 2005). However, accounting studies have shown that analysts' forecasts do not fully incorporate all information to which the market reacts (e.g., Abarbanell and Bernard 1992; Abarbanell and Bushee 1997; Kim et al. 2001; Amir et al. 2003; Cheng 2005). In particular, findings reveal that analysts are inefficient in their incorporation of the fundamentals signals, and that this inefficiency results in forecast errors. These studies implicitly warn investors to be cautious when using analysts' reports and suggest that investors may benefit from performing their own analyses of financial statements even when analysts' reports are available.

Intangibles and Error/Dispersion in Analysts' Forecasts. Although there is no published evidence that the level of consensus analysts' forecasts is impacted by advertising, some literature has considered the possibility that the dispersion of analysts' forecasts may be impacted by advertising or other marketing-related measures.

Taking SG&A as a proxy for marketing, Kwon (2002) asked whether SG&A (scaled by sales) and/or R&D (scaled by assets) affect forecast dispersion for low-tech firms and for high-tech firms. The study showed that only R&D significantly increased forecast dispersion and that those effects held only for the sample of high-tech firms. Kwon (2002) interpreted the finding as suggesting a *noise effect* for intangibles: Higher intangibles created by R&D make future earnings of high-tech firms less predictable. Barron et al. (2002) showed that both advertising and R&D (each scaled by total operating expense) increased the dispersion of analysts' forecasts in a much broader sample that included 1,103 firm-year observations across industries. They argue that analysts who believe that advertising and R&D create an asset will seek private information in order to assess the value of that asset. If these analysts tap different information sources, they might arrive at different forecasts, hence increasing forecast dispersion.

On the other hand, Srinivasan (2007, working paper) hypothesized that higher levels of advertising and R&D (each scaled by sales) will lower forecast dispersion because higher advertising and R&D will increase analysts' attention. This study found that, for successful firms (*Fortune 300*), higher levels of advertising spending and/or R&D spending are, in fact, associated with lower forecast dispersion.

Given the conflicting results, further research is warranted. However, the question of whether advertising increases or decreases forecast dispersion is beyond the scope of this paper. In this paper, we are concerned with the impact of advertising on the *level* of consensus analysts' forecasts.

Is S_{ADV} Incorporated in Analysts' Future Earnings Forecasts?

Accounting can be viewed as a "language" that may predispose users of financial information to a given model of perception and behavior (Belkaoui 1978, 1980). Literature that takes this perspective considers a financial statement user's "vocabulary" to be the set of accounting numbers[13] that the user has learned to employ in his/her analysis of a firm's financial performance. This literature suggests that an analyst who works with and understands the accounting vocabulary associated with a particular industry will more accurately value firms in that industry. This "accounting vocabulary" is analogous to the "consumption vocabulary" in the consumer behavior literature, which is hypothesized to govern the quality of a consumer's evaluation of choice alternatives (West, Brown, and Hoch 1996). As a consumer's vocabulary "grows" (i.e., as the consumer develops an understanding of additional variables important in the evaluation of choice alternatives), that consumer's evaluations become more accurate. From these

[13] Accounting numbers should be understood to include specific numbers from financial reports and functions (such as ratios) of those numbers.

two literatures, we infer that analysts who have not developed an understanding of the ways in which advertising enhances firm value (i.e., analysts who do not have the advertising-firm value link in their vocabularies) will be unlikely to pick up on advertising's value-enhancing impact on firm value.

To consider the advertising-firm value vocabulary analysts are taught during their business school training, we examined 11 Corporate Finance, Security Valuation, and Financial Statement Analysis textbooks published between 1986 and 2007.[14] Specifically, we scanned these texts for discussion of the link between advertising and firm value. While most of these text books discuss no specific link between advertising and firm value, most do link SG&A (which includes advertising) to firm value. In every case, these links are assumed to be negative—higher SG&A expense is taken as a signal of inadequate cost control and is, therefore, expected to lower firm value. Among the texts, only three of them (Hawkins 1986; Siegel 1991; Bernstein and Wild 2000) suggest that one go beyond the consideration of SG&A to investigate an independent impact for advertising. These books also suggest that reducing advertising is not always positively related to firm value. Siegel (1991) advocates reducing advertising only when the reduction is designed to eliminate waste or inefficiency. Bernstein and Wild (2000) suggest that advertising has effects on firm value beyond the current period, hence reduction of advertising can harm future cash flows and hence firm value.

[14] We reviewed the texts in corporate finance from Hawkins (1986), Rob (2007), Ross, Westerfield, Jaffe, and Jordan (2007), and texts in financial statement analysis from Foster (1986), Siegal (1991), Bernstein and Wild (2000). We also reviewed practical textbooks specifically focusing on stock valuation (Cornell 1993, Guatri 1994, Ferris and Petitt 2002, Hoover 2006, Stowe, Robinson, Pinto, and McLeavey 2007).

In addition to finance and accounting textbooks' relative silence regarding advertising's role in creating firm value, surveys report that senior management does not regularly track or report marketing and/or advertising information to the board of directors (Ambler 2003; Quelch and McGovern 2006). Consistent with the fact that analysts are not likely to have heard from textbooks or from senior management that advertising is a creator of firm value, an IPA survey of analysts (2005 UK) found that only 6 percent of surveyed analysts reported using publicly reported advertising spending when they construct their earnings forecasts. Finally, recall that Lev and Thiagarajan's (1993) study of analysts' reports and commentaries found that advertising was not among the signals that analysts found important in determining firm value.

Beyond the fact that analysts are not likely to have learned that advertising is a creator of firm value and the fact that analysts do not report using advertising when they assess firm value, the literature shows that analysts do not even fully impound those accounting signals that they have been taught to use and that they do report using. Abarbanell and Bushee (1997) tested the effects of the Lev-and-Thiagarajan-identified fundamental accounting signals on analysts' future earnings forecasts. They found that, relative to the reaction to those signals by the capital market, financial analysts' one-year-ahead earnings forecasts reflected an under-reaction to fundamental signals. Recently, Cheng (2005) confirmed that analysts under-react to, or ignore, some fundamental signals.

In summary, finance and accounting textbooks we reviewed make almost no mention of the possibility that advertising might enhance firm value. Typically, these texts leave students to draw inferences about the relationship between advertising and firm value based on what is taught about the relationship between SG&A (which includes advertising) and firm value. We conclude that the most likely inference to be drawn is that advertising is an expense to be controlled, not a creator of firm value. Combining this with analyst's silence about the relationship between advertising and firm value, and with the fact that analysts may not fully impound even those variables they do believe to be related to firm value, we should not expect that financial analysts will consider the impact of advertising when they predict future firm value:

H2: The level of S_{ADV} is not related to analysts' estimate of a firm's value (PVE).

If the market reacts to S_{ADV} (H1) but analysts do not (H2), we should expect the errors in analysts' earnings forecasts to be related to S_{ADV}. Our third hypothesis is, then:

H3: The level of S_{ADV} is associated with the level of error in analysts' next-year forecasts (FERR).

As pointed out when we defined PVE, convention in the valuation literature leads us to calculate PVE over a five-year time window. Convention in the forecast error literature, however, leads us to calculate forecast error using a one-year time window (e.g., Abarbanell and Bushee 1997). That is, FERR is calculated as next year's actual earnings minus the consensus analysts' forecast for next year's earnings. (Perhaps a shorter time window is thought to provide a fairer test of analysts' forecasting abilities.) To be sure that one-year relationships do not differ from the five-year relationships, we develop two sub-hypotheses related to H3. We ask, in H3-a), whether S_{ADV} is related to next year's earnings as one would expect based on the logic supporting H1, and in H3-b), whether S_{ADV} is *not* related to next-year earnings forecasts as one would expect based on the logic supporting H2:

H3-a): The level of S_{ADV} is associated with the level of next year's actual earnings (AEPS).

H3-b): The level of S_{ADV} is not associated with the level of analysts' next-year earnings forecasts (FEPS).

CHAPTER 9: DEFINITIONS OF VARIABLES

The primary purpose of our study is to examine the impact of a fundamental signal from advertising (S_{ADV}) on (1) analysts' forecasts of firm value and on (2) firm value as revealed in the market. Adapting Amir et al. (2003), we address the first of these research questions by modeling analysts' forecasts as a function of S_{ADV} and traditional accounting and finance control and predictor variables. We address the second research question by modeling firm value as a function of S_{ADV} and the same control and predictor variables. In this section, we define the important variables used in the models to address our research questions.

Firm Value: Annual Cumulative Abnormal Stock Returns (CAR)

Finance and accounting scholars often model a firm's value in terms of the return that the firm's stock provides to investors. To understand the value of fundamental signals, accounting researchers ask whether the unexpected change in some predictor variable (reported in a fundamental signal) is associated with "abnormal returns," which are *actual* minus *expected* returns (Lev and Thiagarajan 1993; Abarbanell and Bushee 1997; Amir et al. 2003). Because information flows into the market continuously, abnormal returns are typically calculated monthly and then summed across the months of a year to yield the stock's "cumulative abnormal return," or CAR.

Actual monthly return for a stock i in month t is $R_{it} = \ln\left[\frac{D_{it} + P_{it}}{P_{it-1}}\right]$, where D_{it} is cash dividend payable on common stock i in month t, P_{it} is closing price of common stock i at end of month t, and P_{it-1} is closing price at the end of month t-1, adjusted for capital changes such as stock splits and stock dividends. For the *expected* return for a stock at the end of month t, we apply the three factor model of Fama and French (1993)[15] using 60 *ex post* historical monthly returns. We use the predicted return ($\overline{R_{it}}$) from that model as the "expected return" (see Appendix F for the details). Abnormal return (AR_{it}) for stock i during month t becomes actual minus expected return (i.e., $AR_{it} = R_{it} - \overline{R_{it}}$), and the stock's CAR is the sum of the monthly abnormal stock returns (AR_{it}) across the months of a year.[16] In the rest of the paper, when we use the term "firm value," we will be referring to CAR, the measure typically used by accounting and finance researchers in this context.

Analysts' Expectation of Firm Value: Present Value of Earnings Forecasts (PVE)

Analysts are financial experts who estimate a firm's future earnings and provide those estimates to the stock market. Investors assess stock value on the basis of a firm's expected future earnings, frequently referring to analysts' estimates of those future

[15] We also calculated expected stock returns using the traditional CAPM (Sharpe 1964) and found results consistent with the results from the three factor model that we present in this paper.
[16] Based on a suggestion by Dr. Clement, one of the committee members, I also calculated 'firm value' as the sum of monthly abnormal stock returns between a fiscal-year end and four months after the fiscal-year end and found results consistent with the results from the model using 12-month CAR.

earnings (for example, see Kothari 2002). Thus, analysts' earnings forecasts are important inputs to investment decisions and their consequence, stock returns (Schipper 1991).

A consensus analysts' forecast is the average or median of earnings forecasts from all analysts covering a particular firm. Since a stock's price is the discounted sum of expected future cash flows, the discounted sum of five years of consensus earnings forecasts is a good proxy for financial analysts' estimate of firm value (Frankel and Lee 1998; Amir et al. 2003). We will refer to this discounted sum of consensus earnings forecasts as the present value of future earnings forecasts, PVE. [17]

Traditional Accounting and Finance Control Variables in Models of Firm Value (CAR) and Analysts' Forecasts (PVE)

Accounting scholars studying the drivers of analysts' forecasts and drivers of firm value have included several important control variables. The most obvious of those controls for CAR and PVE is earnings per share (EPS). The change in a firm's effective tax rate (ETR) is another control for CAR and PVE presented in the literature (Lev and Thiagarajan 1993; Abarbanell and Bushee 1997; Amir et al. 2003). Finally, Amir et al. (2003) proposed one-year-lagged firm value (L_CAR) as a control for CAR. Thus, we include EPS and ETR as control variables in our model of PVE, and we include EPS, ETR, and L_CAR as control variables in our model of CAR.

[17] The details of how to measure PVE and all other important variables in this paper are presented in the Appendix D, E, and F.

“Fundamental Signals” Predictor Variables Identified by Lev and Thiagarajan (1993)

Lev and Thiagarajan (1993) introduced fundamental accounting signals (structured as described in the introduction) and showed that these fundamental signals were significant predictors of firm value (CAR). Amir et al. (2003) found these fundamental signals to be significant predictors of analysts’ forecasts (PVE) in addition to being predictors of firm value. Following this research tradition, we include Lev and Thiagarajan’s (1993) fundamental signals as predictor variables in our models of firm value and analysts’ forecasts. Those fundamental signals are:

S_{INV} = ΔINV - ΔSales. A positive value for this indicator (implying that a firm’s inventory is growing faster than its sales) is assumed to be a signal that the firm is having difficulty generating sales.

S_{AR} = ΔAR - ΔSales. A positive value for this indicator (implying that a firm’s accounts receivable are growing faster than its sales) is assumed to be a signal that the firm is having difficulty selling its products and must, therefore, extend its credit terms.

S_{GM} = ΔSales - ΔGM. A positive value for this indicator (implying that a firm’s sales are growing faster than its gross margin) is assumed to indicate inefficiency in operating cost controls.

$S_{SG\&A}$ =ΔSG&A - ΔSales. A positive value for this indicator (implying that the firm’s SG&A is growing faster than its sales) is assumed to imply a loss of managerial control over general expenses.

A firm with a positive value for any of these fundamental signals is expected to be evaluated as less valuable by analysts and the market.

Relationship between $S_{SG\&A}$ and S_{ADV}. Our focal variable, S_{ADV}, is embedded in $S_{SG\&A}$ since SG&A (DATA189) includes advertising expense (DATA45) according to the definition of the SG&A in the COMPUSTAT User's Guide. Defining Partial SG&A (PSG&A) as SG&A minus Advertising, we replace $S_{SG\&A}$ with S_{ADV} and $S_{PSG\&A}$, where $S_{PSG\&A}$ is the percentage change in partial SG&A minus the percentage change in sales. This breakup of $S_{SG\&A}$ into $S_{PSG\&A}$ and S_{ADV} could pose at least two problems for our models. First, if advertising expense were the primary driver of variation in SG&A, then removal of advertising from SG&A might leave $S_{PSG\&A}$ as a poor indicator of that loss of managerial control that Lev and Thiagarajan (1993) proposed $S_{SG\&A}$ would capture. Second, if advertising spending were highly correlated with other costs captured in SG&A, then the two new variables (S_{ADV} and $S_{PSG\&A}$) would be highly correlated, and interpretation of those variables' parameter estimates would be clouded by problems of multicollinearity.

We address these concerns by considering correlations. Rather than consider simple correlations, though, we first account for the unbalanced panel structure of the data and calculate "adjusted" correlations.[18] We find that the adjusted correlation between $S_{SG\&A}$ and S_{ADV} is -0.17 and the adjusted correlation between $S_{SG\&A}$ and $S_{PSG\&A}$ is 0.61, indicating that the variation in SG&A is not driven primarily by advertising spending and further indicating that $S_{PSG\&A}$ is a reasonable proxy for $S_{SG\&A}$. We also find

[18] See *'Empirical Estimation and Results'* section and Table 3 for a more complete explanation of these adjusted correlations.

that the correlation between S_{ADV} and $S_{PSG\&A}$ is -0.06, indicating that the two variables move almost independently and that the relationship between these two variables will not hamper interpretation of their parameter estimates.

Given the above, predictor variables for both our model of firm value (CAR) and our model of analysts' forecasts (PVE) will be S_{INV}, S_{AR}, S_{GM}, $S_{PSG\&A}$, and S_{ADV}.

CHAPTER 10: MODEL DEVELOPMENT

Lev and Thiagarajan (1993) constructed the fundamental signals from publicly reported accounting information to demonstrate that this information provides insights into firm value, CAR. Abarbanell and Bushee (1997) and Amir et al. (2003) confirmed the significance of the fundamental signals as predictors of CAR, and Amir et al. (2003) went on to demonstrate that these fundamental signals are also significant predictors of analysts' forecasts. Further, Amir et al. (2003) added PVE as a predictor variable in their model of CAR to estimate the incremental contribution of analysts' forecasts beyond accounting information in explaining CAR. Likewise, they added CAR as a predictor of PVE, since financial analysts may learn from stock investors and adjust their forecasts based on changes in stock prices (Abarbanell 1991). To address potential endogeneity between CAR and PVE, we applied two-stage least square estimation (2SLS) models with instruments.

If, as hypothesized, the market responds to S_{ADV} but analysts do not, then we would expect errors in analysts' forecasts to be related to S_{ADV}. To address this question, we follow previous accounting studies on analysts' forecast errors, defining forecast error (FERR) as "actual" earnings for the next year minus the forecasts for those earnings. Our model tests the impact of S_{ADV} on FERR, using accounting and finance variables shown to be related to FERR, fundamental signals, and year dummies as control variables (Albrecht et al. 1997; Brown et al. 1987; Abarbanell and Bushee 1997; Amir et al. 2003). Because forecast error models conventionally consider a one-year time horizon, while

CAR and PVE models consider a five-year time horizon, we estimate models to confirm that the relationship between FERR and S_{ADV} is the result of S_{ADV} impacting actual earnings (AEPS) but not earnings forecasts (FEPS).

CAR and PVE Models: Fixed-Effects Two Stage Least Square Estimation (FE-2SLS) Model

Accepting the contention that PVE and CAR need to be included in the models of CAR and PVE, respectively, we build from Amir et al.'s (2003) 2SLS models to test Hypotheses H1 and H2. PVE is an endogenous variable in the model for CAR, and CAR is an endogenous variable in the model of PVE. We treat S_{ADV}, the fundamental signal predictor variables, and the accounting and finance control variables as exogenous variables.

Instruments. To deal with potential endogeneity between CAR and PVE, our models need instruments that will be included during first-stage analyses but will not be included during second-stage analyses. Instruments in Amir et al. (2003) include firm size (SIZE), book-to-market ratio (BTM), one-year-lagged PVE (L_PVE), one-year-lagged CAR (L_CAR),[19] one-year-lagged EPS (L_EPS), and year dummies. Following Amir et al. (2003), we use all of these variables as instruments during first stage analysis of the model for CAR, and use all of these variables except L_CAR as instruments during first-stage analysis of the model for PVE.

[19] L_CAR was used as an instrument in the model of PVE and as a control variable in the model of CAR.

Models. In the first-stage analysis of the model for CAR, we estimate the reduced-form equation for PVE (a variable endogenous to CAR) as a function of exogenous variables (S_{ADV}, fundamental signal predictors, and control variables) and the instruments specified by Amir et al. (2003). In the second-stage analysis of the model for CAR, we estimate the structural equation for CAR as a function of exogenous variables from first-stage analysis and predicted PVE from first-stage analysis ($\overline{\overline{PVE}}$), which has been constructed to also be exogenous.

Similarly, in the first-stage analysis of the model for PVE, we estimate the reduced-form equation for CAR (a variable endogenous to PVE) as a function of exogenous variables (S_{ADV}, fundamental signals, and control variables) and the instruments specified by Amir et al. (2003). In the second-stage analysis of the model for PVE, we estimate the structural equation for PVE with the exogenous variables from the first-stage analysis and with predicted CAR from the first-stage analysis ($\overline{\overline{CAR}}$), which has been constructed to also be exogenous.

Since our data is an unbalanced panel with repeated observations for a firm (Baltagi and Wu 1999; Bhargava, Franzini, and Narendranathan 1982; Wooldridge 2002), we adapt Amir et al.'s (2003) procedure by including firm-specific fixed effects and allow an AR(1) correction of errors at each stage of the 2SLS model. Thus, our fixed-effects two-stage least square estimation (FE-2SLS) models have the following structures:

(1) 1st stage model for CAR: $PVE_{it} = \alpha + X'_{it}\beta + \nu_{1i} + \varepsilon_{1it}$

(2) 2nd stage model for CAR: $CAR_{it} = \alpha + X_{it}\beta + \overline{\overline{PVE}}_{it}\gamma + \nu_{2i} + \varepsilon_{2it}$

(3) 1st stage model for PVE: $CAR_{it} = \alpha + Y'_{it}\beta + \nu_{3i} + \varepsilon_{3it}$

(4) 2nd stage model for PVE: $PVE_{it} = \alpha + Y_{it}\beta + \overline{\overline{CAR}}_{it}\gamma + \nu_{4i} + \varepsilon_{4it}$

where

$i = 1,..,N; t = 1,..,T_i$;

X'_{it}, Y'_{it} = S_{ADV}, S_{INV}, S_{AR}, S_{GM}, $S_{PSG\&A}$, ETR, EPS, L_CAR, BTM, SIZE, L_PVE, L_EPS, year dummies;

X_{it} = S_{ADV}, S_{INV}, S_{AR}, S_{GM}, $S_{PSG\&A}$, ETR, EPS;

Y_{it} = S_{ADV}, S_{INV}, S_{AR}, S_{GM}, $S_{PSG\&A}$, ETR, EPS, L_CAR;

ν_{ji} (j = 1,2,3,4) = fixed-effects for a firm i, which may be correlated with $X'_{it}, Y'_{it}, X_{it}, Y_{it}$;

$\varepsilon_{jit} = \rho\varepsilon_{jit-1} + \eta_{jit}$ (j = 1,2,3,4, $|\rho| < 1$, η_{jit} ~ i.i.d. $N(0, \sigma^2_\eta)$);

$\overline{\overline{PVE}}$ = instrumental variable for PVE, predicted in the first-stage model (1);

$\overline{\overline{CAR}}$ = instrumental variable for CAR, predicted in the first-stage model (3).

CAR and PVE Models: Reduced-form Fixed-Effects Regression Model

We borrowed the instruments from Amir et al. (2003), assuming that those instruments are uncorrelated with errors in the structural equations for CAR and PVE, and are partially correlated with the endogenous variables, PVE and CAR (Wooldridge 2002). However, if pre-specified exogenous variables explain a much larger portion of the variation of the endogenous variable than do the instruments in the reduced-from equations 1 and 3, then the predicted instrumental variables, $\overline{\overline{PVE}}$ and $\overline{\overline{CAR}}$, may cause a multicollinearity problem in the second-stage models (equations 2 and 4). A high degree of multicollinearity between a predicted instrumental variable and the remaining exogenous variables in the second-stage model would increase the asymptotic variances of the FE-2SLS estimators, making the coefficients for our exogenous variables less significant, possibly masking a significant relationship between S_{ADV} and PVE (Wooldridge 2002).

Due to this potential threat, we propose the reduced-form equations for PVE and CAR (equations 1 and 3) as an alternative way to investigate the relationship between S_{ADV} and PVE and the relationship between S_{ADV} and CAR. S_{ADV}'s coefficient in the reduced-form equation will not be affected by the potential multicollinearity in the second-stage analysis just discussed. Hence, consideration of the sign and significance of the coefficients for S_{ADV} in the reduced-form models provides a robustness check on the tests of our hypotheses.

Forecast Error (FERR) Model

Prior studies have shown that analysts often issue biased earnings forecasts (O'Brien 1988; Mendenhall 1991), and that they under- or over-react to publicly available information, lowering the accuracy of earnings forecasts (DeBondt et al. 1990; Abarbanell and Bernard 1992). Abarbanell and Bushee (1997) showed that annual earnings change (d_EPS, which is $(EPS_t - EPS_{t-1})/P_{t-1}$) and some of the fundamental signals described earlier in this paper are associated with forecast error. Amir et al. (2003) found that analysts' failure to account for firms' R&D intensity (PRND) increased forecast error. Because earnings forecasts will be more precise when a firm's actual earnings are stable over time, previous accounting studies (Albrecht et al. 1977; Brown et al. 1987; Amir et al. 2003) have included firm size (SIZE: larger firms should have more stable earnings), firm age (AGE: older firms should have more stable earnings), and earnings variability (EAR_VAR), as predictor variables in models of forecast error.

Definitions of Variables and Forecast Error Models. We examine the effects of S_{ADV} on the quality of analysts' next-period earnings forecasts by regressing forecast error (FERR) on S_{ADV} and the control variables considered in accounting studies of forecast error: fundamental signal predictor variables, d_EPS, PRND, SIZE, AGE, and EAR_VAR.

Since our data are an unbalanced panel with repeated observations, our fixed-effects formulation allows for AR(1) specification of errors:

(5) Forecast error model: $FERR_{it} = \alpha + X_{it}\beta + AdEff_{it}\theta + v_i + \varepsilon_{it}$

where,

$i = 1,....,N; t = 1,....,T_i$;

X_{it} = S_{INV}, S_{AR}, S_{GM}, $S_{PSG\&A}$, ETR, d_EPS, SIZE, EAR_VAR, PRND, AGE, year dummies;

v_i = fixed-effects for a firm i, which may be correlated with X_{it} ;

$\varepsilon_{it} = \rho\varepsilon_{it-1} + \eta_{it}$ ($|\rho| < 1$, η_{it} ~ i.i.d. $N(0, \sigma_\eta^2)$).

CHAPTER 11: ESTIMATION AND RESULTS

Data

The data for our study come from COMPUSTAT, CRSP, and I/B/E/S for 1982 to 2000. From COMPUSTAT, we collected all the items necessary to calculate our focal variable (S_{ADV}), fundamental signal predictor variables, control variables, and instruments. For CAR and PVE models, we retrieved 60 monthly stock returns from CRSP to calculate CAR and the systematic risk of a firm, β. From I/B/E/S, we took consensus analysts' forecasts of earnings for five years into the future to calculate a firm's PVE. For the forecast error model, we took next year's actual earnings from COMPUSTAT and next year's consensus earnings forecast from I/B/E/S.

The dataset used to estimate our CAR and PVE models includes 8,232 firm-year observations for 1,739 firms. The sample includes approximately 500 firms per year from 1982 to 1993, and approximately 350 firms per year from 1994 to 2000. This decline of sample size beginning in 1994 occurred because of missing observations for advertising expenditure (DATA45) in COMPUSTAT. In our models, annual dummies should absorb much of the noise that the sample size reduction might induce.

The observations deleted for lack of data on advertising expenditure also cause our sample to be smaller than the sample analyzed by Amir et al. (2003). To be sure that this reduction did not cause our sample to differ in other important ways from the sample used by Amir et al. (2003), we compared our variables' means, standard deviations, and correlations to those reported by Amir et al. (2003, p. 641-642) and found no important differences. Details of this comparison are available from the authors.

Correlational Evidence Regarding Hypotheses 1 and 2

While we used our raw correlation matrix to check for differences from Amir et al. (2003) that might have been introduced by excluding observations for which advertising expenditure was missing, we do not use those raw correlations to get a preliminary indication of the relationship between S_{ADV} and CAR and PVE, nor do we use those raw correlations to explore possible multicollinearity. Because our data come from an unbalanced panel with repeated observations for a firm, our models include fixed effects and an AR(1) error structure. To create correlations that reflect the fixed effect and AR(1) structure, we created an "adjusted" correlation matrix in which we represent each variable by the residuals from a regression model with that variable as the dependent variable and with fixed effects, year dummies, and an AR(1) correction of autocorrelation in error (McAlister et al. 2007, p 40). We report the "adjusted" correlation matrix in Table 3. Consistent with our hypotheses, the "adjusted" correlation matrix indicates that the correlation between S_{ADV} and CAR is positive and significant (0.04, $p < 0.01$), and that the correlation between S_{ADV} and PVE is insignificant (-0.01, $p > 0.1$). These adjusted correlations are consistent with the stock market responding to S_{ADV} and with financial analysts ignoring S_{ADV}.

The adjusted correlations in Table 3 also suggest that multicollinearity is not likely to be an issue in our CAR and PVE models (the highest correlation in the matrix is 0.49, $p < 0.01$, between L_CAR and L_PVE). Furthermore, the VIFs (Variance Inflation Factors), which assess the potential for a multicollinearity problem in our FE-2SLS models, were well below 5: (average = 1.18, maximum = 1.56 for equation 1 and equation 3; average = 1.30, maximum = 2.05 for equation 2; and average = 1.22 maximum = 1.64 for equation 4), suggesting that our study's findings are not distorted by multicollinearity (Judge et al. 1988).

CAR and PVE Models: Fixed-Effects Two Stage Least Square Estimation (FE-2SLS) Model

We checked first-order autocorrelation in ε_{jit} (j = 1,2,3,4 in models 1-4) based on the AR(1) autocorrelation test in Wooldridge (2002, p. 282). The test rejected the null hypothesis of no AR(1) autocorrelation in ε_{jit} for all four models, supporting the inclusion of the AR(1) error specification. Results of the Hausman specification tests (Hausman 1978) supported that including fixed-effects in all four models was appropriate. We report the estimation results of the second-stage models (equations 2 and 4) in column 1 and column 2 of Table 4.

R-squares (within) for the models (equations 2 and 4) were 0.06 and 0.17, respectively, and the models were statistically significant ($F(8,5138) = 42.6$, $p < 0.01$; $F(9,5137) = 116.5$, $p < 0.01$). The estimated coefficients for our focal variable revealed that S_{ADV} (b = 0.02, p < 0.01) had a significant and positive coefficient in the model of CAR (equation 2), and that S_{ADV} (b = 0.00, p > 0.1) was insignificant in the model of PVE (equation 4). The results strongly support our Hypotheses H1 and H2.

Alternative Specification for Analysts' Forecasts. For a robustness check, we estimated the same 2SLS models (equations 1 - 4) with an alternative measure of analysts' forecasts, N_PVE, which is the present value of consensus earnings forecasts only for the *next* fiscal year (in contrast to PVE which is consensus earnings forecasts for the next five years). While PVE is a measure of analysts' expected value of the firm, that estimate involves expected earnings for the next five years. To rule out the possibility that it is noise in analysts' estimates of earnings two, three, four, and five years out that keep us from detecting analysts' use of S_{ADV} in expected firm value, we test our hypotheses with N_PVE. We report the results in column 3 and column 4 of Table 4. Although the R-squares (within) were lower (0.05 and 0.05 for equations 2 and 4 using N_PVE, versus 0.06 and 0.17 for equations 2 and 4 using PVE), models using N_PVE were statistically significant ($F(8,5138) = 34.8$, $p < 0.01$; $F(9,4300) = 26.3$, $p < 0.01$). Consistent with the 2SLS results reported above, we found that S_{ADV} (b = 0.02, p < 0.01) had a significant positive coefficient in the model of CAR, and that S_{ADV} (b = 0.00, p > 0.1) was insignificant in the model of N_PVE. Thus, our findings relating S_{ADV} to firm value and analysts' forecasts are robust to the alternative measure of the present value of future earnings forecasts, N_PVE.[20]

[20] Based on a suggestion by Dr. Clement, one of the committee members, I also tested a measure for firm value forecasted by analysts, which includes analysts' present expectation of the value of earnings and dividends that continue into perpetuity in the future. Consistent with H2, S_{ADV} was insignificant (b = 0.04, p > 0.1) in the model to predict the alternative measure of analysts' expectation of firm value.

In summary, results of CAR and PVE FE-2SLS estimation consistently show that S_{ADV} has a significant positive coefficient in the model for market value (CAR) and that S_{ADV} has an insignificant coefficient in the model for analysts' forecasts (PVE and N_PVE). Because the strength of the relationship between instruments and endogenous variables can impact the efficiency of estimated coefficients in the second stage of 2SLS estimation (Wooldridge 2002), we next consider results from estimating reduced-form models not vulnerable to that inefficiency.

CAR and PVE Models: Reduced-form Fixed-Effects Regression Model

Our tests for serial correlation rejected the null hypothesis of no first-order autocorrelation in ε_{it} for both the reduced-form model of CAR and for the reduced-form model of PVE, supporting our AR(1) specification for ε_{it}. We report the estimation results of the proposed reduced-form models in column 1 and column 2 of Table 5.

The reduced-form PVE and CAR models (equations 1 and 3) are statistically significant ($F(29,5117) = 37.9$, $p < 0.01$; $F(29,5117) = 47.7$, $p < 0.01$) with R-squares (within) of 0.18 and 0.21, indicating that our models fit well. In considering the impact of our focal variable, the results show that the estimated coefficient for S_{ADV} ($b = 0.02$, $p < 0.01$) is significant and positive in the CAR model and insignificant ($b = 0.00$, $p > 0.1$) in the PVE model, strongly supporting our hypotheses.[21] The results for the reduced-

[21] Since Amir et al. (2003) considered R&D intensity (PRND) as an intangible to be related to firm value, for a robustness check, we estimated the models (equations 1 and 3) with R&D intensity (PRND) as

form model of N_PVE, the alternative one-year measure of analysts' forecasts, also indicate that S_{ADV} (b = 0.00, p > 0.1) was insignificant in the model of N_PVE as hypothesized (column 3 of Table 5). Thus, the finding that S_{ADV} does not have a significant coefficient in the model of analysts' forecasts was robust to the alternative measure, N_PVE, in the reduced-form model.

For another robustness check, we estimated the proposed reduced-form models (equation 1 and equation 3) using a first-differencing method that incorporates firm-specific fixed effects and potential AR(1) autocorrelations in error (Boulding and Staelin 1995). We created a difference variable as the difference between the variable at time t and at time t-1. Using the first-differenced predictor variables and S_{ADV}, we estimated first-differenced CAR and PVE. The results were consistent with our Hypotheses H1 and H2 for S_{ADV}. [22]

In sum, consistent with the results from the FE-2SLS models, the results from the reduced-form models indicate that S_{ADV} enhances the market value of a stock, even after controlling for the factors that accounting researchers have shown to be related to that market value. Further, the results reveal that financial analysts do not incorporate the impact of a firm's advertising effectiveness, S_{ADV}, in their forecasts of that firm's future earnings.

another predictor variable. The results for S_{ADV} were not changed and PRND was not significant in any of the model specifications (results not reported here).

[22] We also tested a model that regressed first-differenced PVE ($PVE_t - PVE_{t-1}$) on the fundamental signals, control variables, and S_{ADV} because first-differenced PVE may be more comparable to CAR which is difference between actual and expected returns. Consistent with H2, the coefficient for S_{ADV} was not significant (b= -0.001, p > 0.1). The results are available on request.

Earnings Forecast Error (FERR) Model

The results in the previous section showed that S_{ADV} did impact firm value but did not affect analysts' forecasts of future earnings (Tables 4 and 5). So long as the firm value, CAR, is closely related to earnings (EPS) (and adjusted correlation of CAR and EPS = 0.4 in Table 3), these findings suggest that S_{ADV} should be positively associated with earnings forecast error (FERR).

Data and Adjusted Correlations. We estimate the model (equation 5) with 3,741 firm-year observations for 782 firms.[23] Consistent with H3, the adjusted correlation between S_{ADV} and FERR is positive and significant (0.05, $p < 0.01$). In addition, multicollinearity should not cloud the interpretation of the coefficient of S_{ADV}, since the highest adjusted correlation with S_{ADV} was with $S_{PSG\&A}$ (adjusted correlation = 0.17), and the mean of VIFs was less than 5: (average = 1.92; maximum = 2.39).

Empirical Results. Tests for serial correlation of error failed to reject the null hypotheses of no AR(1) autocorrelation in ε_{it} ($p = 0.62$). Thus, we estimated the fixed-effects model (equation 5) without AR(1) specification of errors.

In the model for FERR (column 1 of Table 6), the coefficient for S_{ADV} ($b = 0.01$, $p < 0.01$) was significant and positive, indicating that higher levels of S_{ADV} are associated with larger forecast errors, providing strong support for H3.[24]

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[23] Missing observations in actual earnings (AEPS) in I/B/E/S led to smaller sample size for forecast error model than sample size for FE-2SLS model. Adjusted correlation matrix for this data is available from the authors.

[24] I also estimated a forecast revision model. The forecast revision was measured as the difference between analysts' forecasts of next-year EPS before 10-K release date and after 10-K release date. If S_{ADV} surprised

The Impact of S_{ADV} on Actual Next-Period Earnings and on Forecasts of those Earnings. To rule out the possibility that the relationship between S_{ADV} and FERR is driven by a relationship between S_{ADV} and next-period forecasted earnings, we regress both next-period forecasted earnings (FEPS) and actual next-period earnings (AEPS) on S_{ADV} and the control variables specified for the forecast error model. For these models, the null hypothesis of no serial correlation in error was rejected, thus the estimated models include fixed effects and AR(1) specification of errors. Column 2 and column 3 of Table 6 contain the results for the AEPS model and the FEPS model. The models were significant ($F(28,2323) = 21.4$, $p < 0.01$; $F(28,2323) = 14.9$, $p < 0.01$), and R-squares (within) were 0.21 and 0.15, respectively. Consistent with H3-a) and H3-b), the coefficient of S_{ADV} ($b = 0.12$, $p < 0.05$) was significant and positive in the AEPS model (column 2 in Table 6), and the coefficient of S_{ADV} ($b = -0.01$, $p > 0.1$) was insignificant in the FEPS model. These results confirm the fact that the relationship between S_{ADV} and forecast error is driven by S_{ADV}'s impact on actual earnings rather than by a relationship between S_{ADV} and forecasts.

analysts, S_{ADV} is expected to have a significant impact on the forecast revision measure. Consistent with H3, I found no evidence that S_{ADV} was used in the forecast revision.

CHAPTER 12: DISCUSSION

According to the resource-based view of the firm, superior marketing capabilities create competitive advantage, thereby enhancing firm value. Several empirical marketing studies have demonstrated the link between marketing capability and firm value (Dutta et al. 1999; Mittal et al. 2005; Luo and Donthu 2006). However, despite this theory and empirical evidence, it is not clear that the financial community understands or appreciates this link between marketing and firm value (Srivastava and Reibstein 2005).

In our study, we proposed a simple "fundamental advertising signal" that is built from publicly reported accounting numbers. S_{ADV} (ΔSales – ΔAdvertising) reflects the extent to which a firm's sales are growing faster than its advertising expenditure. While this measure does not directly capture advertising's longer term creation of brand equity, it has several virtues as a starting metric for research into the link between advertising effectiveness and firm value. First, the fact that the structure of the advertising effectiveness measure is simple makes it reasonable to imagine that investors and financial analysts could routinely consider such a measure when estimating the value of a firm. Second, the fact that this S_{ADV} is built with publicly reported accounting numbers implies that those component accounting numbers have been audited and are, consequently, credible. Finally, the fact that the structure of S_{ADV} is consistent with the structure that leading accounting researchers have suggested for "fundamental signals" of other forces that might change firm value gives the measure further credibility with a possibly skeptical financial community.

While we would like to study the impact on firm value of marketing effectiveness (rather than exploring just the impact of advertising effectiveness), we are limited by the nature of publicly reported accounting data. We know that non-advertising marketing expenditures are included in publicly reported SG&A, but it is impossible to separate those non-advertising marketing expenditures from other SG&A expenditures using publicly reported data. Consequently, this study focuses on that which we can measure, advertising effectiveness, and it is notable to find that breaking $S_{SG\&A}$ into S_{ADV} and $S_{PSG\&A}$ enhances the accuracy of predictions of firm value.

The Impact of S_{ADV} on Firm Value

Our study joins a growing literature on linking marketing metrics to firm value by showing that advertising effectiveness is positively associated with cumulative abnormal stock returns even after controlling for accounting fundamentals, earnings, firm characteristics, and year dummies, in a fixed-effects formulation with AR(1) correction of errors (Boulding and Staelin 1998). Unlike the prior studies linking marketing effectiveness to firm value that were limited to a specific industry or to "major" firms, we generalize the finding that advertising effectiveness impacts firm value with a large dataset (8,232 observations for 1,739 firms) including firms from many industries for 19 years from 1982 to 2000.

Methodologically, our study introduces to the marketing literature a new approach for demonstrating the link between marketing and firm value using cumulative abnormal stock return, CAR, as firm value.

Analysts' Under-reactions to S_{ADV}

Our finding that consensus analyst forecasts are not impacted by advertising effectiveness is notable. This finding is consistent with Amir et al.'s (2003) demonstration that R&D intangibles are not fully captured in analysts' forecasts. The finding is also consistent with reports from Wall Street and with accounting research that shows that analysts under-react to value-relevant accounting information (Abarbanell and Bushee 1997; Amir et al. 2003; Cheng 2005). Our work contributes to this literature by showing that analysts also under-react to this not-previously-studied signal: S_{ADV}.

Managerial Implications

The results of our study have important implications for managers. First, consistent with Srivastava et al.'s (1998) and Rust et al.'s (2004) exhortation that marketers use the "language of finance" when demonstrating the value of marketing, the proposed metric, S_{ADV}, is based on publicly reported accounting data and is structured in a way that is consistent with existing financial models.

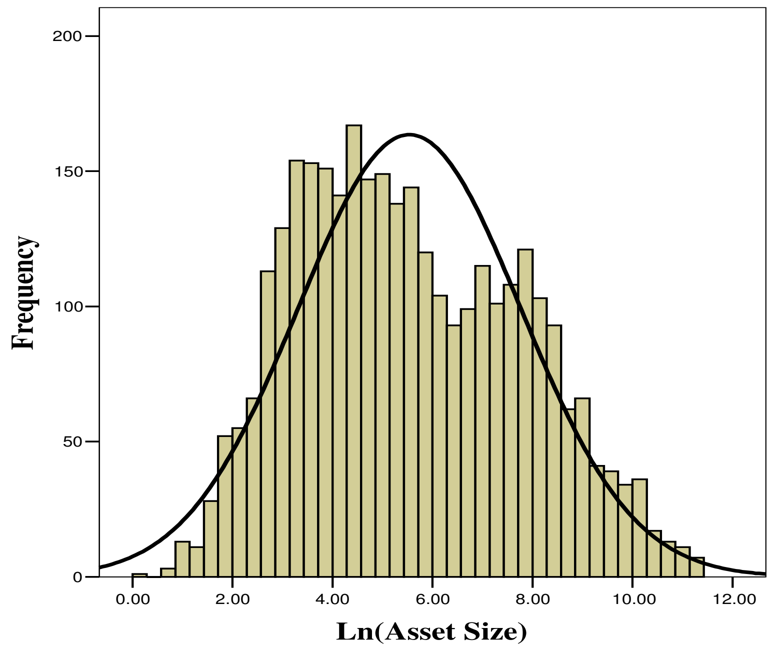
Second, if our results stimulate financial analysts to look at advertising effectiveness separately from general expenses in SG&A, perhaps the importance of recognizing marketing as a value-driver may become clearer to the whole financial community.

Third, our results suggest that top management might find it valuable to also consider longer-term effects of marketing. In a recent Marketing Science Institute's (MSI) Trustees Meeting presentation, Sawhney (2007) proposed that marketing has three primary tasks, each with its own time horizon. In the short run, marketing's challenge is to generate sales. In the medium term, marketing's challenge is to create customer equity and brand equity. In the long term, marketing's challenge is to create new markets. While our proposed S_{ADV} measure is probably a reasonable metric for measuring marketing's progress against its short term challenges, additional metrics need to be created to measure marketing's progress against its medium- and long-term challenges. Calculating marketing's effectiveness against these medium- and long-term measures will make it necessary to understand that some of marketing's spending is investment and should be treated as such in financial planning.

Finally, the study's findings point out the importance of understanding the antecedents of S_{ADV}. At the micro level, it is expected that designing better advertising programs (e.g., more efficient media budget allocation, use of pulsing strategy, etc.) may increase S_{ADV}. Thus, marketing executives need to maintain their vigilance and regularly evaluate their marketing programs in terms of their impact on S_{ADV}. With this metric, it may be time for firms' senior marketing executives to step into the boardroom and report the contribution of their decisions to S_{ADV} and, consequently, to earnings forecasts and firm value.

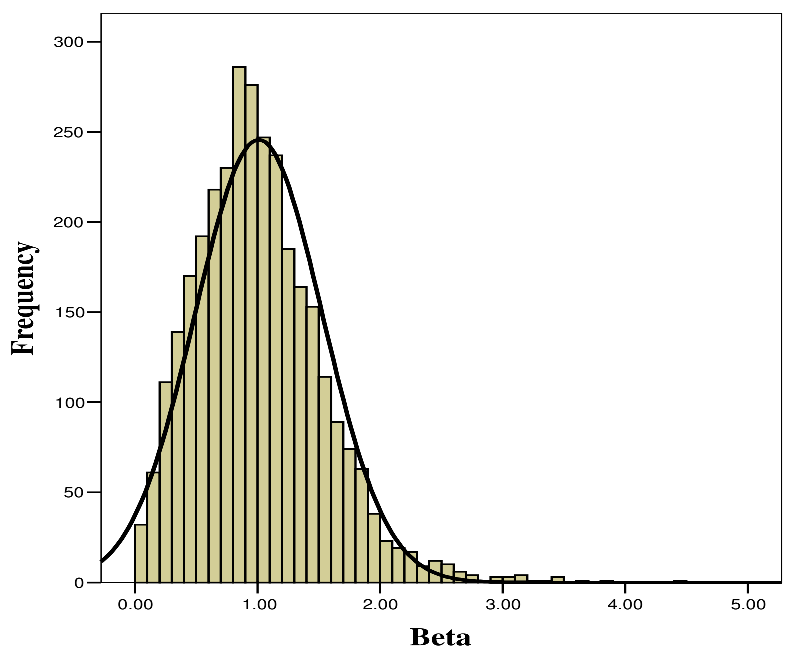
In summary, to our knowledge, this is the first marketing study to go beyond anecdotal evidence or surveys and use a large accounting dataset across industries to examine financial analysts' reactions to the fundamental signal from advertising. We hope that this study's findings facilitate the communication between marketing and finance scholars and practitioners.

FIGURE 1A: FREQUENCY DISTRIBUTION OF FIRM SIZE



Mean (standard deviation) = 5.167 (2.221)

FIGURE 1B: FREQUENCY DISTRIBUTION OF SYSTEMATIC RISK (BETA)



Mean (standard deviation) = 1.042 (0.527)

TABLE 1: DESCRIPTIVE STATISTICS AND BIVARIATE CORRELATION MATRIX FOR VARIABLES IN PROPOSED MODEL

Variables	Mean (Std)	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Systematic risk	1.042 (0.527)	1.000									
2. Lagged advertising/sales	0.040 (0.053)	-0.051	1.000								
3. Lagged R&D/sales	0.068 (0.120)	0.228	0.155	1.000							
4. Growth	0.081 (0.112)	0.147	-0.019	0.002	1.000						
5. Leverage	0.410 (0.237)	0.058	0.068	-0.036	-0.121	1.000					
6. Liquidity	3.153 (2.989)	0.104	0.083	0.380	0.056	-0.369	1.000				
7. Asset size	5.167 (2.221)	-0.389	0.046	-0.164	-0.009	0.105	0.340	1.000			
8. Earnings variability	0.077 (0.159)	0.220	0.005	0.054	-0.250	0.181	-0.052	-0.174	1.000		
9. Dividend payout	0.388 (0.853)	-0.024	-0.004	0.003	-0.025	0.002	-0.012	0.028		1.000	
10. Age	19.152 (0.112)	-0.392	0.079	-0.189	-0.154	0.107	-0.243	-0.105	-0.128	0.022	1.000
11. Competitive intensity	0.399 (0.112)	0.065	-0.182	-0.076	-0.047	0.009	-0.016	0.629	0.060	-0.004	-0.071

Note: All correlations greater than 0.220 are significant at $p < 0.01$, all correlations greater than 0.11 are significant at $p < 0.05$, and all correlations greater than 0.023 are significant at $p < 0.10$.

TABLE 2: ADVERTISING, R&D, AND SYSTEMATIC RISK: ESTIMATION RESULTS

Variable	(Column 1)	(Column 2)	(Column 3)	(Column 4)	(Column 5)	(Column 6)
Minimum number of returns observations for estimating beta	60	60	50	50	60	60
Market return used in estimating beta	Equal-weighted	Value-weighted	Equal Weighted	Value-weighted	Equal-weighted	Value-weighted
Model Specification	Levels of Variables	Levels of variables	Levels of variables	Levels of variables	Changes in variables	Changes in variables [a]
Intercept	-0.54 (0.04)***	-0.22 (0.04)***	-0.60 (0.04)***	-0.28 (0.04)***	-0.03 (0.05)	0.03 (0.01)*
Lagged Advertising/sales	-3.19 (0.75)***	- 2.28 (0.79)***	-3.42 (0.71)***	-1.85 (0.73)***	-2.61 (0.58)***	-0.02 (0.00)***
Lagged R&D/sales	-0.50 (0.18)***	-0.99 (0.19)***	-0.47 (0.18)***	-1.00 (0.18)***	-0.20 (0.12)*	-0.01 (0.00)**
Growth	0.36 (0.08)***	0.40 (0.09)**	0.34 (0.08)***	0.38 (0.09)**	0.44 (0.07)***	0.03 (0.00)***
Leverage	0.52 (0.12)***	0.01 (0.13)	0.48 (0.12)***	-0.07 (0.12)	0.46 (0.09)***	0.02 (0.00)***
Liquidity	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)	0.00 (0.00)
Asset size	-0.09 (0.03)***	-0.09 (0.03)***	-0.11 (0.03)***	-0.09 (0.03)***	-0.01 (0.03)	-0.00 (0.00)
Earnings variability	-0.02 (0.03)	-0.06 (0.03)*	-0.08 (0.03)	-0.02 (0.03)	-0.04 (0.03)	-0.00 (0.00)
Dividend payout	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)
Age	-0.02 (0.01)***	0.02 (0.01)**	-0.02 (0.01)***	-0.02 (0.01)***	-	-
Competitive intensity	-0.89 (0.34)***	-0.60 (0.35)*	-0.83 (0.33)***	-0.07 (0.34)*	-0.53 (0.33)	-0.01 (0.01)
Serial correlation (ρ)	0.67	0.66	0.65	0.64	-	-
Overall R-sq (Within)	0.16	0.11	0.16	0.10	0.05	0.05
Number of firms (observations)	644 (3198)	644 (3198)	711 (3457)	711 (3457)	644 (3198)	644 (3198)
F (d. f.)	17.9 (671, 2527)	11.1 (671, 2527)	18.5 (738, 2719)	11.4 (738, 2719)	6.9 (25, 3172)	6.9 (25, 3172)

Note: Coefficient (standard errors) are in the columns. The models also include window dummies, some of which are significant at $p < 0.01$.
*** denotes $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.
[a] We used factor-scored predictor variables for this model.

TABLE 3: DESCRIPTIVE STATISTICS AND ADJUSTED CORRELATION MATRIX FOR VARIABLES IN PROPOSED FE-2SLS MODELS (EQUATIONS 1 – 4)

Variables	Mean (Std)	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. PVE	0.43(0.28)	1												
2. CAR	-0.03(0.33)	0.39	1											
3. L_PVE	0.46(0.30)	0.35	-0.03	1										
4. L_CAR	-0.02(0.34)	0.09	-0.05	0.49	1									
5. EPS	0.03(0.11)	0.40	0.10	0.28	0.19	1								
6. L_EPS	0.04(0.09)	0.10	-0.14	0.42	0.21	0.16	1							
7. SIZE	5.81(2.03)	0.29	0.02[c]	0.43	0.19	0.31	0.25	1						
8. BTM	0.25(0.54)	-0.02[c]	-0.05	0.03	-0.02[b]	-0.08	-0.00[c]	-0.15	1					
9. S_{INV}	0.03(0.53)	-0.04	-0.08	0.05	0.03	0.00[c]	0.06	0.06	-0.00[c]	1				
10. S_{AR}	0.01(0.32)	0.01[c]	-0.01[c]	0.01[c]	0.01[c]	0.01[c]	0.05	0.02[b]	0.00[c]	0.09	1			
11. S_{GM}	-0.01(0.14)	-0.21	-0.15	-0.16	-0.19	-0.28	0.08	-0.13	-0.01[c]	0.07	0.02[b]	1		
12. $S_{PSG\&A}$	0.01(0.22)	-0.09	-0.11	-0.01[c]	-0.11	-0.13	0.06	-0.02[c]	0.05	0.09	0.06	-0.04	1	
13. ETR	-0.00(0.04)	0.02[b]	-0.02[b]	0.04	0.04	0.24	0.04	0.03	-0.02[c]	-0.00[c]	0.00[c]	-0.05	0.01[c]	1
14. $\mathbf{S_{ADV}}$	-0.04(0.75)	-0.01[c]	0.04	-0.04	0.01[c]	0.02[c]	-0.04	-0.04	-0.02[c]	-0.01[c]	-0.03	0.01[c]	-0.06	0.01[c]

Note: This correlation matrix is based on the residuals obtained by regressing each predictor variable on year dummies and fixed effects, incorporating AR(1) autocorrelations in errors.
[b] $0.05 < p < 0.10$.
[c] $p > 0.10$.

TABLE 4: ESTIMATION RESULTS FOR THE SECOND STAGE MODEL IN FE-2SLS WITH AN AR(1) CORRECTION OF ERRORS (EQUATION 2 AND 4)

	PVE Estimated with 5 years of EPS forecasts		PVE Estimated with 1 year of EPS forecasts	
	(Column 1: Equation 2)	(Column 2: Equation 4)	(Column 3: Equation 2)	(Column 4: Equation 4)
Dependent variable	CAR	PVE	CAR	N_PVE[a]
Intercept	-0.33 (0.03)***	0.40 (0.00)***	0.04 (0.02)*	0.07 (0.00)***
S_{ADV} (Advertising signal)	0.02 (0.01)***	0.00 (0.00)	0.02 (0.01)***	0.00 (0.00)
Fundamental signal predictor variables				
S_{INV} (inventory)	-0.03 (0.01)***	-0.02 (0.01)***	-0.05 (0.01)***	-0.00 (0.00)**
S_{AR} (accounts receivable)	0.01 (0.02)	0.02 (0.01)**	0.02 (0.02)	-0.00 (0.00)
S_{GM} (gross margin)	-0.25 (0.04)***	-0.15 (0.03)***	-0.32 (0.04)***	-0.03 (0.01)***
$S_{PSG\&A}$ (SG&A-ADV)	-0.14 (0.02)***	-0.09 (0.02)***	-0.19 (0.02)***	-0.03 (0.01)***
Accounting/Finance control variables				
ETR (effective tax rate)	-0.19 (0.12)	-0.31 (0.06)***	-0.46 (0.11)***	-0.06 (0.03)**
EPS (earning per share)	-0.32 (0.09)***	0.80 (0.03)***	0.42 (0.07)***	0.22 (0.02)***
L_CAR (lagged CAR)	-	-0.11 (0.01)***	-	-0.03 (0.01)***
Predicted endogenous variables				
$\overline{\overline{CAR}}$	-	-0.05 (0.04)	-	-0.09 (0.02)***
$\overline{\overline{PVE}}$	0.76 (0.09)***	-	-	-
$\overline{\overline{N\_PVE}}$	-	-	-0.83 (0.29)***	-
Serial correlation (ρ)	0.14	0.35	0.11	0.77
Overall R-sq (Within)	0.04 (0.06)	0.18 (0.17)	0.07 (0.05)	0.01 (0.05)
Number of firms (observations)	1347 (6493)	1347 (6493)	1347 (6493)	1110 (5419)
F (d.f.)	42.6 (8,5138)	116.5 (9,5137)	34.8 (8,5138)	26.3 (9,4300)

* p - value < 0.10. ** p < 0.05. *** p < 0.01. Notes: Coefficients (standard errors) are in the columns.
[a] N_PVE is the present value of consensus forecasts of EPS for the next fiscal year-end.

TABLE 5: ESTIMATION RESULTS FOR REDUCED-FORM FIXED-EFFECTS REGRESSION MODEL WITH AN AR(1) CORRECTION OF ERRORS (EQUATION 1 AND 3)

	PVE Estimated with 5 years of EPS forecasts		PVE Estimated with 1 year of EPS forecasts
	(Column 1: Equation 1)	(Column 2 : Equation 3)	(Column 3 : Equation 3)
Dependent variable	CAR	PVE	N_PVE[a]
Intercept	-0.42 (0.04)***	0.12 (0.03)***	0.11 (0.01)***
S_{ADV} (Advertising signal)	0.02 (0.01)***	0.00 (0.00)	0.00 (0.00)
Fundamental signal predictor variables			
S_{INV} (inventory)	-0.03 (0.01)***	-0.02 (0.01)***	-0.00 (0.00)
S_{AR} (accounts receivable)	0.29 (0.01)**	0.02 (0.01)**	-0.00 (0.00)
S_{GM} (gross margin)	-0.32 (0.04)***	-0.13 (0.02)***	-0.01 (0.01)
$S_{PSG\&A}$ (SG&A-ADV)	-0.20 (0.02)***	-0.08 (0.01)***	-0.01 (0.01)
Accounting/Finance control variables			
ETR (effective tax rate)	-0.38 (0.10)***	-0.27 (0.06)***	-0.03 (0.02)
EPS (earning per share)	0.28 (0.05)***	0.70 (0.03)***	0.18 (0.01)***
L_CAR (lagged CAR)	-	-0.08 (0.01)***	0.00 (0.00)
Instruments			
BTM (Book to Market Ratio)	-0.06 (0.01)***	-0.00 (0.01)	-0.01 (0.00)**
SIZE (firm size)	0.08 (0.01)***	0.04 (0.01)***	-0.01 (0.00)**
L_PVE (lagged PVE)	0.04 (0.02)	-0.06 (0.01)***	-0.03 (0.01)***
L_CAR (lagged CAR)	-0.32 (0.01)***	-	-
L_EPS (lagged EPS)	-0.40 (0.06)***	0.00 (0.04)	0.04 (0.02)***
Serial correlation (-)	0.30	0.31	0.73
Overall R-sq (within R-sq)	0.03 (0.18)	0.08 (0.21)	0.01 (0.09)
Number of firms (observations)	1347 (6493)	1347 (6493)	1110 (5419)
F (d.f.)	37.9 (29,5117)	47.7 (29,5117)	13.9 (29,4280)

* p - value < 0.10. ** p < 0.05. *** p < 0.01. Notes: Coefficients (standard errors) are in the columns. The models also included year dummies in all specifications. We do not report estimated coefficients for year dummies. [a] N_PVE is the present value of consensus forecasts of EPS for the next fiscal year-end.

TABLE 6: THE IMPACT OF S_{ADV} ON NEXT-PERIOD EARNINGS, NEXT-PERIOD EARNINGS FORECASTS, AND ERRORS IN NEXT-PERIOD EARNINGS FORECASTS

	(Column 1)Equation 5	(Column 2)	(Column 3)
Estimation Methods	Fixed Effects	Fixed Effects / AR(1)	Fixed Effects / AR(1)
Dependent variable	Forecast Error (FERR)	Actual Earnings (AEPS)	Forecasted Earnings (FEPS)
Intercept	-0.17 (0.06)***	0.35 (0.17)**	-0.15 (0.09)*
S_{ADV} (Advertising signal)	0.01 (0.00)***	0.12 (0.05)**	-0.01 (0.03)
Fundamental signal predictor variables			
S_{INV} (inventory)	-0.00 (0.00)	0.10 (0.04)***	0.07 (0.02)***
S_{AR} (accounts receivable)	0.00 (0.01)	0.05 (0.07)	-0.05 (0.04)
S_{GM} (gross margin)	-0.15 (0.01)***	-1.59 (0.15)***	0.38 (0.09)***
$S_{PSG\&A}$ (SG&A-ADV)	-0.09 (0.01)***	-1.07 (0.12)***	0.19 (0.07)***
Accounting/Finance control variables			
ETR (effective tax rate)	0.11 (0.03)***	0.56 (0.41)	-0.30 (0.25)
d_EPS (annual change in EPS)	0.03 (0.00)***	0.04 (0.03)	-0.05 (0.02)**
SIZE (firm size)	0.02 (0.00)***	0.43 (0.05)***	0.10 (0.03)***
EAR_VAR (earnings variability)	-0.00 (0.00)*	-0.00 (0.00)*	-0.01 (0.00)***
PRND (R&D intensity)	-0.08 (0.01)***	-0.69 (0.20)***	-0.26 (0.13)**
AGE (firm age)	0.00 (0.10)	-0.34 (0.09)***	0.22 (0.06)***
Serial correlation (ρ)	-	0.47	0.57
Overall R-sq (Within)	0.18 (0.25)	0.13 (0.21)	0.13 (0.15)
Number of firms (observations)	782 (3741)	608 (2959)	608 (2959)
F (d.f.)	33.3 (29,2930)	21.4 (28,2323)	14.9 (28,2323)

* p - value < 0.10. ** p < 0.05. *** p < 0.01. Notes: Coefficients (standard errors) are in the columns. The models also included year dummies in all specifications. We do not report estimated coefficients for year dummies.

APPENDIX A: PROPOSED MODEL PREDICTOR VARIABLE DEFINITIONS AND MEASURES

We define the measures for the various predictor variables in the following way for each firm *i* for each of the 19 five-year moving window. Note that all the variables have a subscript *i* for each firm.

Variable	Definition	Measure
Advertising/Sales	The 5-year moving average of advertising/sales.	$(1/5)\times\sum_{t=1}^{5}\frac{Data45}{Data12}$
Research and Development/Sales	The 5-year moving average of Research and Developments/sales	$(1/5)\times\sum_{t=1}^{5}\frac{Data46}{Data12}$
Dividend Payout	5-year moving average of Cash Dividends /Earnings	$DP_{i5}=(1/5)\times\frac{\sum_{t=1}^{5}CashDividend_t}{\sum_{t=1}^{5}AvailIncome_t}$
Growth	5-year moving average of Terminal Total Assets/ Initial Assets	$G_{i5}=\ln\left[\frac{TotalAsset_5}{TotalAsset_1}\right]/5$
Leverage	5-year moving average of Total Senior Securities (Preferred Stocks and Bonds)/Total Assets	$LEV_{i5}=\sum_{t=1}^{5}\frac{TotalSecurity_t}{TotalAsset_t}/5$
Liquidity	5-year moving average of Current ratio	$LiQ_{i5}=\sum_{t=1}^{5}\frac{CurrentAsset_t}{CurrentLiability_t}/5$
Asset Size	5-year moving average of Total Assets	$AS_{i5}=\sum_{t=1}^{5}\ln(TotalAsset_t)/5$
Variability of Earnings	5-year moving average of Standard Deviation of Earnings-Price Ratio ($\frac{E_t}{P_{t-1}}$) where $P_{t,}$ and E_t are the market value of common stocks and earnings at time t respectively.	$VE_{i5}=(\sum_{t=2}^{5}(\frac{E_t}{P_{t-1}}-E(\frac{E_t}{P_{t-1}}))^2/4)^{\frac{1}{2}}$

Firm Age	Number of years since the stock's first listing on the stock market	-
Competitive Intensity	The four-firm Herfindahl's concentration index	Proportion of market share of the top four firms in the industry defined by two digits of the standard industrial classification (SIC) code.

APPENDIX B: COMPUSTAT DATA ITEMS USED IN CONSTRUCTING VARIABLES

Name of Variable Component	**COMPUSTAT Annual Data Items**
Advertising/Sales	DATA45/DATA12
Research and Development (R&D)/Sales	DATA46/DATA12
Total Assets	DATA6
Income Available for Common Stockholders	DATA20
Market Value of Common Stock (P_t)	DATA24× DATA25×1000
Total Senior Securities (*TotalSecurity*)	DATA5+DATA9+DATA10
Current Asset (*CurrentAsset*)	DATA4
Current Liabilities (*CurrentLiability*)	DATA5
Cash Dividends (*CashDividend*)	DATA21
Herfindahl's concentration index	DATA12

APPENDIX C: SPECIFICATION OF VARIABLES IN 2SLS MODELS

Variables	Sources	Variable Constructs
S_{ADV}	COMPUSTAT	ΔDATA(12)[a] - ΔDATA(45)
S_{INV}	COMPUSTAT	ΔDATA(78) (or ΔDATA(3)) - ΔDATA(12)
S_{GM}	COMPUSTAT	ΔDATA(12) - Δ(DATA(12) – DATA(41))
S_{AR}	COMPUSTAT	ΔDATA(2) - ΔDATA(12)
$S_{PSG\&A}$	COMPUSTAT	Δ(DATA(189) – DATA(45)) - ΔDATA(12)
EPS	COMPUSTAT	DATA(58) / P_{it-1}[b]
ETR	COMPUSTAT/CRSP	{DATA(170)/P_{it-1}}×(T_{t-1} - T_t), T_t = DATA(63)/{DATA(18)+(63)+(49)-(48)-(55)}
SIZE	CRSP	log(abs(PRC) * SHROUT); PRC = closing price, SHROUT = number of shares outstanding
BTM	COMPUSTAT	DATA(60) / {DATA(199)×DATA(25)}
PRND	COMPUSTAT	$\sum_{s=1}^{5}(0.1)(11-2s)(DATA(46))_{it-s+1}$

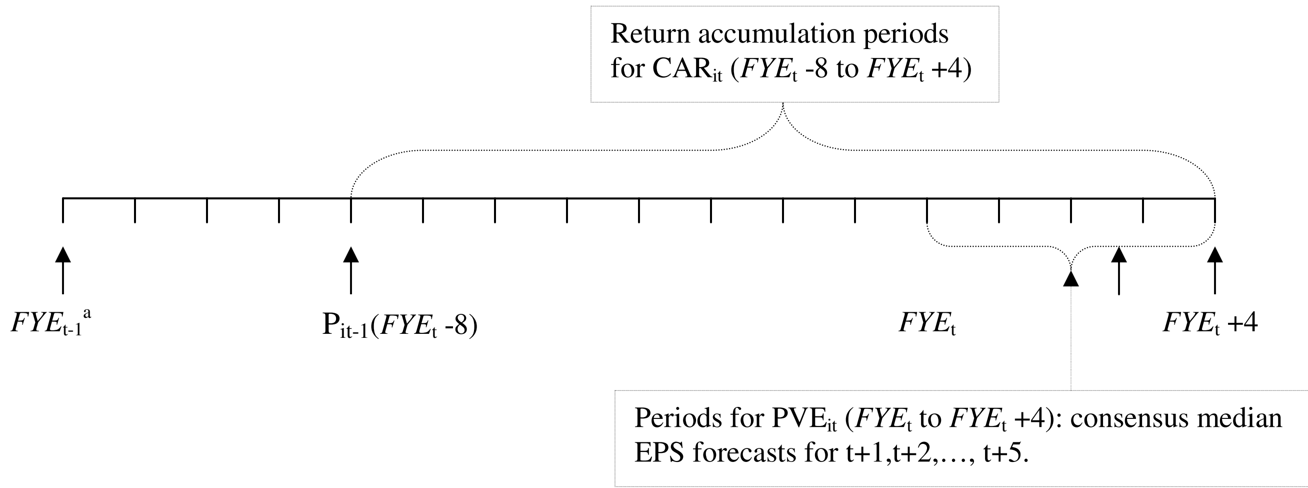
[a]ΔDATA(X) is defined as $(DATA(X)-\overline{DATA(X)})/\overline{DATA(X)}$, where $\overline{DATA(X)}$ is the average of the previous two years' DATA(X).
[b]P_{it-1} is the share price at the beginning month of return accumulation period (see the Appendix E for an explanation of return accumulation periods.).

APPENDIX D: SPECIFICATION OF VARIABLES IN FORECAST ERROR MODEL

Variables	Sources	Variable Constructs
AEPS	I/B/E/S	ACTUAL; actual reported earnings per share
FEPS	I/B/E/S	MEDEST; median estimate of forecasts, reported most recently before 4 months after fiscal year-end
FERR	I/B/E/S	(ACTUAL – MEDEST) / P_{it-1}[a]
AGE	CRSP	log(number of monthly stock returns taped in CRSP)
d_EPS	COMPUSTAT & CRSP	(DATA(58) – L_DATA(58)) / P_{it-1}; L_ = one-year-lagged
EAR_VAR	COMPUSTAT & I/B/E/S	$\left[\sum_{t'=0}^{4}(EPS_{(it-t')}-E(EPS))^2/4\right]^{\frac{1}{2}}/abs(E(EPS))$, where $E(EPS)=\sum_{t'=0}^{4}(EPS_{(it-t')})/5$[b]

[a] P_{it-1} is the share price at the beginning month of return accumulation periods (see the Appendix E about return accumulation periods.).
[b] EPS is AEPS. In case of missing AEPS, we used DATA(58) in COMPUSTAT.

APPENDIX E: TIME FRAME FOR THE CALCULATION OF CAR AND PVE



[a]FYE_t is fiscal-year end for a firm in year t. FYE_t -8 is 8 months before the FYE_t and FYE_t +4 is 4 months after the FYE_t.

APPENDIX F: DEFINIATIONS OF CAR AND PVE

Annual cumulative abnormal stock returns (CAR). Because firms typically issue their annual reports a few months after fiscal year-end, it is the custom in the accounting and finance literature to assume that annual reports are issued sometime between fiscal year-end and 4 months after fiscal year-end. Because we want our measure of the value of firm i in year t (CAR_{it}) to reflect information from the annual report that firm i issued at the end of year t-1, we begin the accumulation period 4 months after i's fiscal year-end t-1 (which is 8 months before i's fiscal year-end t, FYE_t -8). Hence, CAR_{it} is measured as the sum of monthly abnormal stock returns (i.e., $AR_{it} = R_{it} - \overline{R_{it}}$, where R_{it} is actual and $\overline{R_{it}}$ is expected return) from 8 months before to 4 months after i's fiscal year-end t (from FYE_t -8 to FYE_t +4), which is our "return accumulation period."

For the *expected* return for a stock at end of month t, we apply the three factor model of Fama and French (1993). Fama and French (1993) have consistently found that the factors describing "size" and "value", outside of market factor in the Capital Asset Pricing Model (CAPM), significantly improved the prediction of realized stock returns of publicly traded stocks. The three factor model was constructed as follows using monthly value-weighted market return, risk-free rate, monthly size factor (SMB) and value factor (HML) provided by French's website (See Fama and French (1993) about the details of how to measure SMB and HML.).

(6) $$R_{it} = R_{ft} + \beta_{1i}(R_{mt} - R_{ft}) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \varepsilon_{it}$$

where,

$i = 1,..,N; t = 1,..,T_i$; T_i is FYE_i-8;

$R_{it} = \ln\left[\frac{D_{it} + P_{it}}{P'_{it-1}}\right]$, where R_{it} is *ex post* rate of return for stock i during period t;

$R_{mt} = \ln\left[\frac{L_{it'}}{L_{it'-1}}\right]$, where an index of the *ex post* value-weighted return for all NYSE firms during month t (i.e., the market rate of return);

R_{ft} = Risk free return at month t (one month Treasury-bill rate from Ibbotson Associates);

SMB_t = Return to relative size (market capitalization);

HML_t = Return to relative price-to-book ratio; $\varepsilon_{it} \sim$ i.i.d. $N(0,\sigma^2)$.

For the expected return ($\overline{R}_{it}$) during the month t, we estimate the three factor model (equation 6) with 60 *ex post* historical monthly returns before FYE_t -8.[25] Then, we predict return at the end of the month t using the estimated coefficients ($\hat{\beta}_{i1}, \hat{\beta}_{i2}, \hat{\beta}_{i3}$), SMB_t, and HML_t for a month t in return accumulation period (from FYE_t -8 to FYE_t +4). Hence, the expected return for a month t is calculated as follows:

(7) $$\overline{R}_{it} = R_{ft} + \hat{\beta}_{1i}(R_{mt} - R_{ft}) + \hat{\beta}_{2i}SMB_t + \hat{\beta}_{3i}HML_t$$

where t = FYE_{it}-8, … ,FYE_{it}+4; $i = 1,....,N$

[25] While it was our goal to use 60 monthly stock returns in this estimation, it sometimes happened that missing data caused us to have fewer than 60 observations in a 5-year period. In no case did we estimate with fewer than 24 observations in the 5-year period.

Finally, the annual cumulative abnormal stock return, CAR_{it}, for a firm i at year t is measured as follows:

(8) $$CAR_{it} = \sum_{s=FYEi-8}^{FYEi+4} (R_{is} - \overline{R}_{is}) \qquad i = 1,....,N$$

The present value of future earnings forecasts (PVE). The procedure to calculate PVE is summarized as follows:

(9) $$PVE_{it} = [\{\sum_{t'=1}^{5} (FEPS_{i(t+t')} + D_{it})\} / \rho_{it}^{5}] / P_{it-1} \quad ,$$

(10) $$\rho_{it} = 1 + R_{Ft} + (0.03)\beta_{it}, \; i = 1,....,N; t = 1,....,T_i;$$

where $FEPS_{i(t+t')}$ (t' = 1,2,…,5) are consensus median forecasts of earnings (reported in I/B/E/S summary history) for the years (t+1, t+2, …, t+5), made most recently in between FYE_t and FYE_t +4, D_{it} is the dividend (DATA26 in COMPUSTAT) at year t, ρ_{it} is the discount factor for firm i in year t, and R_{Ft} is the risk-free rate in year t (Amir et al. 2003).

We selected median forecasts (FEPS) for five consecutive years which were released most recently before the end of the return accumulation periods (FYE_t +4). Using median forecasts made most recently between FYE_t and FYE_t +4, we ensured that the information from annual financial statements for year t-1 and stock price changes after the release of annual reports were available to financial analysts. In the case of missing forecasts for any of the subsequent five years, we replaced the missing forecast with the forecast of earnings for the previous year times a five-year earnings growth rate forecast.[26] We also combined the consensus forecasts of earnings for each year in the future with the expected future dividend, D_{it}, assuming that the expected future dividend is the same as the current dividend (Amir et al. 2003). Then, the present value of future earnings forecasts for a firm at a year t is determined by discounting the forecasted future earnings plus expected future dividends, with the firm's cost of capital, ρ_{it} ; hence, the discounted sum is $\sum_{t'=1}^{5}\{(FEPS_{i(t+t')} + D_{it}) / \rho_{it}^{t'}\}$. Finally, the present value (PVE) was deflated by share price (P_{it-1}) at 8 months before the end of the fiscal year (FYE_t -8).

[26] For example, if EPS forecast for t+3 ($FEPS_{t+3}$) is missing but there exists earnings growth rate (g), we replaced the missing $FEPS_{t+3}$ with $FEPS_{t+2}$ * (1+g), following Amir et al. (2003).

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