J. of the Acad. Mark. Sci. (2012) 40:605–624
DOI 10.1007/s11747-010-0240-3

ORIGINAL EMPIRICAL RESEARCH

Does advertising spending really work? The intermediate role of analysts in the impact of advertising on firm value

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Received: 15 March 2010 / Accepted: 18 November 2010 / Published online: 4 December 2010

Abstract Both managers and investors are increasingly concerned with the impact of advertising spending on shareholder returns. This study investigates the analyst-based processes by which advertising may create firm value. Using a large longitudinal dataset with 1,052 firms over 20 years, we find that firms decreasing from the top 20% to the bottom 20% of advertising spending group when compared to all industry competitors would experience a drop of abnormal return by 4.08% in 1 year and a cumulative total of 81.6% in 20 years. Also, analyst activities partially mediate the impact of advertising on firm return and risk. These findings indicate that analysts may act to externally validate the business logic underlying the advertising expense. The more analysts factor in firm advertising spending and reflect it in their earnings forecasts, the more likely the benefits of advertising are channeled into firm value. The results bridge research interests across marketing, accounting, and finance disciplines and help managers understand how product and financial markets are united. Main Street could better align with Wall Street via corporate disclosure of advertising spending to equity analysts.

The authors gratefully acknowledge the constructive insights from Donald R. Lehmann at Columbia University.

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Keywords Advertising · Marketing accountability · Strategy · Analysts · Marketing-finance interface

Managers and investors increasingly recognize the need to gauge the impact of advertising spending on shareholder returns. Testing the value and accountability of advertising spending is regarded as a major research priority in marketing (Rust et al. 2004). Recent studies have shown that a firm's advertising expense directly impacts stock returns, over and above its impact on earnings and profits (Joshi and Hanssens 2010). Marketing communication productivity is also found to boost market value (Luo and Donthu 2006). Echoing this, McAlister et al. (2007) suggest that advertising spending lowers systematic risk of the firm,[1] although some authors show that advertising spending may have negative effects on firm profitability (Erickson and Jacobson 1992; Han and Manry 2004).

However, a major challenge in the literature is that simply correlating product market advertising with financial market stock returns might be too big of a stretch, if not misleading. Critics argue that advertising is too far removed from stock price-based firm value and that there must be something in the *middle*. That is, there are many missing links, i.e., other intermediate variables are neglected. In addition, because prior research focuses more on whether the stock returns to advertising are significant, less is known in the literature with respect to the underlying mechanisms accounting for the presence or absence of such returns.

[1] Following the majority of the literature, our study focuses on the impact of advertising spending. We assess the value of advertising-based marketing strategies, rather than advertising information (messages conveyed to consumers about the superiority of one brand over another; Joshi and Hanssens 2010).

To fill in this research gap, we examine whether or not analysts' coverage and earnings forecasts mediate the impact of advertising spending on firm value. Specifically, stock analysts may externally validate the business logic underlying the advertising-based marketing strategies. That is, firms undertake their own internal vetting process to be sure that investing in the advertising-based strategies is effective. Yet, analysts, who can and do interview managers in ways that the press or investors cannot, signal to the marketplace whether those strategies have sound business rationales. It is not that advertising spending in general causes profit, because the spending observed in the marketplace is not random. Instead, investments in advertising may add firm value when a marketing manager can successfully argue within the firm that advertising-based strategies are profitable, as well as outside the firm that analysts validate the wisdom of the strategies.[2]

Indeed, stock analysts are industry experts who gather and analyze public or private information about a firm and disclose the information to investors (Barth et al. 2001; Ivkovic and Jegadeesh 2004; Luo et al. 2010). By scrutinizing and conveying information of firms' advertising spending, analysts help reduce the information asymmetry between product and financial markets (Hou and Robinson 2006; see Appendix A for theoretical and empirical evidence for the assumption of information asymmetry). We believe that the opinions of analysts are important because analysts are able to discuss with managers and probe in ways that the ordinary investors and the trade press cannot. Firms may share competitive information with analysts that they would not give to members of the press or average investors. Analysts make judgments on the soundness of the strategic underpinnings of the advertising-based marketing strategies, and those judgments are closely watched and utilized by investors in the stock market (Kimbrough and McAlister 2009). As such, it is possible that analyst actions are part of the underlying mechanisms that channel the impact of advertising spending on firm value.

Our research offers new contributions over prior work (e.g., Joshi and Hanssens 2010; Luo and Donthu 2006). Specifically, we are not aware of any study that has addressed whether analysts play an intermediary role between advertising and firm value. Prior studies do not explicitly account for the role of analysts' forecasts, even though analysts link firms and investors in such an important way that investors often utilize analyst forecasts for the purposes of estimating firm earnings and buying/selling stocks. New to the literature, our study investigates whether analyst activities help investors discover the benefits of advertising and whether analysts serve as informational conduits through which advertising reaches firm value. That is, we investigate the degree to which analysts can interpret advertising spending and pass this interpretation on to investors and thereby affect firms' stock prices.

Different from prior studies that are limited to shorter time periods, one industry, and other restrictions in methodology, our study gauges returns to advertising on the basis of a large-scale longitudinal dataset with 239,856 firm-month observations from 48 industries. Our data analyses demonstrate that analyst-based processes account for the link between advertising and firm value. Analysts' coverage and earnings forecasts facilitate investors to discover and incorporate the fair value of advertising in firm equity pricing. We find that analyst activities partially mediate the impact of advertising on firm value. The findings indicate that the more analysts scrutinize firms' advertising spending and reflect it in their earnings forecasts, the more likely the benefits of advertising are channeled into firm value. Therefore, we move beyond the theories and variables in prior studies and suggest that there is a need for analysts to monitor and analyze firm advertising spending.

Research background and hypotheses

Advertising spending and firm value

Studies across the disciplines of marketing, accounting, and finance have suggested that advertising spending can directly and indirectly affect firm sales and financial value. Essentially, advertising may generate favorable responses such as greater market awareness, quality competitiveness, customer preference, and brand image (Koslow et al. 2006; Kulkarni et al. 2003; Tellis 2009). West et al. (2008, p. 35) note that "the creativity in advertising is highly prized for its ability to gain consumer attention and bestow value to brands." When brands are under pressure to perform, firms often increase the creativity of their ads and, thus, gain more customer equity and brand value. These benefits induced by advertising, in turn, boost future sales and profits of the firm (Kirmani and Wright 1989; Leone 1995; Mela et al. 1997; Osinga et al. 2010). Further, advertising may accelerate the velocity of consumer responses and induce faster market penetration. Srinivasan et al. (2009, p. 25) point out that "advertising helps develop instant awareness of new products that may accelerate the diffusion process," suggesting that firm advertising leads to more and faster cash flows. In addition, advertising helps smooth out the variability in seasonal demand and reduces consumer risks with safer cash flows. Byzalov and Shachar (2004, p. 283) note that "advertising resolves some of the uncertainty that the risk averse consumers face." Also, advertising can create a barrier to competition, provide bargaining power vis-à-vis

[2] We acknowledge an anonymous reviewer for this insight.

suppliers, and achieve “greater dynamic efficiency and flexibility in adapting environmental changes than its competitors” (McAlister et al. 2007, p. 38). All of these benefits of advertising enable the firm to enjoy higher financial value. Empirically, advertising spending is found to enhance firm returns (Joshi and Hanssens 2009; Luo and Donthu 2006).

The accounting and finance literatures echo the value impact of advertising. For instance, Chemmanur and Yan (2009, p. 41) argue that “advertising can signal quality not only to the product market, thereby allowing consumers to price the firm’s products correctly in equilibrium, but also to stock market investors on the true value of a firm’s projects, thus allowing them to price the firm’s equity correctly in equilibrium.” Boyd and Schonfeld (1972) point out a positive impact of advertising on stock prices because the purchase of products and stocks is similar: individuals who respond to advertising messages in a product setting also respond to advertising messages in a financial setting. That is, investors may pick stocks on the basis of their familiarity with the stocks. Indeed, investors often prefer firms that have higher brand visibility induced by advertising. Further, advertising enables firms to enjoy more information channels to communicate with investors and obtain greater ownership breadth and investor attention (Grullon et al. 2004). Advertising reduces investors’ search costs and signals firm-specific competitiveness regarding its existing products and new projects. Chauvin and Hirschey (1993) conclude that “spending on advertising is a form of investment in intangible assets with predictably positive effects on the size and variability of future cash flows” (p. 128).

Indeed, because intangible assets account for over 80% of firm value of *Fortune 500* companies, and because advertising spending is crucial to developing brand equity and other intangibles, advertising should have a *direct* bearing on firm value. Some ad campaigns explicitly target investors: “United Technologies Corp. is a great investment because it is a leader in innovation and eco-friendly technologies that help the bottom line and cash flows” (*BusinessWeek* 2007, p. 69). Firms are as interested in selling stocks to investors as in selling products to consumers, i.e., they seek to catch investors’ eyes, just as they display ads anywhere customers might turn. Because Super Bowl ads impress fans and Wall Street, many managers appear to believe that advertising impacts investors and thus firm value.

However, as shown in Table 1, some empirical studies have challenged the relationships between advertising and firm value. For example, Joshi and Hanssens (2010) found that advertising increases returns for some firms, but not for IBM and K-Swiss. Joshi and Hanssens (2009) also note that advertising expands the market value of movie studios nonlinearly with negative marginal returns. Also, Shah et al. (2008) reviewed more than 150 empirical studies (most of which are based on small samples over a short time period) and found inconclusive findings. While mostly positive (Boyd and Schonfeld 1972; Chauvin and Hirschey 1993; Chemmanur and Yan 2010a,b), there are still insignificant (Core et al. 2003) and negative (Bublitz and Ettredge 1989; Han and Manry 2004) correlations between adverting and firm value.

We suggest that some of the inconsistency in the literature may arise because prior studies have not adequately examined the underlying processes that connect advertising to firm value. That is, the literature has generally paid scant attention to the intermediate mechanisms through which advertising may create firm value. Research, however, has begun in this direction. For example, Joshi and Hanssens (2010) examined the role of sales and profits in channeling the impact of advertising on firm value. Here, we focus on a different intermediate process with the role of analysts.

Stock analysts

Stock analysts may play an important interpreting role between product markets and financial markets. For firms, analysts act as agents for disclosing advertising spending and the business rational underlying the advertising spending. For investors, analysts provide expectations and forecasts of firm future cash flows (Luo et al. 2010). Stock analysts may act as interpreters facilitating strategic information flow. According to the “schematic of analyst information processing” by Bradshow (2009, p. 1076) and the two-step information flow theory by Katz and Lazarsfeld (1955), information about new entities often passes through intermediaries who interpret it. These interpreters (analysts) then pass the information gleaned from the data on to users (investors). In other words, analysts can be considered a critically important bridge between firm strategic information and financial value.

Indeed, prior research suggests that analysts play an indispensable role in interpreting data because they “gather and process information about a firm and issue earnings forecasts and recommendations to investors” (Chen and Matsumoto 2006, p. 658). Moreover, analysts not only analyze publicly available information, but also expend extra effort to discover and interpret costly firm-specific private information of strategic value that signals a firm’s current strength and future financial prospects (Ivkovic and Jegadeesh 2004). In this sense, firms’ public and private strategic information of advertising data (i.e., advertising spending and the business logic underlying the advertising spending) is first analyzed and interpreted by analysts, then reflected in analysts’ up-to-date earnings forecasts or cash flow prospects, and finally impounded into firm stock prices (Bradshow 2009).

Table 1 Studies on direct associations between advertising and firm value

Authors	Associations	Findings	The Role of Analyst
Marketing			
Srinivasan et al. (2009)	Ad → Return	+, weak association	No
Joshi and Hanssens (2009)	Ad → Return	+/−, nonlinear	No
Joshi and Hanssens (2010)	Ad → Return	+/0	No
McAlister et al. (2007)	Ad → Risk	–	No
Erickson and Jacobson (1992)	Ad → Return	–	No
Osinga et al. (2010)	Ad → Return/Risk	+/−	No
Accounting/Finance			
Chemmanur and Yan (2010a, b)	Ad → Return	+	No
Core et al. (2003)	Ad → Market-to-book ratio	0	No
Han and Manry (2004)	Ad → Stock Prices	–	No
Chauvin and Hirschey (1993)	Ad → Tobin's q	+	No
Bublitz and Ettredge (1989)	Ad → Return	–	No
Hirschey and Weygandt (1985)	Ad → Tobin's q	+	No
Boyd and Schonfeld (1972)	Ad → Stock Prices	+	No
Literature Gap The role of analyst actions in the impact of advertising on firm returns and risks			

+ positive findings, −negative findings, 0 insignificant findings

Anecdotal evidence on the use of advertising by analysts

There is ample anecdotal evidence suggesting that stock analysts indeed use a firm's advertising spending to evaluate firm performance potential and future earnings prospect. For example, Goldman Sachs analysts predict consumer packaged goods firms to have higher future revenues on the basis of the increased spending on advertising (Brandweek 2010). According to Deutsche Bank analyst, Jamie Isenwater, a firm's advertising spending is vital in "appraising future growth and brand values from the market's perspective" (Marketing Week 2010, p. 16). Also, analysts believed that Hershey, America's biggest chocolate-maker, was in trouble with poor performance in the stock market partly because their advertising spending was cut too much (The Economist 2007). Furthermore, it is reported that "equity analysts expect Google to report a quarterly profit of $6.45 per share in January, 2010, because large retailers substantially increased their online advertising budgets during the most recently completed quarter" (The Wall Street Journal 2010, 0. C1). Therefore, this line of initial evidence in the practice supports the notion that stock analysts help investors interpret the informational value of advertising and incorporate it into asset pricing in financial markets.

Also, we conducted in-depth interviews with 35 stock analysts from 21 brokerage firms. On average, each in-depth interview lasts approximately 48 min. We find that more than 93% of the analysts indeed pay attention to advertising positioning messages and media spending on TV, radio, outdoor, print, and online platforms. Our interviews confirm that analysts typically have two ways to look for data on firm advertising. One way is to seek public information, e.g., COMPUSTAT records and 10-Q/10-K filings of advertising and promotion spending. The other way is to look for private information. Analysts may schedule private meetings with CEOs and top executives in sales and marketing to uncover the business rational for the use of ad spending. Analysts indicate that they highly value the importance of advertising creativity in the intended branding messages, as expected. Thus, these in-depth interviews support the role of analysts on the basis of a qualitative approach to advertising information.

Note that the major role of analysts is not to disseminate who is spending on advertising. The trade press such as *AdvertisingAge* and syndicated services do that better and faster. Rather, analysts externally validate a firm's internal strategic decisions unseen by outsiders. Also, it is not that spending more on advertising *per se* is worthwhile. But, intuitively, developing creative advertising strategies with sound business rationales—sound enough to convince analysts—can provide positive returns for the firm.

Next, we present theory-based logic on why analyst activities may mediate the impact of advertising on firm value.

The mediating role of analysts in the impact of advertising spending on firm value

We expect that analyst coverage and earnings forecasts may mediate the impact of advertising spending on firm value. Tellis (2009) holds that the impact of advertising on firm sales and financial performance is highly variable, because some ad campaigns have big returns and others don't (Koslow et al. 2006; Kulkarni et al. 2003; West et al. 2008). In our context, this suggests that using an advertising-based strategy is valuable in some circumstances, but not in other circumstances, and it is analysts who stand as objective observers giving their validation for the advertising spending. From this standpoint, analyst coverage and earnings forecasts may make a better alignment between advertising spending and firm value.

Indeed, analyst coverage and earnings forecasts of the firm may help investors to (i) attend to the signaling effects of advertising spending and (ii) pay more attention to the communication and liquidity benefits of advertising (Kimbrough 2007; Grullon et al. 2004).[3] In the course of preparing and updating firm earnings forecasts for investors, analysts help investors factor in firm advertising's current and future cash flow benefits in terms of enhanced market awareness, product quality, and brand image (Lodish and Mela 2007). As such, analyst coverage and earnings forecasts help investors fairly price the value of firm advertising spending.

In simplest words, we expect that analyst coverage and earnings forecasts serve as conduits through which advertising spending has an impact on investors and ultimately firm value. The more analysts interpret and pass firm-specific advertising spending on to investors, the greater the extent the incremental value of advertising is corroborated in the eye of investors. In contrast, less analyst coverage and transfer of firm advertising spending into earnings forecasts may presage that less value of advertising is channeled to firm equity pricing. Therefore, analyst cover and earnings forecasts mediate the impact of advertising spending on firm value, i.e., account for the presence or absence of the return on advertising. Of course, because advertising may both directly (Joshi and Hanssens 2010; Luo and Donthu 2006) and indirectly affect firm value via other channels such as customer loyalty (Gupta and Lehmann 2008), it is sensible to expect that analyst coverage and earnings forecasts play a partial mediation role in the impact of advertising spending on firm value as measured by stock return and risk.

H1a: Analyst coverage of the firm partially mediates the impact of advertising spending on firm value (stock return and risk).

H1b: Analyst earnings forecasts of the firm partially mediate the impact of advertising spending on firm value (stock return and risk).

[3] Prior research in finance and accounting supports that analysts expend greater effort to cover and interpret firm advertising spending (Barth et al. 2001). It is noted that "because a firm's product quality and the value of its projects might not be perfectly correlated, outsiders such as investors cannot know the true value of firm products" (Chemmanur and Yan 2009, p. 41).

Model

To empirically test the hypothesized role of analyst-based processes in the impact of advertising on firm value, we estimate several models. The baseline model is:

$$\begin{aligned} FV_{it+1|J} = {} & \alpha_0 + \alpha_1\ Advertising_{it} + \alpha_2\ R\&D_{it} + \alpha_3\ ROA_{it} \\ & + \alpha_4\ ROA\ Variability_{it} + \alpha_5\ Assets_{it} \\ & + \alpha_6\ Leverage_{it} + \alpha_7\ Dividend_{it} \\ & + \alpha_8\ Liquidity_{it} + \alpha_9\ Herfindahl_{it} \\ & + \sum Yearly\ fixed\ effects \\ & + \sum Industry\ fixed\ effects + \varepsilon_{1it+j,} \end{aligned} \tag{1}$$

where FV_{it+j}=firm value, and j=0 and 1 (for immediate and delayed) periods. If α_1 is significant, that would indicate a direct impact of advertising on firm value after controlling for alternative explanations. (While Eq. 1 is written in terms of levels, we have also used changes/surprises in all variables in the analyses as well as advertising stock derived on the basis of Koyck modeling as alternative measures.)

It is worth noting that our selection of control variables is grounded in both accounting and marketing literature. For example, accounting studies (Barth et al. 2001; Barron et al. 2008; Chen and Matsumoto 2006; Ivkovic and Jegadeesh 2004) control for fundamental financial variables that are known to affect firm value: total assets, ROA, ROA variability, financial leverage, and dividends. Thus, we control for all of them. In addition, marketing studies (Joshi and Hanssens 2009; Luo and Donthu 2006; McAlister et al. 2007; Srinivasan et al. 2009) have examined other factors such as R&D spending, liquidity, and Herfindahl concentration. As such, we enter them as covariates as well. Given that time-series cross-section panel data may be serially correlated and heteroskedastic, we use the Newly-West robust regression method to correct for possible biases. We also include firm- and time-fixed effects to control for unobserved heterogeneity.

To examine whether analyst activities mediate the impact of advertising on firm value, we follow the logic of the three-step approach (Baron and Kenny 1986). Specifically, in step one, firm value at t+1 is regressed against advertising at t as specified by Eq. 1. In step two, analyst activities at t+1 are regressed against advertising at t as follows:

$$\begin{aligned} AN_{it+1} = {} & \eta_0 + \eta_1\ Advertising_{it} + \eta_2\ RD_{it} + \eta_3\ ROA_{it} \\ & + \eta_4\ ROA\ Variability_{it} + \eta_5\ Assets_{it} + \eta_6\ Leverage_{it} \\ & + \eta_7\ Dividend_{it} + \eta_8\ Liquidity_{it} + \eta_9\ Herfindahl_{it} \\ & + \sum Yearly\ fixed\ effects \\ & + \sum Industry\ fixed\ effects + \varepsilon_{3it+1,} \end{aligned} \tag{2}$$

where AN_{it+1}=analyst activities in terms of $Coverage_{it+1}$ and $Forecast_{it+1}$.

Finally, in step three, firm value at $t+1$ is regressed against analyst activities at $t+1$ and advertising at t as follows:

$$
\begin{aligned}
FV_{it+1} = {} & \gamma_0 + \gamma_1\, Coverage_{it+1} + \gamma_2\, Forecast_{it+1} \\
& + \gamma_3\, Advertising_{it} + \gamma_4\, RD_{it} + \gamma_5\, ROA_{it} \\
& + \gamma_6\, ROAVariability_{it} + \gamma_7\, Assets_{it} + \gamma_8\, Leverage_{it} \\
& + \gamma_9\, Dividend_{it} + \gamma_{10}\, Liquidity_{it} + \gamma_{11}\, Herfindahl_{it} \\
& + \sum Yearly\ fixed\ effects \\
& + \sum Industry\ fixed\ effects + \varepsilon_{4it+1,}
\end{aligned}
\tag{3}
$$

If the impact of advertising on firm value is decreased after the inclusion of analyst activities, that suggests evidence for the mediating (i.e., partial mediation) role of analyst-based processes.

Note that there is a time lag between advertising spending and analyst variables and firm value for two reasons. First, this lagging structure can reduce the reserved causality concern, because it specifies the impact's direction from advertising spending to analyst variables and firm value, not the opposite direction. Second, there are possible time delays of analyst activities and stock prices in reactions to advertising data. Typically, analyst interpretation of new advertising data is not instantaneous, so investors may intertemporally price analyst interpretations in the stock market, i.e., with a time lagging structure (Kimbrough and McAlister 2009; Luo 2009; Srinivasan et al. 2009).

Data

The dataset in this study is from the largest possible sample of publicly traded firms with the universe of all NYSE-, AMEX-, NASDAQ-listed securities that are contained in CRSP and COMPUSTAT) between 1987 and 2006. To be included in our dataset, a firm had to meet the following criteria. First, it had to have advertising data in COMPUSTAT, along with stock price data in CRSP from July of year t to June of year $t+1$. Second, the firm must have appeared in the COMPUSTAT database for two consecutive years to avoid potential survivor-bias problems and not have negative book equity for the end of fiscal year t-1. Third, the firm must have analysts' earnings forecast data available from I/B/E/S. Following these criteria, we compiled a total of 1,052 firms with advertising data over a span of 20 years. Appendix B reports the sample composition and Table 2 presents summary statistics of all variables.

Advertising is measured as the ratio of reported firm advertising spending in the COMPUSTAT database to firm assets. (Scaling with assets or sales does not change our conclusions.) Because COMPUSTAT no longer provides quarterly advertising data, we use annual data for the universe of firms publically traded in the stock market.

Firm value is measured as incremental firm return (abnormal return) and risk (systematic risk). These two measures are derived simultaneously from the well established financial benchmark model in the finance literature (Fama and French 1993).

$$
\begin{aligned}
R_{it} - R_{ft} = {} & a_{i0} + b_{i1}\left(RMF_t - R_{ft}\right) + b_{i2}SMB_t \\
& + b_{i3}HML_t + b_{i4}UMD_t + \varepsilon_{it},
\end{aligned}
\tag{4}
$$

where R_{it} is the observed return (excessive of risk-free rate of R_{ft}). RMF_t, SMB_t, HML_t, and UMD_t are the market, size, value and momentum systematic factors from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We measure incremental return with $\widehat{\alpha}_{p0}$, which is the difference between actual return R_{it} and expected return (or abnormal return over the financial benchmark). In addition, the estimated parameter $\widehat{b}_{i1}$ is the systematic risk of the firm.

We collect *analyst coverage* and *earnings forecasts* data from I/B/E/S. Analyst coverage is measured as the number of analysts covering the firm and making earnings forecasts as reported in I/B/E/S. In addition, directly following prior accounting and finance studies (Barth et al. 2001; Barron et al. 2008), we measure analyst earnings forecasts as the latest analysts' median consensus forecasts reported in I/B/E/S before earnings announcements and scaled by stock prices. Measuring analyst forecasts before earnings reports can accurately assess firm cash flow prospect as expected by the experts. (After earnings reports, the real earnings numbers are available, so there is no need for analyst's *old* earning forecasts/prospects.) Measuring up-to-date analyst variables before earnings reports is standard practice in accounting and finance (Chen and Matsumoto 2006; Ivkovic and Jegadeesh 2004).

Firm assets are measured as the book value of total assets (Data AT) in COMPUSTAT. *Firm profitability* is measured as return on assets (ROA), or the ratio of firms' operating income to total assets (Data item OIBDP). *Profit variability* is measured as standard deviation of the firm ROAs in the previous 5 years. *Financial leverage* is measured as firms' long-term book debt (Data item DLTT) over total assets. R&D is measured as the reported firm spending in research and development (Data XRD) scaled by total assets. *Dividends* are measured as the ratio of cash dividends (Data DVC) to market capitalization (Data item PRCC_C * Data item CSHO) of the firm. *Liquidity* is measured as firms' current ratio (Data item ACT/Data item LCT). *Herfindahl* is measured as the sum of squared market shares (based on firm sales revenue, Data SALE), assessing the concentration and competition of each industry.

Table 2 Summary statistics of variables

Variables	Mean	Median	Minimum	Maximum	St. Dev
Firm Return	0.0003	0.0002	−0.0253	0.0357	0.0022
Firm Risk	1.0480	1.0283	−8.5580	8.9816	0.6346
Research and Development (in $M)	105	7	0	12183	561
Advertising Expense (in $M)	83	4	0	7937	364
Analyst Coverage	7.5957	5.0000	1.0000	48.0000	7.6642
Earnings Forecast Changes	0.0186	0.0700	−62.0400	13.3700	1.0793
Total Assests (in $M)	2032	233	1	275644	9152
Return on Assests	0.2579	0.0987	0.0000	1.8951	0.3327
Return on Assests (5-year var.)	0.0864	0.0366	0.0000	4.9798	0.1966
Liquidity	3.0849	2.2958	0.1109	123.5777	2.9510
Herfindahl Index	0.2851	0.2086	0.0000	1.0000	0.2540
Leverage	0.1208	0.0388	0.0000	0.9841	0.1752
Total Dividend (in $)	48	0	0	8945	299

Firm return is the incremental return (or abnormal return over the financial benchmark), and firm risk is the incremental risk (or systematic risk) as derived from the financial benchmark model at the firm level (Srinivasan et al. 2009). Total asset is measured as book value of firms' total asset (Data 6 in COMPUSTAT). Firm profitability is measured as return on asset (ROA), or the ratio of firms' operating income (Data 21) to total assets. Profit variability is measured as standard deviation of firm ROAs in the previous 5 years. Financial leverage is measured as firms' long-term book debt (Data 9) over total assets. R&D is measured as the reported firm spending in research and development (Data 46). Dividend is measured as the ratio of cash dividends (Data 89) to market capitalization (Data 14×Data 61) of the firm. Liquidity is measured as firms' current ratio (Data 40/Data 49). Industry Herfindahl concentration is measured as the sum of squared market shares (based on firm sales revenue, Data 12) of each industry. These covariates enable us to model incremental value of advertising over firm fundamentals including profitability (McAlister et al. 2007; Srinivasan et al. 2009)

Results

Results on the direct impact of advertising spending on firm value

As shown in Table 3, Model 3 results suggest that advertising has a positive impact on firm return (α=1.098, p<0.01), as expected. Further, in Model 5, advertising has a negative impact on systematic risk (α=−1.442, p<0.01), consistent with the literature (McAlister et al. 2007). These findings indicate that advertising increases firm value in terms of both return and risk metrics and firm financial performance.

The effects of advertising on firm value are robust to hierarchical Bayesian estimation which accounts for within and between industry heterogeneity (Rossi and Allenby 2003), as shown in Appendix C. Moreover, yearly regression results over the twenty-year span largely support the positive effects of advertising on firm return (90% of the years) and negative effects of advertising on firm risk (75% of the years), as reported in Appendix D.

We also conducted portfolio analyses that support the significant incremental value of advertising over and beyond the financial benchmark (see Appendix E). Thus, these results bear out the significant incremental value of advertising. They also extend the findings of prior studies (Joshi and Hanssens 2010; McAlister et al. 2007) to the entire set of publicly traded firms over a longer period, thus providing a stronger test of the impact of advertising on firm value.

Results on the mediating role of analysts in the impact of advertising on firm value

As shown in Table 3, advertising affects analyst coverage (η=0.851, p<0.05 in Model 1). Also, analyst coverage affects return (γ=0.077, p<0.01 in Model 4), which is in line with the accounting literature (Barth et al. 2001; Barron et al. 2008; Chen and Matsumoto 2006). The inclusion of analyst coverage and earnings forecasts in the model reduces the strength of the effects of advertising on return from γ= 1.098 in Model 3–0.13 in Model 4 (both significant statistically). Therefore, our data suggests a partial mediating role of analyst activities in the impact of advertising on firm value, supporting H_1 in terms of firm return.

Likewise, including analyst coverage and earnings forecasts in the model reduces the size of the effects of advertising on firm risk (from γ=−1.442 in Model 5 to −1.146 in Model 6). These results suggest a partial (but smaller) mediating role of analyst activities in the impact of advertising on firm value, thus adding more support for H_1 in terms of firm risk.

Additional data and reverse causality findings

We also collected more data of advertising spending from a different source, TNS media intelligence. TNS is a global firm specialized in the custom market research and media spending across TV, radio, outdoor, print, and Internet media outlets. We collected monthly data of advertising

Table 3 Advertising, analysts, and firm value

Coverage (t+1)			Earnings Forecast (t+1)			Return (t+1)					Risk (t+1)				
Panel A	Model 1		Panel A	Model 2		Panel A	Model 3		Model 4		Panel A	Model 5		Model 6	
Intercept	−0.822	(0.034)[c]	Intercept	−3.163	(0.060)[c]	Coverage (t+1)			0.077	(0.014)[c]	Coverage (t+1)			0.004	(0.000)[c]
Advertising	0.851	(0.086)[c]	Advertising	−1.579	(0.156)[c]	Earnings Forecasts (t+1)			0.206	(0.009)[c]	Earnings Forecasts (t+1)			−0.005	(0.006)
R & D	1.954	(0.102)[c]	R & D	−1.482	(0.186)[c]	Intercept	0.449	(0.067)[c]	1.559	(0.079)[c]	Intercept	0.398	(0.022)[c]	0.434	(0.022)[c]
Total Assets	0.415	(0.006)[c]	Total Assets	0.244	(0.010)[c]	Advertising	1.098	(0.203)[c]	0.130	(0.020)[c]	Advertising	−1.442	(0.067)[c]	−1.146	(0.067)[c]
ROA	0.158	(0.020)[c]	ROA	−0.666	(0.037)[c]	R & D	1.989	(0.201)[c]	1.302	(0.220)[c]	R & D	0.477	(0.066)[c]	0.352	(0.068)[c]
ROE	0.047	(0.012)[c]	ROE	0.217	(0.020)[c]	Total Assets	−0.029	(0.011)[c]	−0.102	(0.014)[c]	Total Assets	0.109	(0.004)[c]	0.098	(0.004)[c]
5-yr. var. ROA	−0.141	(0.045)[c]	5-yr. var. ROA	0.248	(0.081)[c]	ROA	0.017	(0.040)	0.153	(0.043)[c]	ROA	0.090	(0.013)[c]	0.080	(0.013)[c]
Liquidity	0.009	(0.010)	Liquidity	−0.008	(0.019)	ROE	−0.036	(0.023)	−0.013	(0.024)	ROE	−0.021	(0.007)[c]	−0.019	(0.007)[b]
Herfindahl Index	−0.106	(0.016)[c]	Herfindahl Index	0.051	(0.029)[a]	5-yr. var. ROA	0.219	(0.088)[b]	0.353	(0.094)[c]	5-yr. var. ROA	−0.123	(0.029)[c]	−0.118	(0.029)[c]
Leverage	−1.455	(0.033)[c]	Leverage	−0.020	(0.067)	Liquidity	−0.089	(0.020)[c]	−0.001	(0.022)	Liquidity	0.046	(0.007)[c]	0.047	(0.007)[c]
Dividend	−0.011	(0.005)[b]	Dividend	−0.115	(0.008)[c]	Herfindahl Index	0.151	(0.032)[c]	0.041	(0.034)	Herfindahl Index	−0.074	(0.010)[c]	−0.063	(0.010)[c]
Panel B			Panel B			Leverage	0.223	(0.065)[c]	0.040	(0.082)	Leverage	0.127	(0.021)[c]	0.164	(0.022)[c]
Adjusted R square	0.554		Adjusted R square	0.110		Dividend	−0.048	(0.009)[c]	−0.076	(0.010)[c]	Dividend	−0.068	(0.003)[c]	−0.069	(0.003)[c]
F-stat	3157.040		F-stat	209.408		Panel B					Panel B				
BIC	−19185		BIC	−214.976		Adjusted R square	0.013		0.065		Adjusted R square	0.061		0.063	
						F-stat	34.591		98.770		F-stat	164.995		143.571	
						BIC	−335786		−227095		BIC	−41599.2		−41664	

[a] indicates significance at the 10% level, [b] indicates significance at the 5% level, and [c] indicates significance at the 1% level. The parameters in the Return results have multiplied by a factor of 1000 to save space

spending for 319 *Fortune* biggest companies over 1987 M1–2008 M12 (i.e., with a total of 84, 216 firm-month observations). The results are summarized in Appendix F. Again, after entering the mediator variables of analyst coverage and earnings forecast, the impact of advertising spending on return drops from 1.035 to 0.287 (all $p<0.001$). Also, after entering the mediator variables of analyst coverage and earnings forecast, the impact of advertising spending on risk drops from −1.216 to −0.955 (all $p<0.001$). Thus, these results with a different data source and monthly frequencies confirm our conclusion on the partial mediation role of analyst variables in the impact of advertising on firm value.[4]

In addressing reverse causality concerns, we conducted Granger causality tests. The Granger causality models are specified below (Granger 1969).

$$Y_t = \sum_{i=1}^{n} \alpha_i Y_{t-i} + \sum_{j=1}^{m} \beta_j X_{t-j} + \gamma_t$$
$$X_t = \sum_{j=1}^{m} \phi_j Y_{t-j} + \sum_{i=1}^{n} \omega_i X_{t-i} + \tau_{t,} \quad (5)$$

where X can be advertising spending m lags (up to 12 time-period lags). Y is firm value in terms of return and risk with n lags. In the above equations, if all the coefficients are significant, then Y and X mutually Granger cause each other. If only the coefficients of β_j are significant, then X Granger causes Y. If only the coefficients of ϕ_j are significant, then Y Granger causes X. The Wald F test determines the significance of the equations. This test statistics is specified as F_{wald}=[(SSR1–SSR2)/q]/[SSR2/(n-s)], where SSR1 is defined as the sum of squared residuals in the restricted equation (in which β_j and ϕ_j are restricted to be zero) and SSR2 is the sum of squared residuals in the unrestricted equation. In addition, q=the number of restrictions, *n*=the number of observations, and s=the number of independent variables in the unrestricted equation.

The results suggest that the Granger causality analyses confirm the impact direction from advertising to firm return ($F_{wald}=38.676$, $p<0.01$) and firm risk ($F_{wald}=21.395$, $p<0.01$). In addition, the reversed direction from firm value to advertising is not significant statistically (both $p>0.05$ for firm return and risk). We also applied Granger tests in the original data sample and support the impact direction from advertising to firm value ($F_{wald}=30.557$, $p<0.01$ for return and $F_{wald}=12.086$, $p<0.01$ for risk), not from firm value to advertising. Therefore, these lines of empirical evidence add more support for the expected impact of advertising on firm value in this study.

Moreover, we considered the category ad spending because the impact of advertising for top advertisers such as automotive companies may be different from that for smaller advertisers such as machinery firms. To do so, we split our original dataset into top advertiser sample (auto, tobacco, electronics, package good, retail and movie/media companies) and smaller advertiser sample (insurance agents, leather, stone products, educational services, personal and health services, chemical, instrument or machinery firms) on the basis of annual *AdvertisingAge* Top 100 Global Marketers and SIC codes. We found that the impact of advertising on firm return for top advertiser sample ($\gamma=2.386$, $p<0.001$) is indeed bigger than that for smaller advertiser sample ($\gamma=0.619$, $p<0.001$), although both are statistically significant. Again, the partial mediation role of analyst results still holds, using categorical advertising spending or not. Overall, these results show that analyst-based processes partially channel the impact of advertising on firm value.

Managerial implications

When evaluating advertising spending, managers should consider the impact of advertising on the firm's ultimate goal of maximizing shareholder wealth. This corporate goal should significantly determine the size, timing, and allocation of the advertising budget. On the basis of portfolio investment asset-pricing models, we illustrated the long-term consequences of a change in advertising spending on firms' abnormal returns over and beyond the financial benchmark.

More specifically, at the portfolio level, the financial benchmark examines whether advertising spending can generate significant incremental value (higher returns and/or lower risks) in the long run, over and beyond expected returns and risks (Fama and French 1993):

$$R_{pt} - R_{ft} = a_{p0} + b_{p1}\left(RMF_t - R_{ft}\right) + b_{p2}SMB_t + b_{p3}HML_t + b_{p4}UMD_t + \varepsilon_{pt}, \quad (6)$$

where R_{pt} is the observed return on advertising portfolio *p* in month *t* (excessive of risk-free rate of R_{ft}). We denote the subscript *p* as a well-diversified stock portfolio, which should consist of greater than twenty stocks (or firms) from diverse industries. Note that the financial benchmark has

[4] Because our original sample is the universe of the firms, the value of advertising should be quite generalizable to all firms traded in the public. Yet, CRSP/COMPSTAT has no brand-level advertising data. Luckily, the alternative source of TNS media intelligence provides brand-level advertising data. Thus, we now have collected monthly data of advertising spending for 319 big companies over 1987 M1–2008 M12, aggregated from brands of a firm. The brand advertising spending includes expenses in TV, radio, outdoor, print, and Internet media outlets as tracked by TNS. We then aggregate the advertising spending from brand level to firm level so as to match firm stock prices and analyst forecasts (Mizik and Jacobson 2009). Again, the results are robust regarding the partial mediation role of analyst in the impact of advertising spending on firm value.

already accounted for differences in market changes, firm size, growth rates, and momentum effects when testing the incremental value of advertising. Influences of any other variables (e.g., firm- or industry-idiosyncrasies) on stock prices are modeled by either the construction of well-diversified portfolios or the error term ε_{pt}, or noises. Because the benchmark model generally explains 95% of variances of portfolio returns, it would be difficult for investments in high advertising to consistently outperform the benchmark model. We ran the Newly-West robust regression methods to correct possible serial correlation and heteroskedasticity biases, when deriving results for the incremental value (return and risk) of the five advertising portfolios (from top 20% to bottom 20%). See Appendix E for more methodological details.

As reported in Table 4 Panel D, the high-advertising (top 20%) portfolio has a positive and significant incremental return (a_{p0}=0.34% monthly, or 4.08% annually; $p<0.05$) over the twenty-year period. In contrast, return for the low-advertising portfolio is not significant statistically ($p>0.05$), though positive. Regarding risk, results show that the high-advertising portfolio has an estimated systematic risk (b_{p1}=0.861) significantly less than 1.0, thus less risky than the financial benchmark. On the contrary, the low-advertising portfolio has an estimated systematic risk (b_{p1}=1.464) significantly greater than 1.0, thus more risky than the financial benchmark.

These findings suggest that advertising indeed enhances firm value, after accounting for diversifiable unsystematic risks (company or industry specific idiosyncrasies affecting stock prices) and non-diversifiable systematic risks (market changes, size, growth, and momentum effects). Our findings with a monthly incremental return of 0.34% are in line with the recent finance literature. For example, Chemmanur and Yan (2010b, p. 2) report that "1% increases in firm advertising intensity enable firms to gain 1.5%–3% increases in market valuation at the time of initial public offerings" (i.e., advertising could double firm value in a single day).

These results are actionable and significant because they suggest that firms decreasing from top 20% to bottom 20% advertising spending when compared to all industry competitors would experience a drop of abnormal return by 4.08% in 1 year and a cumulative total of 81.6% in 20 years. Evidently, the findings highlight the strategic importance of advertising in increasing returns and reducing systematic risk, thus enhancing shareholder wealth. The long-term abnormal return of advertising is indicative of market inefficiency and a possibility that firms can beat competition with long-term superior shareholder value via advertising. Therefore, a key managerial message is that firms should strike a balance in budgeting advertising expense to optimize the long-term benefits on the basis of shareholder value maximization.

Discussion and conclusion

Does advertising really work? The particular angle that this study takes is whether or not spending on advertising increases share price and how analysts' opinions contribute to the link between advertising and share price. This study is intended to test how analyst-based processes account for the effects of advertising on firm value. Using a large scale of longitudinal dataset with 1,052 firms over 20 years, we find that analyst activities partially mediate the impact of advertising on firm return and risk. These findings indicate that the more analysts discover firm advertising spending and reflect it in their earnings forecasts, the more likely the benefits of advertising are channeled into firm financial value. As a result, Main Street may better align with Wall Street via corporate disclosure of advertising spending to analysts. Apparently, there is a need for analysts to monitor and analyze firm advertising. Analysts facilitate investors to discover and incorporate the fair value of advertising in firm equity pricing.

Responding to the critique that simply correlating product market advertising with financial market stock returns may miss many intermediate variables, this research is among the first to examine the underlying processes that account for the impact of advertising on firm value. Although some studies find that advertising spending directly impacts firm return and systematic risk (Hanssens et al. 2009; Luo and Donthu 2006), the literature has generally paid scant attention to the intermediate mechanisms through which advertising may create firm value. There exists a "black box" between inputs and outputs. Our findings serve to open the black box and fill this literature gap with analyst-based mechanisms.

Indeed, without mapping out the related processes, it is hard for advertising and brand managers to defend advertising budgets and, at the same time, easy for CEOs to cut marketing expenses and focus their attention and budgets elsewhere. That leads to a looming danger: "marketing could lose its way" to other functions in the organization (Reibstein et al. 2009, p. 1). The supported evidence of advertising accountability and the processes would make advertising spending more "essential to firm organic growth" (Gupta and Steenburgh 2008, p. 1). As such, a direct managerial implication is that marketing practitioners could gain a stronger voice at the corporate strategy table if they communicate and articulate the paths through which advertising creates shareholder value with enhanced returns and decreased risks.

In a broad sense, our findings contribute to marketing-finance interface research (Gupta et al. 2004; Luo 2009; Hanssens et al. 2009). Extending prior studies that are based on subsets of publicly traded firms and non-diversified investments, this work reveals evidence for the

Table 4 Advertising portfolios and firm value

Portfolio		Alpha	RMF	SMB	HML	UMD
Low advertising	Estimates	−0.0005	1.0603	−0.03273	−0.9534[c]	−0.1100
Panel A: Advertising Portfolios (5-year period)						
	Standard Error	(0.0028)	(0.0639)	(0.1222)	(0.1693)	(0.0957)
2	Estimates	−0.0009	1.0945	0.2671	−0.1471	−0.0505
	Standard Error	(0.0029)	(0.0665)	(0.1271)	(0.1761)	(0.0995)
3	Estimates	−0.0042	1.4354	0.2235	−0.2258	0.0785
	Standard Error	(0.0061)	(0.1387)	(0.2652)	(0.3674)	(0.2076)
4	Estimates	0.0025	1.0321	−0.0468	−1.1966[c]	0.1611
	Standard Error	(0.0039)	(0.0890)	(0.1701)	(0.2357)	(0.1332)
High advertising	Estimates	0.0048[a]	0.8695	−0.3993	−0.6912[c]	−0.0547
	Standard Error	(0.0027)	(0.0619)	(0.1183)	(0.1640)	(0.0927)
Panel B: Advertising Portfolios (10-year period)						
Low advertising	Estimates	0.0025	1.0291[c]	−0.1131	−0.6552[c]	−0.0289
	Standard Error	(0.0025)	(0.0630)	(0.0977)	(0.1124)	(0.0893)
2	Estimates	0.0021	1.0422[c]	0.1976[b]	−0.2361[b]	−0.0421
	Standard Error	(0.0023)	(0.0600)	(0.0931)	(0.1071)	(0.08511)
3	Estimates	−0.0009	1.4070[c]	0.0342	−0.1003	0.0158
	Standard Error	(0.0039)	(0.1008)	(0.1563)	(0.1798)	(0.1429)
4	Estimates	0.0069[a]	1.1179[c]	−0.0767	−0.7389[c]	0.2032
	Standard Error	(0.0037)	(0.0937)	(0.1454)	(0.1672)	(0.1329)
High advertising	Estimates	0.0050[b]	0.8725[c]	−0.4613[c]	−0.5878[c]	−0.0471
	Standard Error	(0.0019)	(0.0488)	(0.0756)	(0.0870)	(0.0691)
Panel C: Advertising Portfolios (15-year period)						
Low advertising	Estimates	0.0024	1.0138[c]	0.2323[c]	−0.4085[c]	−0.1140[b]
	Standard Error	(0.0026)	(0.0622)	(0.0732)	(0.0911)	(0.0528)
2	Estimates	0.0011	1.0609[c]	0.3134[c]	−0.5977[c]	−0.0087
	Standard Error	(0.0035)	(0.0844)	(0.0994)	(0.1235)	(0.0716)
3	Estimates	0.0051	1.2242[c]	−0.0007	−0.1085	−0.2376[c]
	Standard Error	(0.0032)	(0.0772)	(0.0909)	(0.1130)	(0.0655)
4	Estimates	0.0069[b]	1.0357[c]	−0.2448[b]	−0.3748[c]	0.0111
	Standard Error	(0.0034)	(0.0817)	(0.0963)	(0.1197)	(0.0694)
High advertising	Estimates	0.0045[b]	0.8168[c]	−0.3812[c]	−0.3682[c]	0.0333
	Standard Error	(0.0020)	(0.0473)	(0.0557)	(0.0692)	(0.0401)
Panel D: Advertising Portfolios (20-year period)						
Low advertising	Estimates	0.0011	1.4640[c]	0.9635[c]	−0.8971[c]	−0.0886
	Standard Error	(0.0043)	(0.1087)	(0.1282)	(0.1582)	(0.0926)
2	Estimates	−0.0014	1.3181[c]	0.5593[c]	−0.5085[c]	−0.2381[c]
	Standard Error	(0.0035)	(0.0877)	(0.1034)	(0.1276)	(0.0747)
3	Estimates	0.0017	1.1439[c]	0.4970[c]	−0.7014[c]	−0.1731[c]
	Standard Error	(0.0031)	(0.0784)	(0.0925)	(0.1141)	(0.0668)
4	Estimates	0.0043[a]	1.0876[c]	0.2404[c]	−0.7792[c]	0.0683
	Standard Error	(0.0025)	(0.0633)	(0.0747)	(0.0921)	(0.0540)
High advertising	Estimates	0.0034[b]	0.8607[c]	−0.2981[c]	−0.2976[c]	−0.0567[a]
	Standard Error	(0.0014)	(0.0359)	(0.0423)	(0.0522)	(0.0306)

Financial benchmark models are run with the excess value-weighted returns (average raw return minus the risk-free rate) as the dependent variable. This table reports the slope coefficients and their respective standard errors (in parentheses) from the time-series regressions of excess returns on various asset pricing factors in the time period of 228 months (July 1987 to June 2006) on sorted quintile portfolios based on advertising. The factors are: *RMF*, excess return (in excess of the risk-free rate) of the value-weighted market portfolio, *SMB*, the return on an arbitrage (zero-investment) portfolio consisting of the return on the big-company portfolio subtracted from the return on the small-company portfolio, *HML*, the return on an arbitrage portfolio of high book-to-market ratio (*BE/ME*) stocks minus the return on the portfolio of low *BE/ME* stocks, and *UMD*, the return on an arbitrage portfolio of the return on the last year's high returns portfolio subtracted from the return on the last year's low return portfolio. [a] indicates significance at the 10% level, [b] indicates significance at the 5%level and [c] indicates significance at the 1% level generalizabilility and validity of advertising value to the universe of stocks for all public firms. Our portfolio analyses that support the significant incremental value of advertising over and beyond the financial benchmark bear out the significant incremental value of advertising. They also extend the findings of prior studies (Joshi and Hanssens 2010; McAlister et al. 2007) to the entire set of publicly traded firms over a longer period, thus providing a stronger test of the impact of advertising on firm value. Thus, we help advance the marketing accountability literature with solid empirical building blocks, large scale datasets, and value implications of advertising spending.

The findings are also relevant to the financial community. For example, according to the American Institute of Certified Public Accountants' Statement of Position 93-7, advertising costs are expended in the same period as they are incurred. Such practice ignores (and adds uncertainty to) future cash receipts resulting from advertising and branding efforts (Amir and Lev 1996). We encourage firms to voluntarily engage in more complete reporting of advertising spending (along with other operating expenditures) to the public and the Wall Street community as part of corporate announcements, annual reports, and SEC 10-K/10-Q filings. To the extent that the investor community pays attention to firm equity fostered by advertising, the efficiency of the stock market can be improved.

However, there is a catch. Advertising did increase returns, but few marketing managers in companies in the current data set might have increased ad spending willy-nilly. Instead, there had to be a cogent business logic inside the firm for top executives to approve such an expenditure. That is, firms may not decide a random use of advertising spending as a marketing strategy. Rather, the third-party of stock analysts may play a role in validating the firm decisions and inherent business rationales underlying a strategic use of advertising spending.

Regarding future research, the results suggest that analyst variables should be useful metrics and mechanisms for understanding the impact of other marketing variables on financial value. In addition, research examining how well analysts interpret advertising spending in competition and other decisions seems well worth pursuing. One limitation of the data in this regard is the focus on quantitative aspects of advertising (i.e., ad spend) to the exclusion of qualitative factors (e.g., hiring a new ad agency, advertising during the Super Bowl, developing a high impact campaign that receives significant news coverage). Thus, an interesting challenge for future works is to include data with both quantitative and qualitative advertising factors that might impact analysts' impressions and valuations of the firm. More broadly, future research in marketing, accounting, and finance areas should orchestrate in sync in order to better understand fundamental processes behind the possible long-term stock returns to marketing metrics.

In conclusion, this study provides a beginning point for uncovering analyst-based processes through which advertising spending is incorporated into shareholder wealth. We hope that this work stimulates more research interest in the impact of advertising spending on firm value.

Appendix A: Assumption of information asymmetry

The assumption of information asymmetry between product markets and financial markets is valid for two reasons. First, theoretically, prior research in finance and accounting (Barth et al. 2001; Barron et al. 2002; Chen and Matsumoto 2006; Ivkovic and Jegadeesh 2004; Kimbrough 2007) has shown that managers are insider strategic decision makers of the firm and, thus, have more information of the firm operations and advertising strategies than outsiders. In contrast, investors are outside observers of the firm and do not know details of the advertising budgeting processes or resources allocations. Chemmanur and Yan (2009, p. 41) explicitly hold that outsiders such as investors in financial markets don't know the true informational value of advertising data. Rather, they can only indrectly *infer* the value of firm products and advertising spending via analyst interpretations. Srinivasan and Hanssens (2009) and Kimbrough and McAlister (2009) all acknowledge that managers have more firm-specific information than investors and that this information asymmetry gives rise to the importance of using the third-party analysts' forecasts to fairly price firm intangibles.

Second, empirically, Hou and Robinson (2006) find a high asymmetry between product markets and financial markets. They demonstrate that a portfolio investment strategy of holding stocks from industries with high product market competition may produce significant abnormal return in the stock market. This abnormal return suggests some market inefficiencies. That is, if there is complete information and no information asymmetry between product markets and financial markets, then this abnormal return should not exist. Per an anonymous reviewer, we replicate Hou and Robinson's (2006) findings with our dataset on the basis of the portfolio sorting analyses methodology. Our portfolio results indeed suggest significant abnormal return to product market competition (as measured by the *Herfindahl* concentration index, or the sum of squared market shares based on firm sales revenue). As such, these lines of theoretical and empirical evidence provide reasonable support for the information asymmetry assumption between product markets and financial markets.

Appendix B: Sample composition

The sample includes all NYSE/AMEX/NASDAQ–listed securities that are contained in the intersection of the CRSP monthly returns file, the COMPUSTAT industrial annual file, and the I/B/E/S summary file between January 1987 and December 2006. This table reports the number of firms and the percentage of firms relative to the total sample for each industry according to the Standard Industrial Classification (SIC) codes system.

Table 5 Sample composition

SIC codes	# of Firms	Percentage	SIC description
1	2	0.19%	Agricultural Production Crops
12	1	0.10%	Coal Mining
13	2	0.19%	Oil and Gas Extraction
14	1	0.10%	Mining and Quarrying Of Nonmetallic Minerals, Except Fuels
15	1	0.10%	Building Construction General Contractors and Operative Builders
17	1	0.10%	Construction Special Trade Contractors
20	27	2.57%	Food and Kindred Products
21	4	0.38%	Tobacco Products
23	2	0.19%	Apparel and Other Finished Products Made from Fabrics
24	1	0.10%	Lumber and Wood Products, Except Furniture-
25	11	1.05%	Furniture and Fixtures
26	10	0.95%	Paper and Allied Products
27	9	0.86%	Printing, Publishing, and Allied Industries
28	120	11.41%	Chemicals and Allied Products
29	4	0.38%	Petroleum Refining and Related Industries
30	15	1.43%	Rubber and Miscellaneous Plastics Products
31	3	0.29%	Leather and Leather Products
32	6	0.57%	Stone, Clay, Glass, and Concrete Products
33	5	0.48%	Primary Metal Industries
34	15	1.43%	Fabricated Metal Products, Except Machinery
35	130	12.36%	Industrial and Commercial Machinery and Computer Equipment
36	127	12.07%	Electronic and Other Electrical Equipment and Components
37	23	2.19%	Transportation Equipment
38	143	13.59%	Measuring, Analyzing, and Controlling Instruments
39	22	2.09%	Miscellaneous Manufacturing Industries
47	1	0.10%	Transportation Services
48	16	1.52%	Communications
49	2	0.19%	Electric, Gas, and Sanitary Services
50	4	0.38%	Wholesale Trade-durable Goods
51	7	0.67%	Wholesale Trade-non-durable Goods
54	1	0.10%	Food Stores
57	1	0.10%	Home Furniture, Furnishings, and Equipment Stores
58	3	0.29%	Eating and Drinking Places
59	5	0.48%	Miscellaneous Retail
60	1	0.10%	Depository Institutions
61	1	0.10%	Non-depository Credit Institutions
62	4	0.38%	Security and Commodity Brokers, Dealers, Exchanges, and Services
63	1	0.10%	Insurance Carriers
64	2	0.19%	Insurance Agents, Brokers, and Service
67	6	0.57%	Holding and Other Investment Offices
72	1	0.10%	Personal Services
73	286	27.19%	Business Services
78	1	0.10%	Motion Pictures
79	4	0.38%	Amusement and Recreation Services
80	7	0.67%	Health Services
82	1	0.10%	Educational Services
87	9	0.86%	Engineering, Accounting, Research, Management
99	3	0.29%	Non classifiable Establishments
Total	1052	100%	

Appendix C: Hierarchical Bayesian approach to advertising value

We also apply hierarchical Bayesian approach (HBA) to enhance the rigor of modeling analyses and enrich implications of findings. HBA is advantageous in several aspects. For example, HBA allows for parameter variations across firms (Bradlow and Rao 2000; Rao et al. 2004). It generates disaggregated effects of advertising on financial value for each firm (with a distribution of estimates), rather than aggregated effects (with only point or interval estimates). Also, it separates between-industry variance from within-industry variance. Bayesian estimates are "free from the use of asymptotical approximations and are grounded in formal probability theory" (Rossi and Allenby 2003, p. 305). HBA provides precise, firm-specific inference on the exact probability that relations between advertising and value exist in a given firm. As such, HBA produces estimates that reveal more insights regarding results heterogeneity, or by what probabilistic predictive inference advertising is related to firm value. Specifically, the HBA model is specified as:

$$\begin{aligned} FV_{it+j|J} = {} & \phi_0 + \phi_{1(\mathrm{h})}\, Advertising_{it} + \phi_{2(\mathrm{h})} Advertising_{it} \\ & \times Coverage_{it} + \phi_{3(\mathrm{h})}\, Advertising_{it} \times Forecast_{it} \\ & + \phi_4\, Coverage_{it} + \phi_5\, Forecast_{it} + \phi_6\, RD_{it} \\ & + \phi_7 ROA_{it} + \phi_8\, ROAVariability_{it} + \phi_9 Assets_{it} \\ & + \phi_{10} Leverage_{it} + \phi_{11}\, Divident_{it} \\ & + \phi_{12} Liquidity_{it} + \phi\gamma_{13}\, Herfindahl_{it} \\ & + \sum yearly\ fixed\ effects \\ & + \sum industry\ fixed\ effects + \varepsilon_{it+j}, \end{aligned} \tag{A1}$$

where $\varphi_{i(h)}$ is the Bayesian random estimates for the effects of advertising and its interactions with analyst coverage and earnings forecasts. We summarize HBA analyses results (mean, minimum, 10%, 90%, and maximum coefficients) in Table 6.

As shown in Table 6, HBA results suggest that similar to results in Table 3, advertising has significant effects on firm incremental return and risk. The posterior density of these effects is presented in Fig. 1. The posterior estimates suggest additional insights beyond the non-Bayesian results in Table 3. While non-Bayesian results suggest *average* effects of advertising on return/risk, Bayesian results provide full probabilistic predictive inference on the likelihood of such effects. For example, Fig. 1 Panel A shows that the likelihood of advertising's effects on return is asymmetrically distributed (both *t* and *t*+1). The bell-shaped curves determine the exact probability of any estimate within the distribution for the effect size of advertising value. As such, these HBA results indicate that advertising value is not distributed with strictly equal probabilities across firms. Rather, they are heterogeneous across firms with different likelihoods of occurrence.

Table 6 Bayesian estimates: return and risk effects of advertising

	t+0						t+1					
	Mean	SD	Min.	10%	90%	Max.	Mean	SD	Min.	10%	90%	Max.
Advertising - Return	0.00103	0.0013	0.0081	0.00084	0.00118	0.00120	0.00125	0.00017	0.00096	0.00102	0.00156	0.00156
Advertising- Risk	−1.48550	0.04340	−1.55890	−1.54890	−1.43670	−1.42930	−1.39070	0.05630	−1.48760	−1.46740	−1.28920	−1.28920

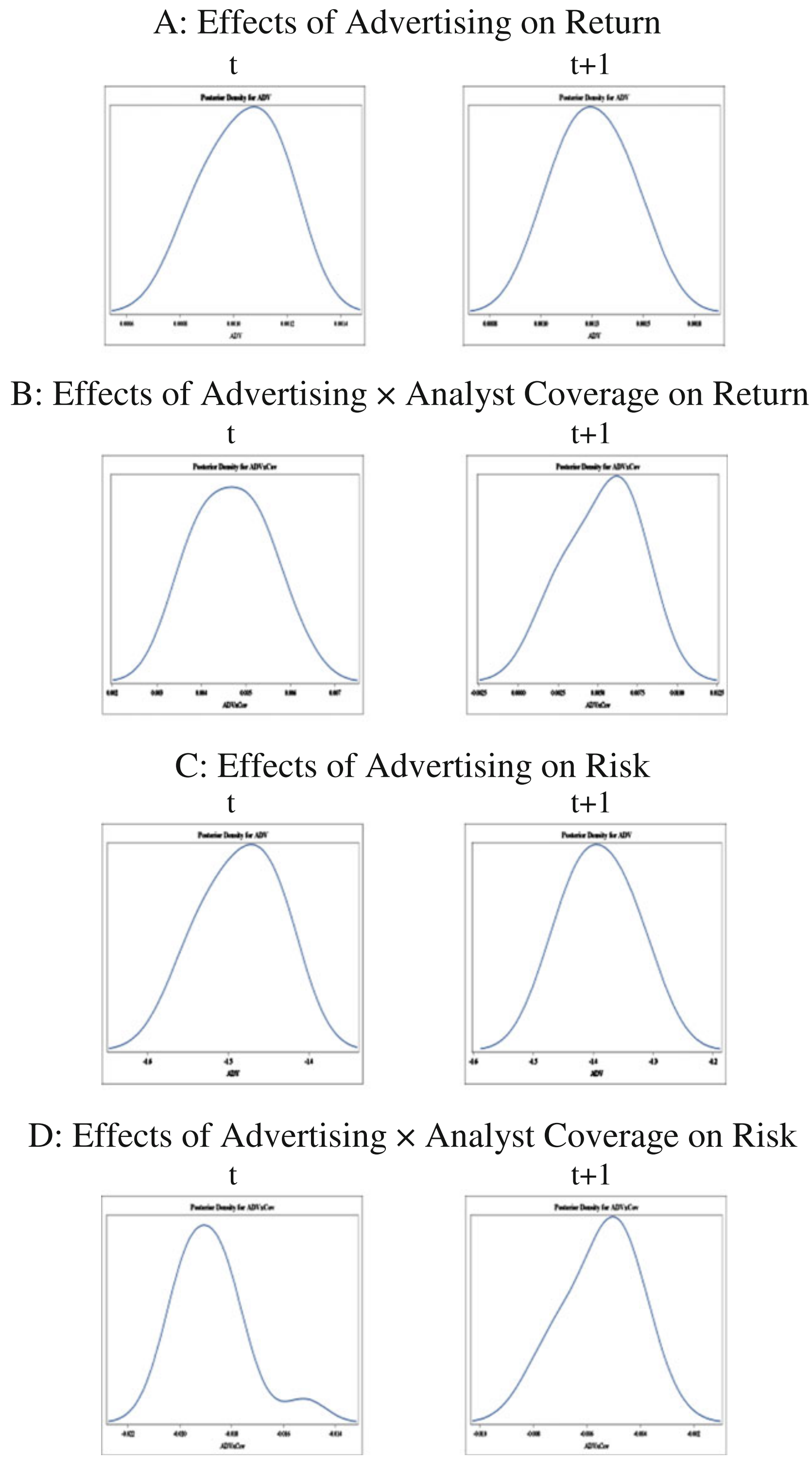

Fig. 1 Posterior density of hierarchical bayesian estimates. Panel **a**: Effects of Advertising on Return. Panel **b**: Effects of Advertising × Analyst Coverage on Return. Panel **c**: Effects of Advertising on Risk. Panel **d**: Effects of Advertising × Analyst Coverage on Risk

Appendix D: Yearly regression results of advertising value

Because each year the impact of advertising on firm value can vary, we also conduct yearly regressions. The annual results over the 20 years are plotted in below. Again, findings largely support positive effects of advertising on firm return for 90% (=18/20) of the years in the sample and negative effects advertising on firm risk for 75% (=15/20) of the years. Also, as shown in the figure, the magnitude of the effects is heterogeneous, indicating different degrees of advertising value across years.

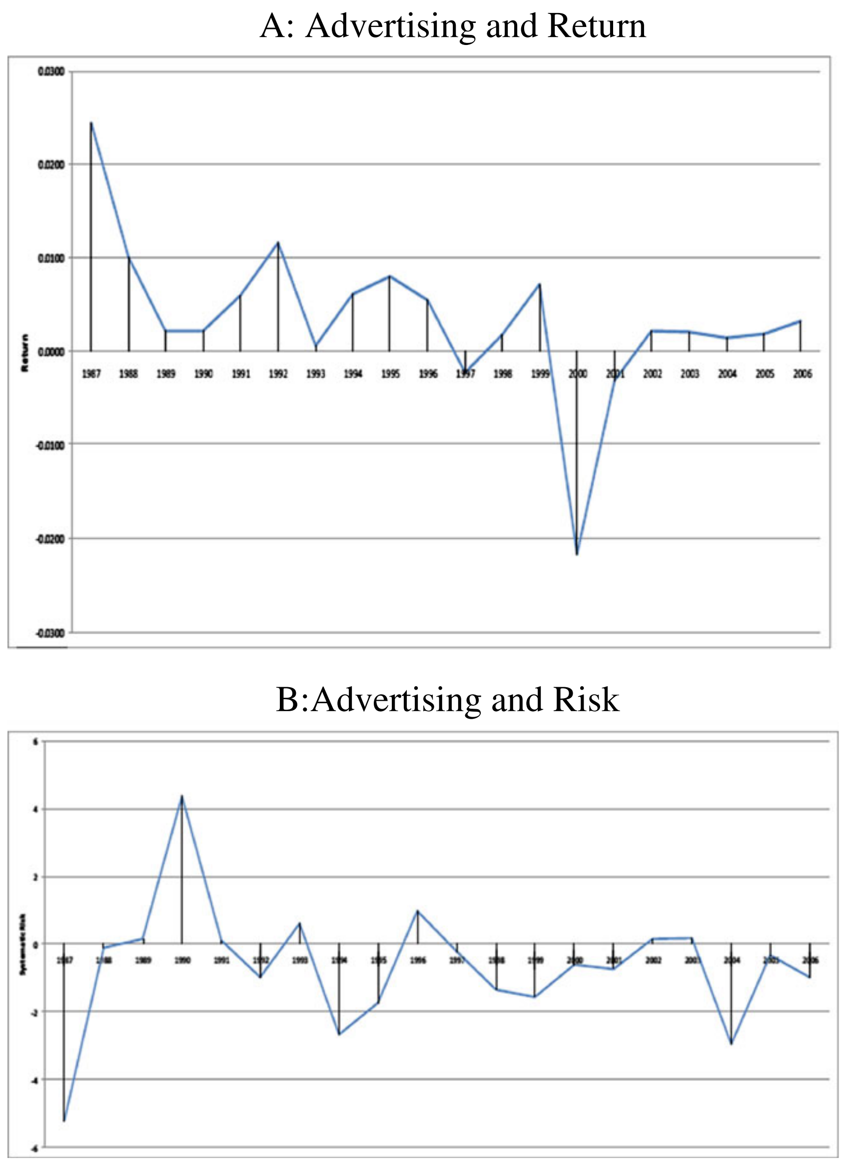

Fig. 2 Panel **a**: Advertising and Return. Panel **b**: Advertising and Risk

Appendix E: Portfolio analyses of advertising value

Methodology

At the portfolio level, the financial benchmark examines whether advertising investments can generate significant incremental value (higher returns and/or lower risks) in the long run, over and beyond expected returns and risks:

$$R_{pt} - R_{ft} = a_{p0} + b_{p1}\left(RMF_t - R_{ft}\right) + b_{p2}SMB_t + b_{p3}HML_t + b_{p4}UMD_t + \varepsilon_{pt}, \qquad \text{(A2)}$$

where R_{pt} is the observed return on advertising portfolio p in month t (excessive of risk-free rate of R_{ft}). We denote the subscript p as a diversified stock portfolio, which should consist of greater than 20 stocks (or firms) from diverse industries. Time t is the month (July 1987–June 2006). If $\widehat{\alpha}_{p0} > 0$, then investments on the advertising portfolio generate significant incremental returns for the time period (1987–2006), over and beyond the financial benchmark. If $\widehat{b}_{p1} < 1$, advertising portfolio is less risky than the financial benchmark (no risk premiums). In addition, if and only if both conditions are satisfied, investments on the advertising portfolio can consistently outperform the stock market with higher returns and lower risks, above and beyond the financial benchmark model.

It is worthy to note that portfolios with less than 20 stocks even from multiple sectors are not well-diversified (too few stocks to hedge unsystematic risks), nor are portfolios with over 20 stocks from a single sector (all eggs in one basket). In general, not-well-diversified portfolios are subject to omitted variable biases (confounds with firm- or industry-specific idiosyncrasies) and cannot rule out alterative explanations. Only well-diversified portfolios can minimize the threat of company- and industry-specific idiosyncrasies that are unmeasured but affect stock prices. The more stocks in an investment portfolio, the lower unsystematic risk exposure to structural and institutional factors.

In addition, we stress the importance of using the entire publicly traded firms in portfolio construction. This is because subsets of publicly traded firms are biased sample and thus subject to sample-selection problems, threatening the validity of results. Essentially, effective risk management and asset allocation in portfolio analyses require the use of full sample to generate well-diversified portfolios. This requirement also serves as a rigorous grilling of the true value of advertising investments.

Moreover, the financial benchmark has already accounted for differences in market changes, firm size, growth rates, and momentum effects, when testing the incremental value of advertising. Influences of any other variables (e.g., firm- or industry-idiosyncrasies) on stock prices are modeled by either the construction of well-diversified portfolios or the error term ε_{pt}, or noises. According to the financial benchmark, the noises are not substantial because the R^2 of portfolio-level regression is around 95% (Fama and French 1993). In other words, because the benchmark model generally explains 95% of variances of investment portfolio returns, it would be difficult for investments in high advertising portfolios to consistently outperform the benchmark model.

Based on the sorting of advertising intensity data from COMPUSTAT across all firms each year, we construct value-weighted quintile portfolios (from 1=low through 5= high advertising). Specifically, following standard finance practices of portfolio construction (Fama and French 1993; Hou and Robinson 2006), at the end of June of each year, we sort advertising intensity from low to high for all publicly traded firms. Then, we group stocks of firms sorted as the bottom 20% together and label this group as the low-advertising portfolio. On the same token, we classify stocks of firms ranked as the top 20% as the high-advertising portfolio. In this way, five portfolios are formed on the basis of low to high advertising intensity each year. Each advertising portfolio is held for 12 months and has monthly returns on the basis of the stocks in the specific portfolio. All advertising portfolios are rebalanced annually. That is, after holding the old portfolios for 12 months, we conduct a new cycle of sorting the advertising intensity data and create new quintile portfolios next June. In this way, the quintile advertising portfolios consist of stocks that are *different* year by year, depending on the relatively high or low advertising intensity among the entire publicly traded firms. In the dataset, we find that the quintile advertising portfolios are well diversified across industries. On average there are 205 stocks in each advertising portfolio (with minimum 203 and maximum 206 firms) that are randomly distributed across all industry sectors in the economy. In other words, the portfolio construction has also accounted for advertising differences across industries (business-to-business vs. business-to-consumer).

For each month and each advertising portfolio, we match the observed monthly advertising portfolio returns with the monthly RMF_t, SMB_t, HML_t, and UMD_t data. Thus, we have 228 monthly data points (over July 1987–June 2006). Then, we run the financial benchmark models with the Newly-West robust regression methods to correct possible serial correlation and heteroskedasticity biases (Fama and French 1993), when deriving results for the incremental value (return and risk) of the five advertising portfolios.

Results

As reported in Table 4 Panel D, the high-advertising portfolio has a positive and significant incremental return (a_{p0}=0.34% monthly, or 4.08% annually; $p<0.05$) over the twenty-year period. In contrast, return for low-advertising portfolio is not significant statistically ($p>0.05$), though positive. Regarding risk, results show that the high-advertising portfolio has an estimated systematic risk (b_{p1}=0.861) significantly less than 1.0, thus less risky than the financial benchmark. On the contrary, the low-advertising portfolio has an estimated systematic risk (b_{p1}=1.464) significantly greater than 1.0, thus more risky than the financial benchmark.

Collectively, these findings suggest that advertising goes hand in hand with firm value on the basis of the universe of stocks over 1987–2006, after accounting for diversifiable unsystematic risks (company or industry specific idiosyncrasies affecting stock prices) and non-diversifiable systematic risks (market changes, firm size, growth rates, and momentum effects). Our findings with a monthly incremental return of 0.34% are in line with the recent finance literature. For example, Chemmanur and Yan (2010b, p. 2) report that “1% increases in firm advertising intensity enables firms to gain 1.5%–3% increases in market valuation at the time of initial public offerings” (i.e., advertising could double firm value in a single day).

For more robustness checks, we reran the financial benchmark models with different time periods: five (1987–1992), ten (1987–1997), and 15 years (1987–2002). We report the results in Table 4 Panels A, B, and C, respectively. Again, results support higher returns and lower risk for the high-advertising portfolio across the time periods.

In addition, as reported below, our results are also robust to decile portfolios from 1 to 10=high advertising. Therefore, these results shore up more empirical evidence for incremental value of advertising in the long term.

Table 7 Decile advertising portfolios and firm value

20-year period 5-Year period 10-year period 15-year period

Portfolio		Alpha	RMF	Alpha	RMF	Alpha	RMF	Alpha	RMF
Low advertising	Estimates	0.0029	1.2263***	0.0000	1.0646***	0.0057	1.1575***	0.0059	1.1851***
	Standard Error	(0.0038)	(0.0974)	(0.0035)	(0.0760)	(0.0057)	(0.1453)	0.0045	(0.1118)
2	Estimates	0.0021	1.3635***	0.0045	1.0386***	0.0032	1.0498***	0.0065	1.2650***
	Standard Error	(0.0038)	(0.0956)	(0.0091)	(0.1952)	(0.0045)	(0.1162)	0.0047	(0.1153)
3	Estimates	0.0016	1.1304***	0.0000	1.1977***	0.0065	0.9638***	−0.0020	1.0932***
	Standard Error	(0.0033)	0.0834	(0.0072)	(0.1549)	(0.0043)	(0.1089)	(0.0041)	(0.1019)
4	Estimates	0.0003	1.3547***	−0.0085	1.1037***	−0.0013	1.0817***	0.0039	1.3262***
	Standard Error	(0.0031)	0.0781	(0.0063)	(0.1347)	(0.0040)	(0.1015)	(0.0043)	(0.1056)
5	Estimates	0.0064	1.1382***	0.0026	0.9330***	0.0065	1.1147***	0.0081	1.0470***
	Standard Error	(0.0041)	0.0782	(0.0040)	(0.0861)	(0.0046)	(0.0921)	(0.0051)	(0.0999)
6	Estimates	0.0013	1.3115***	−0.0015	1.0133***	0.0025	1.2812***	0.0027	1.2695***
	Standard Error	(0.0028)	0.0702	(0.0053)	(0.1130)	(0.0044)	(0.1138)	(0.0037)	(0.0913)
7	Estimates	−0.0001	1.2136***	0.0005	1.2938***	0.0039	0.9534***	0.0017	1.1223***
	Standard Error	(0.0027)	0.0674	(0.0071)	(0.1529)	(0.0038)*	(0.0978)	(0.0033)	(0.0807)
8	Estimates	0.0032	1.1576***	−0.0086	1.1042***	−0.0031	1.1261***	0.0012	1.1016***
	Standard Error	(0.0027)	0.0697	(0.0070)	(0.1497)	(0.0035)	(0.0903)	0.0035	(0.0870)
9	Estimates	0.0021	1.1642***	0.0069	0.9259***	0.0038	1.0378***	0.0024	1.606***
	Standard Error	(0.0022)	0.0549	(0.0037)	(0.0786)	(0.0022)	(0.0561)	(0.0027)	(0.0672)
High Advertising	Estimates	0.0041***	0.8555***	0.0170**	1.0644***	0.0060***	0.9304***	0.0062***	0.8453***
	Standard Error	(0.0014)	0.0356	(0.0083)	(0.1780)	(0.0016)	(0.0413)	(0.0019)	(0.0456)

Appendix F

Table 8 Additional results for advertising and firm value: mediating role of analyst-based processes

Firm Value with Stock Return	Model 7	Model 8	Firm Value with Stock Risk	Model 9	Model 10
Analyst Coverage	–	0.071***	Analyst Coverage	–	0.006***
Analyst earnings forecast	–	0.215***	Analyst earnings forecast	–	−0.003
Advertising spending	1.035***	0.287***	Advertising spending	−1.216***	−0.955***

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