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Product advertising and financial analyst forecasts

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A B S T R A C T

We examine whether product advertising provides value-relevant information that enables financial analysts to make better earnings and sales forecasts. Our analysis reveals that a firm's product advertising intensity is positively related to the informativeness and accuracy of analyst forecasts. A difference-in-differences test and an instrumental variable analysis identify the causal relationship. Additionally, the effect of advertising on analyst forecast quality is stronger when a firm has greater coverage from industry-expert analysts, exhibits more volatile operating performance, and holds newly registered trademarks. Overall, our evidence suggests that product advertising conveys valuable information that analysts can utilize to produce higher-quality forecasts for investors, highlighting the role of advertising in a firm's overall information environment.

1. Introduction

Product advertising activities (hereafter, "advertising" or "product advertising") are known to influence consumer behavior.[1] Marketing literature demonstrates that consumers utilize advertising information in their decision-making processes. For example, prior studies show that advertising can enhance consumer knowledge about products and brands, thereby facilitating more informed purchase decisions (e.g., Kanetkar et al., 1992; Abernethy and Franke, 1996; Erdem et al., 2008). While marketing studies have extensively explored the role of advertising in influencing consumer behavior, a notable gap remains in the accounting and finance literature regarding its relevance to capital markets. This paper aims to bridge this gap by exploring whether advertising contains value-relevant information that can improve analyst forecasts and, in turn, influence investor decisions.

This inquiry is particularly interesting in light of the debate on whether advertising contains value-relevant information for financial markets. Although some classical studies suggest that a firm's product advertising signals product quality and sales potential (Milgrom and Roberts 1986), others argue that most advertising does not provide substantive content that directly signals product quality (Nelson, 1970). Bertrand et al. (2010) argue that "advertisers also spend resources trying to persuade consumers with 'creative' content that does not appear to be informative." They also note that "firms spend billions of dollars developing advertising content, yet

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[1] Here, we note that throughout the paper, product advertising conceptually refers to "*real* advertising activities," rather than the advertising expenditure reported in the financial statement, although the latter is used to measure (i.e., as a proxy for) the former.

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there is little field evidence on how much or how it affects demand." However, this view has been challenged by some marketing studies on consumer behavior in certain industries (Erdem and Keane, 1996; Ackerberg, 2001; Song et al., 2016). These studies provide evidence that advertising indeed contains significant information content that influences consumer decisions. For example, Abernethy and Franke (1996) systematically analyze television advertisements and find that more than 80 % of them included at least one informational cue. These conflicting perspectives suggest that the information embedded in product advertising is likely to be complex and less straightforward to process. Furthermore, even if advertising contains valuable product-level information for consumers, aggregating this information at the firm level to predict a firm's future performance remains a challenging task, necessitating industry knowledge and financial expertise. Therefore, it remains unclear whether product advertising is a valuable information source for analysts and investors in their forecasts.

Prior studies and anecdotal evidence offer hints that product advertising conveys valuable information to analysts and benefits their forecast quality. Specifically, some anecdotes suggest that equity analysts, as financial experts, use firms' product advertising in forming or updating their forecasts or recommendations. For example, analysts at Goldman Sachs make use of the information in advertising when they forecast firms' future performance (Brandweek., 2010). Deutsche Bank analyst Jamie Isenwater believes that companies that continue to invest in marketing grow faster and that product advertising information is vital for analysts to appraise a firm's future growth and brand values (Jack, 2010). Interviews with 35 analysts, conducted by Luo and De Jong (2012), reveal that more than 93 % of the analysts pay attention to advertising positioning messages and look for information from product advertising. Consistent with these observations, Barth et al. (2001) find that analysts are more likely to follow firms with greater intangibles, such as product advertising, and expend greater effort to cover these firms. Collectively, these discussions imply that advertising is likely to contain value-relevant information appealing to analysts. Given that analysts have greater expertise in processing public information than unsophisticated investors (Asquith et al., 2005; Frankel et al., 2006), analysts should be able to utilize advertising to inform their predictions about future firm performance. Therefore, we conjecture that a firm's product advertising intensity should be *positively* related to the informativeness and accuracy of forecasts issued by analysts following this firm.

However, the relationship between product advertising and analyst forecast quality may be more nuanced. Some studies (Gu & Wang, 2005; Lev & Zarowin, 1999) conceptualize advertising as an intangible investment, positing that its prolonged impact on revenues increases the difficulty of using advertising to predict a firm's future performance. In addition, some studies argue that advertising decisions may involve strategic or self-serving considerations (Chemmanur and Yan, 2009; Lou, 2014; Cuny et al., 2023). For example, Lou (2014) empirically examines managers' opportunistic behavior in advertising decisions and finds a significant increase in advertising expenditures preceding insider sales, suggesting that managers may strategically change advertising to temporarily inflate stock prices. These studies imply that advertising, as a noisy signal, could obscure the true quality of a firm's products, worsen the information environment, and complicate the task for investors and analysts to predict firms' true prospects.[2] Taken together, the following research question remains open: Does advertising provide valuable information for analysts to make better forecasts, thereby aiding investors in their trading decisions?

To answer this research question, we primarily examine the effect of product advertising on analysts' *earnings* forecasts for the following reasons. First, earnings are the primary metric driving investors' trading decisions. Given its centrality to investment decisions, it is essential to understand how advertising impacts the earnings forecasts that analysts prepare for investors. Second, while advertising may directly influence sales, earnings capture the complex interplay between sales, expenses, and other factors related to accounting practices. Focusing on earnings forecasts provides a more complete picture of advertising's overall effect on a firm's financial performance. Third, earnings are more difficult to forecast, because they are inherently more susceptible to strategic incentives and are noisier than sales. For these reasons, it is interesting to examine whether advertising helps analysts navigate the complexities and produce high-quality earnings forecasts for investors where they are needed most.

Following prior studies (e.g., Francis & Soffer, 1997), we measure analysts' earnings forecast informativeness as the market reaction (CAR) to the dissemination of analysts' new earnings forecast (i.e., cumulative abnormal returns over the three-day window surrounding an analyst's forecast revision) and capture forecast accuracy using earnings forecast error (ERROR). We calculate these two measures using annual earnings forecasts that are issued *after* the fiscal period ends, ensuring that the forecasts are issued after the firm's product advertising activities in the fiscal year are completed and *before* the actual earnings announcement date. To supplement our main analyses on earnings forecasts, we also compute two similar measures based on sales forecasts. We use advertising expenditure during a fiscal year, deflated by the prior year's sales, to measure product advertising intensity for the year.

Using a sample of U.S. firms from 2001 to 2015, we first investigate how product advertising affects analyst forecast informativeness and accuracy by estimating firm fixed-effect regressions.[3] Our results indicate that the revisions of earnings forecasts elicit stronger investor reactions when a firm has greater product advertising activities, indicating a positive relationship between product advertising intensity and analyst forecast informativeness. These forecasts also become more accurate. We further test our main conjecture using *change specifications* and find that an increase in a firm's product advertising relative to the previous year is associated with both a stronger market reaction to earnings forecast revisions and a reduction in earnings forecast errors. In the supplement al analyses on sales forecasts, we find qualitatively unchanged results. Overall, these findings are consistent with our main conjecture

[2] Furthermore, a large body of literature shows that financial analysts do not efficiently process available public information, particularly information that is new (Elliot et al., 1995), complex (Abarbanell and Bushee, 1997; Chang et al., 2016), and intangible (Gu and Wang, 2005). For example, Altinkilic et al. (2013. p.2250) find that "announcements of analysts' forecast revisions release little new information, on average.".

[3] We use firm fixed-effect regression models for the following reasons. Intangible investments, including advertising, are correlated with firm-level time-invariant firm characteristics. Accordingly, the firm fixed-effect specification is advantageous to isolate the effects of omitted firm attributes.

that analysts can discover new information from product advertising to produce more informative and accurate forecasts.

We use a variety of tests to identify the causal relationship, including an instrumental-variable two-stage regression analysis and a difference-in-differences analysis that exploits an exogenous advertising shock in the pharmaceutical industry, i.e., the FDA's deregulation of direct-to-consumer (DTC) advertising in 1997. Our main finding also holds when subjected to robustness tests using alternative measures.

Next, we conduct cross-sectional analyses to shed light on the channels through which product advertising is conducive to higher-quality analyst forecasts. First, we conjecture that, to draw inferences from advertising, analysts should have a deep understanding of an industry's competitive dynamics and customer preferences. Consistent with this view, we find a more pronounced positive effect of advertising on analyst forecast quality when a firm is covered by a higher percentage of industry-expert analysts (Gilson et al., 2001). In addition, we posit that the information value of product advertising should be greater for analysts when a firm's performance is more difficult to predict or when a firm has a new trademark to promote. In line with this conjecture, we find that the positive effect of advertising intensity on analyst forecast quality is stronger in firms with more volatile performance and in firms with newly registered trademarks (Heath & Mace, 2020).

If the observed improvements in analyst forecast quality are indeed driven by analysts' ability to discover value-relevant information from advertising, then the positive relationship between advertising and analyst forecast quality should vary with the extent to which advertising is useful for analysts. To examine this, we conduct an event-based analysis on Regulation Fair Disclosure (Reg FD). We find that the positive effect is more pronounced in the post-Reg FD period than in the pre-Reg FD period, suggesting that Reg FD's prohibition of selective disclosure by management increased analysts' reliance on a public information source, i.e., advertising, in assessing firms' future performance.[4]

This paper contributes to the literature in several ways. The primary contribution is to the literature exploring the interaction between product markets and capital markets (e.g., Chemmanur and Yan, 2009; Jiang et al., 2024; Liang, 2024; Noh et al., 2025; Valta, 2012). A fundamental question in the accounting, finance, and marketing literature is: how do product markets influence capital markets? Our study sheds light on this question by investigating the informational role of product advertising in shaping analyst forecasts and, ultimately, influencing investor trading decisions, as evidenced by our CAR tests. In doing so, we extend the literature on the informative view of advertising (Boyd & Schonfeld, 1977; Chauvin & Hirschey, 1993; Cheong et al., 2021; Hyman et al., 2021; Fich et al., 2024) by revealing an important channel through which product advertising has an information spillover effect on capital markets and stock returns. To the best of our knowledge, our study is the first to show that, through the lens of analysts, product advertising provides value-relevant information that informs capital markets and investor trading decisions.

Second, our study adds to a long stream of literature (e.g., Clement, 1999; Frankel et al., 2006; Lee et al., 2013; Chang et al., 2016; Joos et al., 2016) that aims to understand whether and how financial analysts serve as effective information intermediaries. Although some studies provide evidence supporting analysts' information discovery role, this evidence is usually confined to periods preceding corporate information events (Ivkovic & Jegadeesh, 2004; Park & Stice, 2000). Additionally, some recent studies argue that "analysts' role in reducing information asymmetry may be overstated" (Li & You, 2015, p. 142) and present evidence that "analysts are not vital information agents" (Altınkılıç & Hansen, 2009; Altınkılıç et al., 2013, p. 254; Kim & Song, 2015). Given the ongoing debate in the literature regarding analysts' information-intermediary role, it is imperative to revisit this important issue. Unlike prior studies, our study contributes new evidence to this debate by demonstrating that analysts can provide higher-quality forecasts by deriving information from a soft, noisy, and intangible information source—product advertising.

Third, this study contributes to the literature on intangibles (e.g., Barth et al., 2001; Lev, 2019), which often treats advertising merely as part of intangibles and has not attempted to isolate its unique role from an informational perspective. Our study is one of the first efforts to distinguish advertising from other types of intangible investments in terms of their differential impact on analyst forecasts. While prior studies often identify a *negative* cross-sectional relationship between other intangible investments, such as R&D, and analyst forecast quality (e.g., Barron et al., 2002; Gu & Wang, 2005; Lev & Zarowin, 1999; Palmon & Yezegel, 2012), our study suggests that the quality of analyst forecasts *increases* with product advertising intensity.[5]

2. Hypotheses

Product advertising informs consumers about product quality and provides other cues that influence purchase decisions (Ackerberg, 2003; Nelson, 1974). Some studies on capital markets (e.g., Boyd & Schonfeld, 1977; Cheong et al., 2021) have adopted

[4] In untabulated ancillary tests, we also examine the impact of advertising on analysts' forecast optimism and stock recommendations. While we find no evidence that increases in advertising intensity lead to more optimistic earnings or sales forecasts, analysts appear more likely to upgrade stock recommendations as advertising intensity rises, particularly for high-volume stocks. This finding suggests that analysts may capitalize on advertising's attention-grabbing effect on retail investors to stimulate trading activity, complementing the findings of Madsen and Niessner (2019) and Liaukonytė and Žaldokas (2022).

[5] Several reasons may explain the different results. First, prior studies find that the high informational complexity of intangible investments increases the difficulty for analysts to assimilate information and predict the future performance of intangible-intensive firms. However, these studies typically consider advertising as a mere component of intangibles overlooking its unique informational and attention-grabbing roles. Second, intangible investments, including advertising, are often correlated with firm-specific characteristics, potentially leading to spurious results when analyzing the impact of advertising on analysts without accounting for firm heterogeneity. Unlike prior studies that rely on cross-sectional models (e.g., Barron et al., 2002; Gu & Wang, 2005), we use firm fixed-effect regression specifications to address the omitted variable bias.

this informative view and show that advertising, traditionally viewed as a tool for influencing consumer behavior, also provides useful information about firms' future performance.[6] Additionally, anecdotal evidence suggests that firm managers "do keep analysts and other commentators informed with top-line data on increases in media investment" to aid analysts' understanding of a firm's "overall marketing strategy and marketing activities" (Marketing Week, 2010). Overall, product advertising should be an important source of information for sophisticated market participants.

To interpret and extract useful information from advertising, a market participant must possess superior abilities and industry expertise. This is because the impact of advertising on a firm's future earnings is contingent upon various factors, such as the nature of products, the dynamics of industry competition, the appetites of customers in a particular industry, and the overall economic climate (Bruce et al., 2012; Darrat et al., 2016; Lodish et al. 1995; McAlister et al., 2016). Prior studies find that financial analysts have a superior ability "to interpret public information better than the market does" (Ivkovic & Jegadeesh, 2004). For example, Asquith et al. (2005), Frankel et al. (2006) and Joos et al. (2016) find that analysts are skilled at processing public information and can generate new knowledge for unsophisticated investors. In addition, other researchers find that analysts, especially those with industry expertise, provide more informative forecasts and help investors appraise the valuation implications of public information (Bradley et al., 2017; Gilson et al., 2001; Hong et al., 2000; Zhang, 2008). As such, we posit that financial analysts have the ability and industry expertise to derive useful information from product advertising and reduce disclosure processing costs (Blankespoor et al., 2020) for investors, leading to *more informative* earnings forecasts.

Additionally, to evaluate and interpret the soft information embedded in advertising (e.g., a firm's marketing strategy), analysts may engage in additional efforts to gain insights into the strategic value of a firm's advertising. Soltes (2014) argues that "softer information can be interpreted from in-person dialogue," and Brown et al. (2015) find that over half of analysts make extra efforts to communicate privately with management to glean qualitative insights. These two studies are consistent with anecdotal evidence that analysts have been calling for "greater detail about marketing in company reports" and trying to find answers to "the big questions, such as what is the company's approach to marketing overall" (Marketing Week, 2010). Given that analysts do expend greater effort to analyze high-advertising firms (Barth et al., 2001), it is a plausible conjecture that analysts privately communicate with the management of high-advertising firms to comprehend the marketing strategies underlying advertisement spending, leading to *more informative* forecasts.

On the other hand, product advertising may *not* be positively related to the informativeness of analysts' forecasts for several reasons. First, although product advertising contains value-relevant information, its noisy nature increases the complexity of using it to predict a firm's future performance. For example, some studies (e.g., Lou, 2014) suggest that managers may strategically, or even opportunistically, use advertising to draw investor attention and temporarily inflate stock prices. Therefore, these increases in advertising are less likely to be informative for analysts' forecasting purposes. Second, there is an ongoing debate about whether analysts have superior abilities to discover and interpret information. Altınkılıç and Hansen (2009) and Li and You (2015) provide evidence that analysts' research is "information free." Hansen (2015) concludes that analysts "are often assumed to be able to 'process public information' to discover unused information – there is little evidence showing that analysts have this knowhow." If advertising is too noisy and analysts lack the superior abilities to process it, then analyst forecast revisions might hold less value for investors, unlikely eliciting a significant stock market reaction. Accordingly, we test the following *non-directional* hypothesis:

Hypothesis 1. Product advertising intensity is *not* significantly related to the informativeness of analyst forecasts

Similarly, if advertising contains valuable information and financial analysts possess superior abilities and industry expertise to extract this information for their predictions, then advertising should help better align analyst forecasts with actual earnings or sales numbers, leading to more accurate forecasts. Additionally, Harford et al. (2019) find that analysts strategically allocate greater effort to high-volume stocks and stocks with greater institutional ownership, and this increased effort should translate to more accurate forecasts. To the extent that advertising can attract more institutional investors and generate larger trading volumes (Bobinski and Ramírez, 1994; Grullon et al., 2004), greater advertising should positively influence the effort analysts allocate to a firm and lead to *more accurate* analyst forecasts.

However, as noted above, the question of whether analysts possess superior information processing abilities remains a topic of ongoing debate. Additionally, it is difficult to use intangible investments to predict future firm performance. Barron et al. (2002) show that analyst forecast errors increase with the level of a firm's intangible investments, suggesting that analysts have difficulty processing intangible information. In a similar context, Gu and Wang (2005) argue that intangible investments, including technology-based intangibles, brand names, and recognized intangibles, entail high information complexity and therefore increase the difficulty of predicting firms' future operating performance. Furthermore, analysts sometimes have cognitive biases (Andersson and Hellman, 2007) or herd toward the consensus forecast in the presence of complex or incomplete information (Trueman, 1994; Welch, 2000). Given its intangible nature and complexity, advertising may not improve and could even deteriorate analyst forecast accuracy. We formulate these competing predictions as the following *non-directional* hypothesis.

Hypothesis 2. Product advertising intensity is *not* significantly related to the accuracy of analyst forecasts

[6] Although the findings are somewhat mixed, marketing literature (e.g., Peterson & Jeong, 2010; Joshi & Hanssens, 2010; Osinga et al., 2011; Srinivasan et al., 2009) that uses product-level data and focuses on a small number of industries generally finds that advertising has predictably positive effects on firm value and stock returns.

3. Variables and sample Construction

3.1. Measures of advertising intensity and analyst forecast quality

Following prior studies (e.g., Chemmanur & Yan, 2009), the intensity of advertising activities for fiscal year *t* is measured as advertising expenses during year *t*, deflated by the previous year's sales (AD_S = advertising_t /sales_{t-1}).

In this study, we focus on earnings forecasts of analysts, with additional analyses on sales forecasts to provide complementary insights. Following prior studies (e.g., Francis & Soffer, 1997), we measure analyst forecast informativeness as market-adjusted cumulative abnormal returns per unit of earnings forecast revision for the following reason: If investors are less able to interpret the information in advertising and therefore rely on analyst forecasts to make decisions, then investors should have significant market reactions to analysts' forecast revisions. We obtain market-adjusted cumulative abnormal returns (CAR) over the three-day (−1, +1) window around the analyst earnings forecast revision date. In line with previous studies (e.g., Bonner et al., 2007; Clement & Tse, 2003; Gleason & Lee, 2003; Kim & Song, 2015), the corresponding analyst earnings per share forecast revision (AFR) is measured as an analyst's last earnings per share forecast, issued after the fiscal year-end date but before the actual earnings announcement date, minus the analyst's second-to-last earnings per share forecast, scaled by the stock price a week before the preceding earnings forecast announcement date. We adopt this approach partly because this difference is more likely to capture how an analyst's new forecast surprises market participants.[7] Following prior studies (Hotchkiss and Strickland, 2003; Kasznik and McNichols, 2002; Sun, 2009), analyst earnings forecast error (ERROR) is defined as the absolute value of the average of analysts' last earnings forecasts issued after the fiscal year-end date but before the earnings announcement date, minus actual earnings, scaled by the firm's stock price at the beginning of the fiscal year. Similarly, we obtain market-adjusted cumulative abnormal returns (SCAR) over the three-day (−1, +1) window around the analyst sales forecast revision date. The corresponding analyst sales forecast revision (SAFR) and sales forecast error (SERROR) are defined in a similar manner based on analyst sales forecasts. Analyst sales forecast revision (SAFR) is measured as an analyst's last sales forecast, issued after the end date of fiscal year *t* but before the actual earnings announcement date, minus the analyst's second-to-last sales forecast, scaled by the firm's market capitalization at the beginning of fiscal year *t*. Following Mest and Plummer (2003), analyst sales forecast error (SERROR) is defined as the absolute value of the average of analysts' last sales forecasts issued after the end date of fiscal year *t* but before the earnings announcement date, minus actual sales, scaled by the firm's market capitalization at the beginning of the fiscal year *t*.[8]

3.2. Sample and descriptive statistics

We construct our initial sample of firm-year observations with analyst earnings or sales forecast data from the Institutional Brokers' Estimate System (I/B/E/S) database for the period from 2001 to 2015. The period begins in 2001 because analysts' information environment changed dramatically after Regulation FD in 2000 (e.g., Kross & Suk, 2012). Following Payne and Thomas (2003), we use I/B/E/S unadjusted files to avoid rounding errors in adjusted forecasts. We focus on annual earnings or sales forecasts rather than quarterly forecasts because advertising expense (XAD) is available only at an annual frequency in Compustat.

We collect other variables from various data sources. Analyst forecast horizon (HORIZON_E) and analysts' experience for certain firms (EXPERI_E) are obtained from I/B/E/S for earnings forecast regressions; corresponding variables (HORIZON_S and EXPERI_S) are calculated for sales forecast regressions. We also use earnings data from I/B/E/S to identify a loss firm-year (LOSS) and calculate earnings change (ΔEPS). Compustat data are used to compute log of market value of equity (FIRMSIZE), log of market to book ratio (LMB), R&D intensity (RD), and balance sheet intangible assets ratio (INTANG). We use CRSP data to measure total trading volume and stock returns. Institutional ownership data are retrieved from the Thomson Reuters Ownership database, and management earnings forecasts are obtained from the First Call's CIG (Company Issued Guideline) file. In the end, we estimate the abnormal return (CAR)

[7] We define an alternative earnings forecast revision measure (AFR_A) as the difference between an analyst's last earnings per share forecast, issued after the fiscal year-end date but before the actual earnings announcement date, and the *first* earnings per share forecast issued after the prior-year announcement date, scaled by the stock price a week before the preceding earnings forecast announcement date. For brevity, we do not tabulate this robustness test, but the results are available upon request. Consistent with the findings in Table 3, the coefficients on the interaction terms (e.g., AD_S*AFR_A) are significantly positive, confirming our baseline regression finding that analyst earnings forecast revisions elicit a greater stock market reaction when advertising intensity is higher.

[8] We construct the analyst forecast error measures at the firm-year level (analyst consensus) rather than at the individual analyst level for two reasons. First, our variable of interest, advertising intensity, is measured at the firm-year level, so it is appropriate to align the measurement of analyst forecast error at the same level. Second, as suggested by Kesavan et al. (2010, p. 1527), comparing individual analysts' forecast errors can introduce bias due to cross-sectional dependencies, which could "violate the independence assumption necessary for conducting *t*-tests" in OLS regressions. However, when using market-based event tests to examine the informativeness of analysts' forecasts, we rely on individual analysts' forecast revisions to identify the specific revision event dates.

regressions based on 25,856 analyst-year observations and the earnings forecast error (ERROR) regressions based on 11,814 firm-year observations. For the tests on sales forecasts, the sample consists of 23,054 analyst-year observations and 9,736 firm-year observations for the abnormal return (SCAR) and sales forecast error (SERROR) regressions, respectively.

Table 1 provides detailed definitions of the variables and presents the descriptive statistics.[9] The mean value of sales-deflated advertising intensity is 0.0308, indicating that firms spend, on average, 3.1 % of sales on advertising their products. The standard deviations suggest that advertising intensity and other firm characteristic variables vary significantly across firms and time. The cumulative abnormal returns around the earnings forecast revision date (CAR) is, on average, −0.0030, while the mean of corresponding earnings revisions (AFR) is −0.0009. The cumulative abnormal returns around the sales revision date (SCAR) is, on average, −0.0027, while the mean of corresponding sales forecast revisions (SAFR) is −0.0002. The mean values of analyst earnings forecast error (ERROR) and sales forecast error (SERROR) are 0.0087 and 0.0203, respectively. These statistics are generally in line with those reported in prior studies (e.g., Chemmanur & Yan, 2009; Choi et al., 2020; Chu & Zhai, 2021).

Table 2 presents the Pearson (below the diagonal) and Spearman (above the diagonal) correlations between the variables used in the study. Consistent with our conjecture, advertising intensity (AD_S) is significantly and negatively associated with earnings forecast error (ERROR) and sales forecast error (SERROR). Analyst earnings forecast revisions (AFR) and sales forecast revisions (SAFR) are positively correlated with stock market reactions, suggesting that investors respond significantly when analysts update their projections. Although the correlation coefficients appear to provide preliminary evidence that product advertising reduces analyst forecast error, it is important to estimate multivariate regressions to isolate the effects of firm characteristics and other unobservable time-invariant firm-level factors. In the next section, we address this issue using firm fixed-effect regressions and change specifications.

4. The effect of advertising on analyst forecast informativeness and accuracy

4.1. Baseline firm Fixed-Effect regressions and change specifications

4.1.1. The effect of product advertising on analysts forecast informativeness

To examine the effect of advertising on analyst forecast informativeness, we follow prior studies (e.g., Heflin et al., 2016) to estimate a firm fixed-effect regression model:

$$CAR_{ijt} = \beta_0 + \beta_1 AD\_S_{it} + \beta_2 AFR_{ijt} + \beta_3 AD\_S_{it} * AFR_{ijt} + X'\gamma + \lambda IMR_{it} + \eta_i + \nu_t + \varepsilon_{it}, \quad (1)$$

where the dependent variable, CAR, is the market-adjusted cumulative abnormal return over the three-day window around the analyst forecast revision (AFR) date, as defined in Section 3. CAR and AFR in Equation (1) are analyst-year variables. AD_S is a proxy for advertising activities during the year. Similar to prior studies (e.g., Francis & Soffer, 1997), we gauge analyst forecast informativeness based on the price impact of new information disseminated by financial analysts. To isolate the unobserved time-invariant firm-specific effects and macroeconomic year-fixed effects in our unbalanced panel data, we follow Gormley and Matsa (2014) and demean both dependent and independent variables by subtracting the firm-specific time-series mean of each variable (denoted as firm fixed effects, η_i, for notational convenience).[10] We include year fixed effects (ν_t) throughout the regression models. Following prior literature (e.g., Clement, 1999; Kross & Suk, 2012), we include a vector of time-varying covariates (X). Please refer to Table 1 for the detailed definitions of these control variables. Overall, we are particularly interested in the interaction term, AD_S* AFR, which captures how market response (CAR) per unit of analysts' forecasts revisions (AFR) is influenced by advertising intensity. If the informativeness of earnings forecast revision increases with advertising intensity (**Hypothesis 1**), the coefficient on AD_S* AFR (β_3) should be positive.[11]

We also use the following *change specification* to test whether the change in advertising intensity relative to the previous year is related to a stronger market reaction to forecast revision:

$$CAR_{ijt} = \beta_0 + \beta_1 \Delta AD\_S_{it} + \beta_2 AFR_{ijt} + \beta_3 \Delta AD\_S_{it} * AFR_{ijt} + \Delta X'\gamma + \lambda IMR_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (2)$$

[9] Table 1 presents the summary statistics for all the key independent and dependent variables. For brevity, we provide summary statistics for the control variables using the earnings forecast error (ERROR) regression sample, which comprises 11,814 firm-year observations. A similar approach is applied to the reporting of the variables used in the sales forecast regression. In addition, we also check into the summary statistics of change variables. We find that the mean value of the change in forecast error is close to zero, which is consistent with the expectation that forecast errors are equally distributed above or below zero. The standard deviation of ΔERROR is about 0.02, similar to those reported in prior studies (e.g., Hahn and Song, 2013).

[10] Because our firm fixed-effects model subsumes industry fixed effects, we do not include industry fixed effects.

[11] Before estimating the baseline regression, it is important to examine what the coefficients on advertising intensity (AD_S) and earnings forecast revisions (AFR) would look like if we remove the interaction term. To do this, we drop the interaction term from Eq. (1) and present the regression results in Table S1 of the Appendix. We find that the coefficients on AFR is positive and statistically significant. This finding aligns with our expectation, as greater upward revisions indicate that the new positive information released by analysts is more substantial and, thereby, should elicit a greater positive market reaction. In addition, we find that the coefficients on AD_S (advertising intensity) are statistically insignificant, consistent with the findings in Focke et al. (2020). This is probably because advertising intensity, while potentially informative about a firm's overall strategy and market presence, does not *directly* influence short-term market reactions to analysts' forecast revisions. In other words, although advertising may improve the overall informational environment and have a diffuse long-term impact on stock returns, this influence may not translate into immediate, discrete market reactions captured by CAR within the three-day window surrounding analyst forecast revisions.

Table 1
Descriptive Statistics.

Variable	N	Mean	STD	P25	Median	P75
CAR	25,856	−0.0030	0.0614	−0.0236	−0.0005	0.0233
AFR	25,856	−0.0009	0.0081	−0.0016	0.0004	0.0015
SCAR	23,054	−0.0027	0.0431	−0.0177	−0.0001	0.0157
SAFR	23,054	−0.0002	0.0090	−0.0021	0.0001	0.0020
ERROR	11,814	0.0087	0.0218	0.0008	0.0021	0.0062
SERROR	9,736	0.0203	0.0473	0.0018	0.0051	0.0156
AD_S	11,814	0.0308	0.0609	0.0059	0.0140	0.0334
HORIZON_E	11,814	20.4460	10.1875	13.0000	20.0000	27.0000
HORIZON_S	9,736	22.3127	11.9784	14.0000	20.5000	29.0000
EXPERI_E	11,814	6.4351	2.9700	4.0000	6.0000	8.0000
EXPERI_S	9,736	6.5718	3.2267	4.0000	6.0000	8.5000
LOSS	11,814	0.1377	0.3446	0.0000	0.0000	0.0000
ΔEPS	11,814	0.0433	1.1525	−0.2100	0.1100	0.3900
LMB	11,814	0.8448	0.7750	0.3348	0.7926	1.2931
FIRMSIZE	11,814	7.2909	1.7696	5.9960	7.1459	8.4705
RD	11,814	0.0363	0.0709	0.0000	0.0000	0.0475
INTANG	11,814	0.1884	0.2381	0.0138	0.0849	0.2902

This table presents summary statistics of the variables. The variable definitions are as follows. CAR = Cumulative abnormal return over the 3-day (−1, +1) window surrounding the analyst earnings forecast revision date. AFR = the analyst's last earnings per share (EPS) forecast, issued after the fiscal year-end date but before the actual earnings announcement date, minus the analyst's second-to-last EPS forecast issued, scaled by stock price a week before the preceding earnings forecast announcement date. SCAR = Cumulative abnormal return over the 3-day (−1, +1) window surrounding the analyst sales forecast revision date. SAFR = the analyst's last sales forecast, issued after the fiscal year-end date but before the actual earnings announcement date, minus the analyst's second-to-last sales forecast, scaled by the firm's market capitalization at the beginning of the fiscal year. ERROR = the absolute value of the average of analysts' last EPS forecasts issued after the fiscal year end date but before the earnings announcement date, minus actual EPS, scaled by stock price at the beginning of the fiscal year. SERROR = the absolute value of the average of analysts' last sales forecasts issued after the fiscal year end date but before the earnings announcement date, minus actual sales, scaled by the firm's market capitalization at the beginning of the fiscal year. AD_S = the advertising expense during the fiscal year, scaled by sales at the beginning of the fiscal year. HORIZON_E (HORIZON_S) = the number of days between analyst EPS (sales) forecast date and earnings announcement date. EXPERI_E (EXPERI_S) = the average number of years for which analysts have followed a given firm with EPS (sales) forecasts. LOSS = 1 if the year's actual EPS is negative and 0 otherwise. ΔEPS = the change in the actual EPS. LMB = the natural logarithm of the firm's market-to-book ratio at the beginning of the fiscal year. FIRMSIZE = the natural logarithm of the firm's market value of equity at the beginning of the fiscal year. RD = the R&D expense scaled by operating expense at the beginning of the fiscal year. INTANG = balance sheet intangible assets that include goodwill, scaled by total assets at the beginning of the fiscal year. All continuous variables are winsorized at the top and bottom 1 % level.

where Δ represents the change in a variable relative to the previous year. For example, ΔAD_S is the difference between AD_S in year t and AD_S in year t-1. We also use the changes in control variables to better isolate the effects of changes in confounding factors that are correlated with the change in advertising intensity. Industry fixed effects (μ_i) and year fixed effects (ν_t) are included. As in Equation (1), if our main argument holds true, then the coefficient on ΔAD_S*AFR (β_3) should be significantly positive.

In both specifications, we add the Inverse Mills Ratio (IMR) to address the potential self-selection bias arising from missing advertising expenses. Specifically, if advertising expenses are not material, some firms do not separately report advertising expenses in their 10-K filings (Heitzman et al., 2010) as it is not required by the SEC's Financial Reporting Release 44 (FRR 44) since 1994. These firms may include advertising spending as part of selling, general, and administrative (SG&A) expenses (i.e., XSGA in Compustat). To address this potential bias, we estimate a probit model with a binary dependent variable, ADD, which equals one if the firm has advertising data in Compustat for year *t*, and zero otherwise. The explanatory variables (measured in year *t*-1) in this probit model include marketing and sales-related expenditures ($MSSPEND_{t-1}$) in addition to all control variables in Equation (1). Following Dutta et al. (1999), we measure $MSSPEND_{t-1}$ as SG&A minus R&D expenses, scaled by total assets. Because $MSSPEND_{t-1}$ provides a benchmark for the materiality of advertising expenses, $MSSPEND_{t-1}$ is strongly associated with the likelihood of a firm separately reporting advertising in Compustat. After ensuring that $MSSPEND_{it-1}$ meets the exclusion restriction, we estimate the probit model and calculate the Inverse Mills Ratio (IMR) as the ratio of the probability density to the cumulative density function (Heckman, 1979). We include the IMR in both the firm fixed-effect regression and the change specification.

In the left panel of Table 3, column 1 presents the firm fixed-effect regression results based on Eq. (1). The coefficient on AD_S*AFR is significantly positive, consistent with our main argument that analyst earnings forecast revisions elicit a greater stock market reaction when advertising intensity is higher. This finding is also economically meaningful. The standard deviations of AD_S and AFR are 0.061 and 0.008, respectively. The coefficient on AD_S*AFR suggests that a one-standard-deviation increase (0.061) in AD_S is associated with a 11-basis-point increase in the 3-day cumulative abnormal returns (CAR) around analyst forecast revisions, assuming AFR is held constant at 0.008.[12] Given that the sample average market value of equity is around $1.76 billion, the 11 basis points can be

[12] Holding one variable constant while changing the other variable is a more appropriate approach to interpreting the interaction term. Assuming that AFR is held constant at 0.008, then a one-standard-deviation increase (0.06) in AD_S would result in a (0.061)*(β_1 + 0.008 * β_3) increase in CAR, which suggests a 0.0011 increase in CAR after plugging in the regression coefficients from column 1 of Table 3.

Table 2
Spearman (Pearson) Correlation Coefficients.

Panel A. Earnings Forecast	1	2	3	4	5	6	7	8	9	10	11	12
1.CAR		0.16***	0.02***	0.00	−0.00	0.01	0.01*	0.05***	−0.02***	−0.04***	0.00	−0.01**
2.AFR	0.13***		0.03***	0.00	−0.03***	−0.01	−0.13***	0.15***	0.10***	0.05***	−0.01	−0.02***
3.ERROR	0.01**	−0.11***		−0.09***	−0.03***	0.10***	0.16***	−0.03***	−0.22***	−0.23***	−0.00	−0.05***
4.AD_S	0.00	−0.01	−0.03***		0.02***	−0.13***	0.00	0.07***	0.10***	0.09***	0.04***	0.07***
5.HORIZON_E	−0.01	−0.02***	0.00	0.01**		−0.07***	−0.01	−0.02***	0.03***	−0.02***	0.01**	−0.00
6.EXPERI_E	−0.00	−0.01	0.03***	−0.08***	−0.07***		0.02***	0.07***	−0.14***	0.18***	−0.03***	0.03***
7.LOSS	0.02***	−0.17***	0.27***	0.08***	−0.01**	0.02***		−0.16***	−0.15***	−0.21***	−0.03***	−0.07***
8.ΔEPS	0.06***	0.18***	−0.15***	0.03***	−0.02***	0.04***	−0.19***		0.22***	0.21***	0.05***	0.03***
9.LMB	−0.01**	0.14***	−0.14***	0.04***	0.03***	−0.10***	−0.16***	0.20***		0.56***	0.09***	−0.02**
10.FIRMSIZE	−0.06***	0.12***	−0.23***	0.03***	−0.03***	0.18***	−0.25***	0.19***	0.56***		0.00	0.20***
11.RD	0.01**	0.01	−0.00	0.02***	0.02***	−0.03***	−0.02**	0.02**	0.08***	−0.02**		0.04***
12.INTANG	0.00	0.01	−0.04***	0.05***	−0.02***	0.07***	−0.05***	0.03***	−0.02***	0.21***	0.08***	

Panel B. Sales Forecast	1	2	3	4	5	6	7	8	9	10	11	12
1. SCAR		0.02***	0.03***	0.00	−0.00	0.02**	−0.00	0.00	−0.06***	−0.05***	0.03***	−0.00
2. SAFR	0.04***		0.04***	0.15***	0.01	−0.05***	−0.07***	0.30***	0.19***	0.15***	0.09***	0.10***
3. SERROR	0.02***	−0.00		−0.05***	0.02***	0.02**	0.03***	0.03**	−0.10***	−0.14***	0.01	−0.01
4. AD_S	−0.01	0.08***	−0.02**		0.03***	−0.08***	−0.00	0.08***	0.10***	0.06***	0.06***	0.06***
5. HORIZON_S	−0.00	0.02***	0.01***	0.03***		−0.04***	−0.00	−0.02***	0.02***	−0.02***	0.00	−0.00
6. EXPERI_S	0.02***	−0.03***	0.00	−0.04***	−0.05***		0.02***	0.08***	−0.14***	0.20***	−0.05***	0.04***
7. LOSS	−0.01	−0.08***	0.06***	0.06***	−0.01	0.03***		−0.16***	−0.12***	−0.17***	−0.03***	−0.05***
8. ΔEPS	0.01	0.19***	0.02**	0.05***	−0.02***	0.03***	−0.20***		0.24***	0.24***	0.06***	0.03***
9. LMB	−0.05***	0.16***	−0.04***	0.07***	0.01**	−0.10***	−0.13***	0.21***		0.53***	0.08***	−0.04***
10. FIRMSIZE	−0.04***	0.16***	−0.11***	0.05***	−0.03***	0.17***	−0.20***	0.21***	0.54***		0.01	0.19***
11. RD	−0.01	0.03***	−0.00	0.03***	0.02***	−0.05***	−0.01	0.03***	0.09***	−0.03**		0.06***
12. INTANG	0.01	0.11***	−0.02	0.08***	−0.00	0.05***	−0.03***	0.03***	−0.04***	0.21***	0.08***	

This table reports Spearman (Pearson) correlation coefficients between the variables above (below) the diagonal. Panel A and B show the correlation for the sample with earnings and sales forecasts, respectively. The variables are defined as in Table 1. ***, **, and * represent significance at the 1%, 5%, and 10% levels (two-sided), respectively.

Table 3

The Effect of Product Advertising on Analyst Forecast Quality: Forecast Informativeness and Accuracy.

Earnings Forecast Regressions	Level: AD_S		Change: ΔAD_S			Level: AD_S		Change: ΔAD_S	
	(1) CAR	(2) ERROR	(3) CAR	(4) ΔERROR		(5) SCAR	(6) SERROR	(7) SCAR	(8) ΔSERROR
AD_S (ΔAD_S)	−0.0377*	−0.0271***	−0.1345***	−0.0718**	AD_S (ΔAD_S)	−0.0391	−0.0568**	−0.1247***	−0.1376***
	(−1.86)	(−2.76)	(−4.27)	(−2.23)		(−1.16)	(−2.46)	(−4.09)	(−2.70)
AFR	0.0442***		0.1043***		SAFR	0.0102**		0.0221***	
	(3.97)		(8.93)			(2.07)		(5.03)	
AD_S (ΔAD_S)*AFR	6.9596***		3.7652**		AD_S (ΔAD_S)*SAFR	0.8567***		1.3614***	
	(3.42)		(1.99)			(5.27)		(4.01)	
HORIZON_E (ΔHORIZON_E)	−0.0001**	−0.0001	−0.0000	0.0000	HORIZON_S (ΔHORIZON_S)	−0.0000	0.0000	0.0002***	−0.0000
	(−2.12)	(−1.43)	(−0.97)	(0.31)		(−0.41)	(0.29)	(5.51)	(−0.71)
EXPERI_E (ΔEXPERI_E)	0.0001	0.0002	−0.0002*	0.0002	EXPERI_S (ΔEXPERI_S)	0.0005***	0.0000	−0.0004***	0.0004**
	(1.35)	(1.44)	(−1.74)	(1.29)		(4.17)	(0.26)	(−3.13)	(1.99)
LOSS (ΔLOSS)	0.0016	−0.0026**	0.0037**	0.0047***	LOSS (ΔLOSS)	−0.0012	0.0036***	0.0049***	0.0068**
	(1.45)	(−2.40)	(2.32)	(3.20)		(−1.01)	(3.69)	(2.91)	(2.47)
ΔEPS	0.0022***	0.0018***	−0.0002	0.0048***	ΔEPS	0.0005	0.0019***	−0.0003	0.0004
	(6.98)	(6.43)	(−0.94)	(19.32)		(1.56)	(5.13)	(−1.08)	(0.77)
LMB (ΔLMB)	−0.0001	−0.0003	0.0041***	0.0050***	LMB (ΔLMB)	−0.0047***	0.0021**	0.0004	0.0189***
	(−0.06)	(−0.28)	(2.79)	(3.74)		(−4.84)	(2.23)	(0.31)	(7.72)
FIRMSIZE (ΔFIRMSIZE)	−0.0121***	−0.0115***	−0.0042***	−0.0054***	FIRMSIZE (ΔFIRMSIZE)	−0.0058***	−0.0091***	−0.0022	−0.0139***
	(−13.21)	(−12.68)	(−2.77)	(−3.89)		(−6.05)	(−10.29)	(−1.42)	(−5.43)
RD (ΔRD)	0.0121	0.0120	−0.0114	0.0051*	RD (ΔRD)	−0.0061	0.0126	−0.0142*	0.0184***
	(0.58)	(0.59)	(−1.27)	(1.71)		(−0.55)	(0.74)	(−1.68)	(3.83)
INTANG (ΔINTANG)	0.0077**	0.0099***	−0.0000	−0.0234**	INTANG (ΔINTANG)	−0.0035	0.0062**	−0.0097***	−0.0296
	(2.34)	(3.03)	(−0.00)	(−2.05)		(−1.27)	(2.12)	(−3.57)	(−1.55)
IMR	−0.0017	−0.0047*	−0.0122***	0.0163***	IMR	−0.0017	0.0049*	−0.0055	0.0045
	(−0.52)	(−1.73)	(−2.79)	(3.81)		(−0.51)	(1.70)	(−1.28)	(0.56)
Year Fixed	Yes	Yes	Yes	Yes	*Year Fixed*	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	No	No	*Firm Fixed*	Yes	Yes	No	No
Industry Fixed	No	No	Yes	Yes	*Industry Fixed*	No	No	Yes	Yes
Constant	Yes	Yes	Yes	Yes	*Constant*	Yes	Yes	Yes	Yes
# of obs	25,856	11,814	21,270	9,410	*# of obs*	23,054	9,736	19,011	7,835
Adj. R^2	0.0254	0.1205	0.0459	0.0663	*Adj. R^2*	0.0363	0.1257	0.0520	0.0279

This table reports regression results of the effect of product advertising on analyst earnings and sales forecast quality: informativeness and accuracy. Columns 1 and 3 (5 and 7) present the regressions of earnings (sales) forecast informativeness. In these regressions of columns 1 and 3 (5 and 7), the dependent variable CAR (SCAR) is the cumulative abnormal return over the three-day (−1, +1) window surrounding the analyst earnings (sales) forecast revision date. For forecast accuracy tests in columns 2 and 4 (6 and 8), the dependent variable ERROR (SERROR) is the absolute value of median consensus earnings (sales) forecast minus actual earnings (sales), scaled by the stock price (the firm's market capitalization) at the beginning of the fiscal year. The explanatory variables are defined as in Table 1. *T*-statistics are in parentheses. ***, **, and * represent significance at the 1 %, 5 %, and 10 % levels (two-sided), respectively.

translated into a change of around $1.94 million in market value within a 3-day window. In addition, column 3 of Table 3 reports the change specification Eq. (2). Consistent with our main conjecture, the coefficient on ΔAD_S*AFR is significantly positive, suggesting that an increase in advertising intensity relative to the previous year is associated with greater market responses to analyst sales forecast revisions.

Turning to the tests on sales forecasts, we estimate a modified version of Eq. (1) by replacing AFR with SAFR and replacing CAR with SCAR. The right panel of Table 3 reports the results. Consistent with the findings from the earnings forecast regressions in left panel, the coefficients on AD_S*SAFR are significantly positive in columns 5 and 7, indicating that analyst sales forecast revisions also generate a stronger market response when advertising intensity is higher.

4.1.2. The effect of product advertising on analyst forecast accuracy

To assess the impact of advertising on analyst forecast accuracy, we estimate the following firm fixed-effect regression model:

$$ERROR_{it} = \beta_0 + \beta_1 AD\_S_{it} + X'\gamma + \lambda IMR_{it} + \eta_i + \nu_t + \varepsilon_{it} \tag{3}$$

where the dependent variable, ERROR, is the analyst earnings forecast error measure defined in Section 3. Additionally, we use the following *change specification* to test whether the change in advertising intensity relative to the previous year is related to an increase in analyst earnings forecast accuracy:

$$\Delta ERROR_{it} = \beta_0 + \beta_1 \Delta AD\_S_{it} + \Delta X'\gamma + \lambda IMR_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{4}$$

where ΔERROR is the difference between ERROR in year t and the corresponding value in year t-1. The independent variables of Eqs. (3) and (4) are largely the same as those in Eqs. (1) and (2), respectively; please refer to Section 4.1.1 for details. In these specifications, the variables of interest are advertising intensity (AD_S) and change in advertising intensity (ΔAD_S). If advertising leads to more accurate forecasts of a firm's future performance (**Hypothesis 2**), the coefficients of AD_S or ΔAD_S (i.e., β_1) should be significantly negative.

In the left panel of Table 3, column 2 presents the firm fixed-effect regression results based on Eq. (3), while column 4 presents the results for change specification based on Eq. (4). Consistent with our main conjecture, the coefficients on AD_S and ΔAD_S are significantly negative in these regressions, suggesting that analyst forecast accuracy increases with advertising intensity. These effects are also economically significant. For instance, the coefficient of AD_S in column 2 suggests that a one-standard-deviation increase in AD_S can reduce analyst forecast error by 0.00165, representing an 18.9 % decrease relative to the sample mean of 0.0087 for analyst earnings forecast error. The results on control variables are generally consistent with those in prior studies. For example, firm size (FIRMSIZE) is negatively related to forecast error, while balance-sheet intangible assets (INTANG) are positively related to forecast error. In the right panel of Table 3, columns 6 and 8 present the modified version of equations (3) and (4), respectively, where earnings forecast variables are replaced with sales forecast variables. We continue to find negative and statistically significant coefficients on AD_S in these regressions. Taken together, these findings from both panels are consistent with our main conjecture that analyst forecast quality increases with a firm's advertising intensity.

One may argue that this decreased forecast error may be driven by reduced analyst optimism, which is measured as the signed analyst forecast errors. To address this concern, we further examine the effect of advertising on forecast error in two subsamples: one with optimistic forecasts (which are greater than actual earnings) and the other consisting of pessimistic forecasts (which are smaller than actual earnings) only. Untabulated results indicate that our main finding holds in both subsamples, suggesting that the decreased forecast error is not solely driven by either decrease in analyst optimism or decrease in pessimism.

Additionally, we evaluate whether our main findings are robust to an alternative measure of advertising intensity (AD_X), defined as advertising expense scaled by operating expense. For brevity, we report these tests in Online Appendix Table S2. We find our main findings hold in both robustness checks.

4.2. Cross-Sectional analyses

So far, we have found a significant and positive effect of product advertising on analysts' forecast informativeness and accuracy in both the firm fixed-effect and change specifications. In this section, we examine potential mechanisms through which product advertising influences analyst forecast quality. Specifically, we use cross-sectional analyses to explore whether factors such as analyst industry expertise or certain firm characteristics moderate the effect of product advertising on analyst forecast quality.

First, as discussed in Section 2, the impact of advertising on a company's operating performance depends on certain industry-level factors (e.g., the nature of products and the appetites of customers within a specific industry). Thus, analysts with industry expertise are likely to make more accurate predictions of future sales and earnings based on advertising (Fairfield et al., 2009; Lodish et al. 1995). This is a reasonable conjecture, given that prior studies (e.g., Gilson et al., 2001) document the importance of analysts' industry expertise in using non-financial information and providing accurate forecasts based on the information. If industry expertise indeed enables analysts to make better predictions based on product advertising information, we should observe a more pronounced positive relationship between advertising and analyst forecast quality among firms followed by a greater percentage of industry-expert analysts.

To test this prediction, we construct an indicator variable, *AIE* (analyst industry expertise), that equals one if a firm's ratio of industry-expert analysts to total analysts following is above the median in a given year and zero otherwise. An analyst is identified as an industry expert if this analyst covers at least four firms within the same industry (Gilson et al., 2001). We use both firm fixed-effect and change models to test the prediction as follows:

$$CAR_{ijt} = \beta_0 + \beta_1 AD\_S_{it} + \beta_2 AFR_{ijt} + \beta_3 AD\_S_{it}*AFR_{ijt} + \Delta_4 AIE_{it} + \Delta_5 AIE_{it}*AD\_S_{it} + \Delta_6 AIE_{it}*AFR_{ijt} + \Delta_7 AIE_{it}*AD\_S_{it}*AFR_{ijt} + X'\gamma + \lambda IMR_{it} + \eta_i + \nu_t + \varepsilon_{it} \tag{5}$$

$$CAR_{ijt} = \beta_0 + \beta_1 \Delta AD\_S_{it} + \beta_2 AFR_{ijt} + \beta_3 \Delta AD\_S_{it}*AFR_{ijt} + \Delta_4 AIE_{it} + \Delta_5 AIE_{it}*\Delta AD\_S_{it} + \Delta_6 AIE_{it}*AFR_{ijt} + \Delta_7 AIE_{it}*\Delta AD\_S_{it}*AFR_{ijt} + \Delta X'\gamma + \lambda IMR_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{6}$$

$$ERROR_{it} = \beta_0 + \beta_1 AD\_S_{it} + \Delta_2 AIE_{it} + \Delta_3 AIE_{it}*AD\_S_{it} + X'\gamma + \lambda IMR_{it} + \eta_i + \nu_t + \varepsilon_{it} \tag{7}$$

$$\Delta ERROR_{it} = \beta_0 + \beta_1 \Delta AD\_S_{it} + \Delta_2 AIE_{it} + \Delta_3 AIE_{it}*\Delta AD\_S_{it} + \Delta X'\gamma + \lambda IMR_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{8}$$

These four regression models are revised versions of Equations (1) through (4), respectively, with the addition of the dummy variable AIE and its interaction terms with the key independent variables. In Equations (5) and (6), the variables of interest are the interaction terms AIE*AD_S*AFR and AIE*ΔAD_S*AFR, while the variables of interest in Equations (7) and (8) are AIE*AD_S and AIE*ΔAD_S. If our conjecture is correct, then the coefficients on the former two terms (the latter two terms) should be significantly positive (significantly negative).

In Panel A of Table 4, columns 1 and 3 indicate that the coefficients on AIE*AD_S*AFR and AIE*ΔAD_S*AFR are both significantly positive, confirming our prediction that industry expertise enables analysts to derive useful information from advertising and make more informative forecasts. In columns 2 and 4, the coefficients on AIE*AD_S and AIE*ΔAD_S are both significantly negative, suggesting that analysts' industry specialization enhances the effect of advertising on forecast accuracy. We also estimate modified versions of Equations (5) to (8) by replacing earnings forecast variables with sales forecast variables, and we report the results in columns 5 through 8 of Panel A. The findings from these regressions are qualitatively identical to those in columns 1 through 4, further supporting the argument that industry expertise is a mechanism that enables analysts to better evaluate product advertising information.

Second, we also argue that investors are less able to navigate the information environment in light of advertising and, therefore, rely more on analyst forecasts to make decisions. If analysts indeed possess superior abilities relative to investors, we should observe a more pronounced effect of advertising on forecast quality among firms where it is more difficult for investors to predict earnings and sales growth. To proxy for this difficulty, we code a dummy variable, *EVL*, that equals one if a firm is within the top quartile of earnings volatility (EVL) over the 5 years prior to the fiscal year-end, and zero otherwise. We use the same testing models as Eqs. (5) to (8), except replacing AIE with EVL. In Panel B of Table 4, columns 1 through 4 present the results. In line with our prediction, the coefficients on EVL*AD_S*AFR and EVL*ΔAD_S*AFR in columns 1 and 3 are significantly positive, while the coefficients on EVL*AD_S and EVL*ΔAD_S in columns 2 and 4 are significantly negative.

Additionally, the regressions using sales forecast variables and sales volatility (SVL) in columns 5 through 8 in Panel B, Table 4, show similar results. Overall, these findings further support the argument that analysts have superior abilities to process advertising information relative to investors. To further support this inference, we conduct an untabulated test and find that the effect of advertising on analyst forecast quality is more pronounced in firms with more unsophisticated investors (i.e., firms with lower institutional ownership).

Third, the predictability of advertising on future sales and earnings should be stronger in firms that have new products or trademarks, because these firms are more likely to adopt aggressive marketing strategies to establish a brand name (McAlister et al., 2016). Additionally, the information effect of advertising should be particularly strong when consumers have never tried a new brand (Ackerberg, 2001). Therefore, product advertising and its related information (e.g., underlying marketing strategies) should be particularly informative for predicting future operating performance for these firms. Accordingly, we expect that advertising should have a more pronounced effect on the informativeness and accuracy of their forecasts in firms with new products. To test this conjecture, we first use the data provided by Heath and Mace (2020) to identify whether a firm registers new trademarks in a given year. Then, we set an indicator variable, *NTM*, to one if a firm registers at least one new trademark during the year, and zero otherwise. We apply the same regression models as in Equations (5) to (8), except replacing AIE with NTM. Consistent with our conjecture, Panel C of Table 4 indicate that the coefficients on NTM*AD_S*AFR and NTM*ΔAD_S*AFR in columns 1 and 3 are significantly positive, while the coefficient on NTM*AD_S in column 2 is significantly negative. The results from the sales forecast regressions in columns 5 through 8 echo these findings. Overall, these findings provide further support for the argument that product advertising contains useful information that helps analysts make more informative and accurate predictions.

Lastly, we conduct several additional cross-sectional analyses. To save space, we report these tests in the Online Appendix and focus on the level specifications. First, the voluntary disclosure of managers should diminish the information value of advertising for analysts. If our information-based argument is correct, then the effect of advertising on analyst forecast quality should be attenuated in firms with management forecasts. We collect management earnings forecasts (MFs) from First Call for a sample period from 2001 to 2011. Consistent with this prediction, Panel A of Appendix Table S3 shows that management forecasts moderate the positive effects of advertising on both earnings and sales forecast quality of analysts. Second, when a firm's product quality cannot be straightforwardly assessed, analysts as industry experts and information intermediaries should have greater informational advantages than unsophisticated investors in using advertising to predict future earnings and sales. We measure a firm's product quality using an indicator variable, DPQ, that equals one if a firm is in industries where product quality is more difficult to evaluate (e.g., pharmaceutical, chemistry, and financial industries), and zero otherwise. The findings reported in Appendix Table S3, Panels B, are consistent with our

Table 4
Potential Channel Analysis.

Panel A: The Effect of Analyst Industry Expertise (AIE)

	Earnings Forecast Regressions					Sales Forecast Regressions			
	Level: AD_S		Change: ΔAD_S			Level: AD_S		Change: ΔAD_S	
	(1) CAR	(2) ERROR	(3) CAR	(4) ΔERROR		(5) SCAR	(6) SERROR	(7) SCAR	(8) ΔSERROR
AD_S (ΔAD_S)	−0.0328	−0.0197*	−0.0205	−0.0303	AD_S (ΔAD_S)	0.2387***	−0.0477**	−0.0400	−0.0652
	(−0.97)	(−1.90)	(−0.56)	(−0.79)		(3.63)	(−2.02)	(−0.92)	(−1.04)
AFR	0.0010**		0.1172***		SAFR	0.0228***		0.0189***	
	(2.34)		(8.56)			(2.68)		(4.05)	
AD_S (ΔAD_S)*AFR	0.5128**		−0.1642		AD_S (ΔAD_S)*SAFR	−0.4825*		−0.0799	
	(2.20)		(−0.21)			(−1.74)		(−0.15)	
AIE	−0.0005	0.0009	0.0054***	−0.0014	AIE	−0.0040***	−0.0009	0.0044***	0.0009
	(−0.61)	(1.2)	(4.67)	(−1.22)		(−4.88)	(−0.51)	(3.11)	(0.54)
AIE*AD_S (ΔAD_S)	−0.0036	−0.1544**	−0.4233***	−0.1933**	AIE*AD_S (ΔAD_S)	−0.3688***	−0.1977*	−0.3075**	−0.2044**
	(−0.09)	(−2.27)	(−6.18)	(−2.00)		(−4.88)	(−1.85)	(−2.52)	(−2.00)
AIE*AFR	−0.0127***		−0.0410		AIE*SAFR	−0.0192*		−0.0450***	
	(−2.90)		(−1.61)			(−1.86)		(−2.93)	
AIE*AD_S (ΔAD_S)*AFR	3.2641***		5.0174**		AIE*AD_S (ΔAD_S)*SAFR	2.0422***		3.0076***	
	(5.80)		(1.99)			(5.98)		(2.84)	
Controls	Yes	Yes	Yes	Yes	Controls	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	*Year Fixed*	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	No	No	*Firm Fixed*	Yes	Yes	No	No
Industry Fixed	No	No	Yes	Yes	*Industry Fixed*	No	No	Yes	Yes
Constant	Yes	Yes	Yes	Yes	*Constant*	Yes	Yes	Yes	Yes
# of obs	25,856	11,814	21,270	9,410	*# of obs*	23,054	9,736	19,011	7,835
Adj. R^2	0.0258	0.1208	0.0474	0.0667	*Adj.* R^2	0.0397	0.1259	0.0550	0.0282

Panel B: The Effect of Earnings and Sales Volatility (EVL and SVL)

	Earnings Forecast Regressions					Sales Forecast Regressions			
	Level: AD_S		Change: ΔAD_S			Level: AD_S		Change: ΔAD_S	
	(1) CAR	(2) ERROR	(3) CAR	(4) ΔERROR		(5) SCAR	(6) SERROR	(7) SCAR	(8) ΔSERROR
AD_S (ΔAD_S)	−0.0618*	−0.0147	−0.1909***	−0.0159	AD_S (ΔAD_S)	0.0297	−0.0030	−0.0538	−0.0287
	(−1.91)	(−1.20)	(−4.83)	(−0.36)		(0.68)	(−0.10)	(−1.07)	(−0.47)
AFR	0.0571***		0.0719***		SAFR	0.0144**		0.0165***	
	(4.47)		(5.33)			(2.39)		(3.09)	
AD_S (ΔAD_S)*AFR	1.6030		−1.2324		AD_S (ΔAD_S)*SAFR	0.1869		−0.1545	
	(1.54)		(−1.49)			(0.89)		(−0.28)	
EVL	0.0043***	0.0030***	0.0030***	−0.0015	SVL	0.0002	−0.0001	−0.0052***	−0.0011
	(4.90)	(5.89)	(2.65)	(−1.41)		(0.26)	(−0.06)	(−4.70)	(−0.56)
EVL*AD_S (ΔAD_S)	0.0438	−0.0658**	0.1618**	−0.1679**	SVL*AD_S (ΔAD_S)	−0.1618**	−0.1104**	−0.1807***	−0.2211**
	(0.90)	(−2.04)	(2.43)	(−2.00)		(−2.41)	(−2.42)	(−2.59)	(−2.16)
EVL*AFR	−0.0980***		0.1392***		SVL*SAFR	−0.0061		0.0138	
	(−4.34)		(4.98)			(−0.59)		(1.47)	
EVL*AD_S (ΔAD_S)*AFR	3.5497**		4.0152**		SVL*AD_S (ΔAD_S)*SAFR	1.6573***		3.2788***	
	(1.98)		(2.02)			(4.96)		(4.18)	
Controls	Yes	Yes	Yes	Yes	Controls	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	*Year Fixed*	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	No	No	*Firm Fixed*	Yes	Yes	No	No

(*continued on next page*)

Table 4 (*continued*)

Panel B: The Effect of Earnings and Sales Volatility (EVL and SVL)

	Earnings Forecast Regressions					Sales Forecast Regressions			
	Level: AD_S		Change: ΔAD_S			Level: AD_S		Change: ΔAD_S	
	(1) CAR	(2) ERROR	(3) CAR	(4) ΔERROR		(5) SCAR	(6) SERROR	(7) SCAR	(8) ΔSERROR
Industry Fixed	No	No	Yes	Yes	*Industry Fixed*	No	No	Yes	Yes
Constant	Yes	Yes	Yes	Yes	*Constant*	Yes	Yes	Yes	Yes
# of obs	24,815	10,980	20,588	8,656	*# of obs*	22,640	9,362	18,657	7,497
Adj. R^2	0.0293	0.1214	0.0464	0.0687	*Adj.* R^2	0.0375	0.1249	0.0541	0.0253

Panel C: The Effect of New Trademark (NTM)

	Earnings Forecast Regressions								
	Level: AD_S		Change: ΔAD_S			Level: AD_S		Change: ΔAD_S	
	(1) CAR	(2) ERROR	(3) CAR	(4) ΔERROR		(5) SCAR	(6) SERROR	(7) SCAR	(8) ΔSERROR
AD_S (ΔAD_S)	−0.0551**	−0.0022	−0.1640***	−0.0450	AD_S (ΔAD_S)	−0.0884*	0.0202	−0.0849*	0.2276
	(−2.15)	(−0.14)	(−3.89)	(−0.72)		(−1.95)	(0.40)	(−1.88)	(1.51)
AFR	0.0578***		0.1135***		SAFR	0.0229***		0.0166***	
	(4.30)		(7.81)			(3.62)		(3.01)	
AD_S (ΔAD_S)*AFR	1.3201		−0.5229		AD_S (ΔAD_S)*SAFR	0.4224*		−0.0031	
	(1.61)		(−0.66)			(1.89)		(−0.01)	
NTM	−0.0025***	0.0009**	0.0005	−0.0003	NTM	−0.0006	−0.0002	0.0003	0.0011
	(−3.54)	(2.17)	(0.56)	(−0.31)		(−0.85)	(−0.31)	(0.28)	(0.52)
NTM*AD_S (ΔAD_S)	0.0487	−0.0535**	0.0293	−0.0372	NTM*AD_S (ΔAD_S)	0.1016	−0.0969*	−0.1612**	−0.4097***
	(0.88)	(−2.13)	(0.48)	(−0.50)		(1.54)	(−1.73)	(−2.27)	(−2.58)
NTM*AFR	−0.0370*		−0.0358		NTM*SAFR	−0.0311***		0.0155*	
	(−1.91)		(−1.64)			(−3.16)		(1.70)	
NTM*AD_S (ΔAD_S)*AFR	4.6018**		4.2665**		NTM*AD_S (ΔAD_S)*SAFR	0.9717***		2.8211***	
	(2.26)		(2.00)			(2.97)		(3.57)	
Controls	Yes	Yes	Yes	Yes	Controls	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	*Year Fixed*	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	No	No	*Firm Fixed*	Yes	Yes	No	No
Industry Fixed	No	No	Yes	Yes	*Industry Fixed*	No	No	Yes	Yes
Constant	Yes	Yes	Yes	Yes	*Constant*	Yes	Yes	Yes	Yes
# of obs	25,856	11,814	21,270	9,410	*# of obs*	23,054	9,736	19,011	7,835
Adj. R^2	0.0259	0.1210	0.0446	0.0682	*Adj.* R^2	0.0368	0.1258	0.0528	0.0279

This table reports regression results of the impacts of analyst industry expertise (Table S), sales volatility (Table B), and new trademark (Table C) on the relationship between product advertising and analyst forecast quality. In Panel A, AIE is an indicator variable of analyst industry expertise, which equals one if a firm's ratio of industry-specialist analysts to total analysts following is above the sample median, and zero otherwise, where financial analysts are defined as industry specialists if they cover at least four firms within the same industry (Gilson et al., 2001). In Panel B, EVL (SVL) is an indicator variable of high earnings (sales) volatility that equals one if a firm is within the top quartile of earnings (sales) volatility, EVOL (SVOL) over 5 years prior to the fiscal year end, and zero otherwise. In Panel C, NTM is an indicator variable of new trademark that equals one if a firm registers at least one new trademark (Heath & Mace, 2020). Other variables are defined as in Table 1. *T*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels (two-sided), respectively.

prediction.

4.3. Identification strategies

4.3.1. Instrumental variable approach

In this section, we employ instrumental variable (IV) regressions to further address potential biases arising from omitted variables in our analysis. While firm fixed effects in our main regression models should have mitigated the concerns of time-invariant omitted variable bias, there are remaining concerns about time-variant omitted variables that may confound the relationship between advertising intensity and analyst forecast quality. These potential time-variant omitted variables, such as changes in consumer preferences for a firm's product over time, could introduce bias into our estimates, thereby undermining the validity of our findings. Instrumental variable (IV) regression could address this concern by leveraging exogenous variation in advertising intensity that is unrelated to these time-variant omitted variables. Therefore, we further address the omitted-variable concern by employing an instrumental variable approach that utilizes a two-step generalized method of moments (GMM) estimation. We estimate the following first-stage regression model to obtain fitted values of advertising intensity:

$$AD\_S_t = f(INDAD_{t-1}, COMPETITION_{t-1}, \text{Controls in the second-stage regressions}) \quad (9)$$

For brevity, Eq. (9) omits the firm and analyst subscripts. We employ two instruments that are expected to be closely related to advertising but not directly affect analyst forecast quality. The first instrument, $INDAD_{t-1}$, is the industry average of advertising intensity in the previous year. The rationale for this instrument is that firms are likely to increase their advertising activities if their competitors within the same industry invest more in marketing. A similar approach is used by Lev and Sougiannis (1996), who use the industry average of R&D intensity in the previous year as the instrument in their first-stage regression of firm-level R&D intensity. Similarly, the executive compensation literature (e.g., Kini & Williams, 2012; Shen & Zhang, 2018) often uses industry averages of compensation variables as exogenous instruments for firm-level compensation variables. The second instrument, $COMPETITION_{t-1}$, is Hoberg et al.'s (2014) product market fluidity measure in the previous year, which is constructed using business descriptions in firms' 10-Ks and captures the competitive threats faced by a firm in its product market. This measure is a relevant instrument because firms often respond to increased competition by ramping up advertising efforts (Xu et al., 2011).[13] To establish the validity of instrumental variables, we confirm that both instruments are significantly (p-value < 0.01) correlated with AD_S, but not significantly (p-value $>$ 0.1) correlated with either the cumulative abnormal return (CAR) or analyst forecast error (ERROR). Furthermore, the weak-instrument test statistic (F-statistics) is 27.23 in the first-stage regression, suggesting that the instruments are not weak. Hansen's J-statistic for overidentifying restrictions is not rejected (p-value = 0.50), further ensuring that the exclusion criterion is satisfied and suggesting that the instruments are exogenous.

In the second stage, we revise the baseline models, Equations (1) and (2), using the fitted values of advertising intensity obtained from the first-stage regressions. Table 5 presents the key independent variables from the second-stage regressions.[14] Columns 1 and 3 show that the interaction terms between the fitted values and analyst forecast revision (AFR) are significantly positive, while columns 2 and 4 indicate that the coefficients on the fitted advertising variables are both negative and statistically significant. We also conduct the instrument variable analyses for sales forecast regressions and find qualitatively similar results. Overall, the results in Table 5 echo our main findings in Table 3 and provide causal evidence to support our main argument.

4.3.2. Exogenous shock on product advertising

To further identify the causal effect of advertising on analyst forecast informativeness and accuracy, we exploit a quasi-natural experiment involving an exogenous deregulation shock to product advertising in the pharmaceutical industry. In 1997, the Food and Drug Administration (FDA) relaxed its regulations on direct-to-consumer (DTC) advertising by pharmaceutical companies, leading to a three-fold growth of DTC advertising expenditure (Iizuka & Jin, 2001).[15] If product advertising contains relevant information about future earnings and analysts are able to process such information, the quality of analysts' forecasts for pharmaceutical firms should improve in response to the FDA's deregulation.

Using the Fama and French (1997) 48-industry classification, we identify pharmaceutical firms (SIC 2830–2836) from 1995 to1998 (two years before and two years after the deregulation). We then construct an indicator variable, PHARMA, which takes the value of one for pharmaceutical firms (i.e., treatment group) and zero for propensity score-matched control firms from other industries (control group) in the Compustat universe. To identify matched firms, we first estimate a logit regression using the PHARMA indicator as the dependent variable, with independent matching variables including performance (LOSS and ΔEPS), market-to-book ratio (LMB), firm size (FIRMSIZE), R&D (RD), and intangible assets ratio (INTANG). Based on the nearest propensity scores, we match each treatment

[13] In the first-stage regression of the change specification, we use the changes in INDAD and COMPETITION as instruments and include the other change-based control variables from the second-stage regression of the change specifications as control variables. In this regression, we find that the weak-instrument test statistics (F-statistics) is 23.71, indicating that these instruments are relevant and significant. Hansen's J-statistic on over-identifying restrictions is not rejected (p-values = 0.46), further supporting the validity of the instruments used.

[14] To save space, we do not tabulate the first-stage regression results and do not report the coefficients on control variables in the second-stage regression. The results are available upon request.

[15] DTC advertising is a form of pharmaceutical product advertising toward patients, rather than healthcare professionals, which includes advertising through TV, print, radio, and other mass media.

Table 5
Instrumental Variable Approach.

	Earnings Forecast Regressions					Sales Forecast Regressions			
	Level: AD_S		Change: ΔAD_S			Level: AD_S		Change: ΔAD_S	
	(1) CAR	(2) ERROR	(3) CAR	(4) ΔERROR		(5) SCAR	(6) SERROR	(7) SCAR	(8) ΔSERROR
FITAD_S (ΔFITAD_S)	0.0041	−0.0197***	−0.0123***	−0.0579***	FITAD_S (ΔFITAD_S)	0.0328***	−0.0480***	−0.0118***	−0.1031**
	(1.37)	(−2.71)	(−3.49)	(−3.85)		(2.62)	(−4.24)	(−3.59)	(−1.97)
AFR	0.0384***		0.1039***		SAFR	0.0315***		0.0209***	
	(3.22)		(6.10)			(7.19)		(3.35)	
FITAD_S (ΔFITAD_S)*AFR	0.1951**		0.2589**		FITAD_S (ΔFITAD_S)*SAFR	0.2168**		0.1399***	
	(1.99)		(2.21)			(2.47)		(3.10)	
Controls	Yes	Yes	Yes	Yes	Controls	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	*Year Fixed*	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	No	No	*Firm Fixed*	Yes	Yes	No	No
Industry Fixed	No	No	Yes	Yes	*Industry Fixed*	No	No	Yes	Yes
Constant	Yes	Yes	Yes	Yes	*Constant*	Yes	Yes	Yes	Yes
# of obs	21,365	9,246	19,242	8,271	*# of obs*	20,959	8,299	18,711	7,089
Adj. R^2	0.0269	0.1402	0.0418	0.0642	*Adj. R^2*	0.0441	0.1268	0.0562	0.0279

This table reports the second-stage regression results of the instrumental-variable analyses. The sample includes firm-year observations over the period from 2001 to 2015. FITAD_S is the fitted value of AD_S obtained from the first-stage regression explained in Section 4.3.2, while ΔFITAD_S is the fitted value of ΔAD_S obtained from an analogous first-stage change specification discussed in the footnote in Section 4.3.2. Other explanatory variables are defined as in Table 1. *T*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels (two-sided), respectively.

Table 6
Differences-In-Differences Regressions with an Exogenous Shock on Product Advertising.

	Earnings Forecast Regressions					Sales Forecast Regressions			
	CAR		ERROR			SCAR		SERROR	
	(1) POST1	(2) POST2	(3) POST1	(4) POST2		(5) POST1	(6) POST2	(7) POST1	(8) POST2
AFR	0.0348	0.0662			SAFR	0.0683**	0.0653*		
	(0.37)	(1.14)				(2.22)	(1.83)		
PHARMA*AFR	−0.4646	−0.2435			PHARMA*SAFR	−0.5453	−0.4123		
	(−0.63)	(−0.38)				(−1.63)	(−1.04)		
POST *AFR	0.2942***	0.0724			POST *SAFR	−0.1432***	−0.2501***		
	(2.69)	(0.87)				(−2.94)	(−6.30)		
POST*PHARMA*AFR	2.6266**	2.3959**			POST*PHARMA*SAFR	1.3571**	1.1021**		
	(2.02)	(2.03)				(1.99)	(2.07)		
PHARMA	−0.0039	0.0013	−0.0016	−0.0010	PHARMA	0.0207	0.0004	0.0552***	0.0463***
	(−0.35)	(0.17)	(−0.68)	(−0.51)		(0.75)	(0.01)	(4.48)	(4.94)
POST	0.0037	0.0005	0.0015	0.0014	POST	0.0013	0.0269***	−0.0033	−0.0035
	(0.93)	(0.17)	(0.75)	(0.72)		(0.17)	(3.52)	(−0.55)	(−1.11)
POST*PHARMA	−0.0124	−0.0063	−0.0086***	−0.0075**	POST*PHARMA	0.0120	−0.0342	−0.0418***	−0.0423***
	(−0.82)	(−0.55)	(−2.65)	(−2.32)		(0.33)	(−1.00)	(−2.64)	(−3.60)
Controls	Yes	Yes	Yes	Yes	Controls	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes	*Constant*	Yes	Yes	Yes	Yes
# of obs	836	1,664	356	702	*# of obs*	436	882	260	524
Adj. R^2	0.0247	0.0277	0.0754	0.0511	*Adj.* R^2	0.0298	0.0326	0.0687	0.0460

This table reports the difference-in-differences regressions. We exploit the 1997 Food and Drug Administration's (FDA) deregulation on direct-to-consumer (DTC) advertising. PHARMA takes the value of one for pharmaceutical firms (i.e., treatment group) and zero for the propensity score-matched control firms in other industries (control group). POST1 takes the value of one for fiscal year 1997 and zero for 1996, while POST2 equals one for fiscal years 1997–1998 and zero for 1995–1996. Other explanatory variables are defined as in Table 1. T-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels (two-sided), respectively.

firm (PHARMA = 1) with a matched control firm (PHARMA = 0). This process yields 178 treatment and propensity score-matched control firms (i.e., 89 matched pairs) that have the requisite variables.

We then examine whether advertising indeed increased in response to the deregulation. As expected, advertising intensity (AD_S) of pharmaceutical firms increased *from* 0.065 in 1995 and 0.070 in 1996 *to* 0.091 in 1997 and 0.099 in 1998. These increases are statistically significant at the 1 % level. In contrast, the PSM-matched firms did not experience a similar increase in advertising over the same period.

Using one-year and two-year window samples that include both the treatment group (pharmaceutical firms) and control group, we estimate the following difference-in-differences regressions:

$$CAR_{ijt} = \gamma_0 + \gamma_1\ PHARMA_i + \gamma_2 POST_t + \gamma_3 AFR_{ijt} + \gamma_4 PHARMA_i{*}AFR_{ijt} + \gamma_5 POST_t\ {*}AFR_{ijt} + \gamma_6 POST_t{*}PHARMA_i + \gamma_7 POST_t{*}PHARMA_i{*}AFR_{ijt} + \sum \gamma_k Controls + \varepsilon_{ijt} \tag{10a}$$

$$ERROR_{it} = \beta_0 + \beta_1 PHARMA_i + \beta_2 POST_t + \beta_3 POST_t{*}PHARMA_i + \sum\beta_k Controls + \varepsilon_{it}, \tag{10b}$$

where we use two POST indicators. POST1 (1-year window) takes the value of one for fiscal year 1997 and zero for 1996, while POST2 (2-year window) equals one for fiscal years 1997–1998 and zero for 1995–1996. If advertising has a positive causal effect on forecast informativeness, we expect the coefficient (γ_7) on the interaction term, POST*PHARMA*AFR, in Equation (10a) to be positive. The coefficient (β_3) on the interaction term, POST*PHARMA, in Equation (10b) captures the difference-in-differences estimates of analyst forecast accuracy between the treatment and control firms across the two periods surrounding the positive exogenous shock to pharmaceutical product advertising. According to our prediction, β_3 should be negative.

Table 6 presents the results. Consistent with our conjecture, the coefficient (γ_7) on the interaction term is significantly positive for both POST1*PHARMA*AFR and POST2*PHARMA*AFR, suggesting that pharmaceutical firms experienced a significant improvement in earnings forecast informativeness after the deregulation compared to the control firms. In columns 3 and 4, the coefficients on POST1*PHARMA and POST2*PHARMA are both negative and significant, indicating that the exogenous increase in product advertising of pharmaceutical firms led to significant decreases in analyst forecast error. We also estimate a modified version of the difference-in-differences regressions by replacing earnings forecast variables with sales forecast variables. The results reported in columns 5 through 8 further confirm that the advertising deregulation event led to improved quality of sales forecasts for pharmaceutical firms relative to control firms. Overall, these results substantiate our findings in Tables 3 to 5 and help identify a causal effect.

Table 7

The Effect of Regulation Fair Disclosure on the Relation between Advertising and Analyst Sales Forecast Quality.

	Earnings Forecast Regressions					Sales Forecast Regressions			
	Level: AD_S		Change: ΔAD_S			Level: AD_S		Change: ΔAD_S	
	(1) CAR	(2) ERROR	(3) CAR	(4) ΔERROR		(5) SCAR	(6) SERROR	(7) SCAR	(8) ΔSERROR
AD_S (ΔAD_S)	−0.0484***	−0.0025	−0.4441***	0.0366	AD_S (ΔAD_S)	−0.2223***	−0.0228***	0.0070	0.0432
	(−3.58)	(−1.30)	(−4.10)	(0.64)		(−2.58)	(−3.49)	(0.07)	(0.31)
AFR	−0.0356		0.0553		SAFR	−0.0244**		0.0422***	
	(−0.98)		(0.53)			(−2.19)		(4.06)	
AD_S (ΔAD_S) *AFR	−0.0189**		−1.8258*		AD_S (ΔAD_S) *SAFR	−1.6333**		−2.3271***	
	(−2.42)		(−1.85)			(−2.51)		(−3.51)	
FD	0.0043*	0.0063***	−0.0085	0.0063	FD	−0.0185***	−0.0070	−0.0182***	0.1348***
	(1.78)	(5.51)	(−1.64)	(1.30)		(−4.00)	(−0.15)	(−2.95)	(4.93)
FD*AD_S (ΔAD_S)	0.0148	−0.0264***	0.2855***	−0.1207*	FD*AD_S (ΔAD_S)	0.2389***	−0.0412*	0.0116	−0.1933
	(0.40)	(−2.81)	(2.79)	(−1.77)		(2.67)	(−1.70)	(0.12)	(−1.30)
FD*AFR	0.0390		0.0570		FD*SAFR	0.0261**		−0.0081	
	(1.06)		(0.55)			(2.34)		(−0.77)	
FD*AD_S (ΔAD_S) *AFR	4.6481***		8.5711***		FD*AD_S (ΔAD_S)*SAFR	1.6844***		1.9687***	
	(2.82)		(3.46)			(2.58)		(2.91)	
Controls	Yes	Yes	Yes	Yes	Controls	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	*Year Fixed*	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	No	No	*Firm Fixed*	Yes	Yes	No	No
Industry Fixed	No	No	Yes	Yes	*Industry Fixed*	No	No	Yes	Yes
Constant	Yes	Yes	Yes	Yes	*Constant*	Yes	Yes	Yes	Yes
# of obs	30,014	14,834	26,133	11,327	*# of obs*	27,245	11,905	24,364	8,252
Adj. R^2	0.0153	0.1085	0.0244	0.0710	*Adj.* R^2	0.0121	0.1614	0.0363	0.0325

This table reports regression results on the impacts of Regulation Fair Disclosure on the relationship between product advertising and analyst earnings and sales forecast quality. FD is an indicator variable that equals one if the fiscal year starts after 2000 and zero if it starts before 2000. Other variables are defined as in Table 1. *T*-statistics are in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels (two-sided), respectively.

4.4. Regulation FD as a shock to analysts' information environment

In this section, we exploit another regulation shock—Regulation FD (hereafter, Reg FD). This regulation, effective since October 23, 2000, dramatically changed analysts' information environment because it prohibits the selective disclosure of material information by management to analysts. Prior literature reports a decrease in the frequency of private disclosures (Francis et al., 2006) and an increase in analysts' reliance on firms' public disclosures (e.g., Heflin et al., 2016; Kross & Suk, 2012) after Reg FD. Given that analysts are no longer allowed to privately communicate with management for material information, including revenue-related proprietary information, in the post-Reg FD period, we expect analysts to have a greater incentive to collect and analyze public information (e.g., product advertising). Thus, we predict a stronger effect of advertising on analyst forecast quality in the post-Reg FD period.

To test this conjecture, we examine an *extended* sample period that includes both the post-Reg FD (2001–2015) and pre-Reg FD (1995–1999) years. The pre-Reg FD period begins in 1995 because of the regulatory change regarding the disclosure of advertising expenditures in 1994 (FRR 44). We exclude the transition year 2000. We then create an indicator variable, FD, which equals one if a fiscal year starts after 2000 and zero if a fiscal year starts before 2000. We estimate revised Eqs. (5) to (8) after replacing AIE with FD and report the results in columns 1 through 4 in Table 7. Consistent with our prediction, the coefficients on the interaction terms, FD*AD_S*AFR and FD*ΔAD_S*AFR, are significantly positive in the forecast informativeness regressions, while the coefficients on FD*AD_S and FD*ΔAD_S are both negative and statistically significant in the forecast error regressions. We also re-run the analyses using sales forecast variables and report the results in the last four columns of Table 7, finding slightly weaker but qualitatively similar results. Overall, these findings lend credence to the information-based argument that advertising, as an information source, enables analysts to make better forecasts when Reg FD causes a negative shock to their information environment.

5. Summary and Concluding Remarks

Using both the firm fixed-effect and change specifications, this paper examines how product advertising affects the quality of sell-side equity analysts' earnings and sales forecasts. We provide evidence that advertising leads to more informative and accurate analyst forecasts. This main finding is robust in several identification tests, including instrumental variable regressions and a difference-in-differences analysis related to the FDA's deregulation of pharmaceutical direct-to-consumer advertising in 1997. Additional tests indicate that the positive effect of advertising on analyst forecast quality is more pronounced in firms followed by more industry-expert analysts, firms with more volatile performance, and firms that register new trademarks.

This study extends the growing literature that examines the flow of information from the product market to the capital market (e.g., Chemmanur & Yan, 2009; Peress, 2010) by linking product advertising to the quality of financial analysts' forecasts. Our findings highlight the informational role of product advertising in improving analyst forecast quality and ultimately influencing investor trading decisions. By uncovering a mechanism through which product market dynamics influence stock market efficiency, our study adds novel evidence addressing a fundamental, interdisciplinary question: how do product markets influence capital markets? Additionally, we address the ongoing debate regarding the effectiveness of financial analysts as information intermediaries, showing that analysts appear to possess superior abilities to extract meaningful insights from product advertising, a typically complex and noisy information source. Lastly, our findings underscore that, unlike other intangible investments such as R&D (Gu & Wang, 2005), product advertising provides value-relevant information that analysts can process and use to improve the quality of their forecasts. Our findings are relevant to both academics and practitioners interested in the implications of product market activities on capital market outcomes.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jaccpubpol.2025.107306.

Data availability

The authors do not have permission to share data.

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